World Electric Vehicle Journal

Article

From Technology Follower to Global Leader: The Evolution of China's New Energy Vehicle Innovation Ecosystem Through Patent Cooperation Networks

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Abstract

This study employs an industry-specific patent classification methodology (ISPCM) and conducts complex network analysis across temporal, industrial, and spatial dimensions to examine China's new energy vehicle (NEV) patent collaboration network and to uncover the mechanisms underlying China's global rise in the NEV sector. The results demonstrate the effectiveness of the ISPCM and reveal a three-phase growth pattern that is driven by policy initiatives and market expansion. Domestic entities dominate the patent landscape, with a noticeable shift from invention patents to utility model patents, which reflects a focus on application-oriented innovation. The collaboration network exhibits a heavy-tailed characteristic, and it forms an oligopolistic structure in which state-owned enterprises (SOEs) act as "innovation orchestrators," while private firms concentrate on specialized R&D. Across the industrial chain, the component segment forms the largest network, the complete vehicle segment comprises the smallest network, and the aftermarket is clustered around battery recycling. A clear divide between domestic and foreign entities suggests potential decoupling risks. The findings reveal a dual-circulation innovation model that combines state-led coordinated research with market-driven independent research, offering valuable insights for sustainable industrial transformation.

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

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Academic Editor: Joeri Van Mierlo

Received: 11 October 2025
Revised: 17 November 2025
Accepted: 24 November 2025
Published: 26 November 2025

Citation: Lyu, X.; Yao, Y.; Wang, J.; Li, H.; Huang, Z.; Jiang, M.; Wu, Q. From Technology Follower to Global Leader: The Evolution of China's New Energy Vehicle Innovation Ecosystem Through Patent Cooperation Networks. *World Electr. Veh. J.* **2025**, *16*, 646. https://doi.org/10.3390/wevj16120646

1. Introduction

Since the initiation of China's "863 Program" in 2001, which focused on electric vehicles, the country has embarked on more than two decades of NEV R&D, evolving from being a technological follower to being a global leader. In 2023, China's NEV sales reached 9.49 million units, representing more than 60% of global sales (approximately 15 million units), significantly exceeding sales in Europe (approximately 3 million) and the United States (approximately 1.4 million). In 2023, the NEV penetration rate in China surpassed 35%, outpacing that in the European Union (approximately 20%) and the United States (7%). Moreover, in 2023, China exported 1.77 million NEVs, representing a 67% year-on-year increase and establishing China as the world's largest NEV exporter, with key markets in Southeast Asia, Europe, and Latin America. These achievements raise a critical question:

what explains the rapid rise of China's NEV industry? This study investigates this question through the lens of patent innovation.

As core embodiments of technological innovation, patents offer valuable insights into industrial dynamics, making patent data analysis a crucial methodology in NEV research. However, the vast volume of patents, coupled with complex technical descriptions and specialized terminology, poses significant challenges to traditional classification methods in terms of both efficiency and accuracy [1]. Furthermore, the NEV industry encompasses multiple layers of the industrial chain: upstream components, midstream complete vehicles, and downstream aftermarket services. For instance, the upstream component layer includes batteries, motors, electronic controls, intelligent connected systems, body systems, power systems, chassis systems, universal components, and environmental perception systems, among others. The battery subcategory alone contains further subdivisions, such as battery packs, cells, battery structural components, and battery management systems. Constructing a precise and hierarchically structured classification framework for such a complex and multilayered industry remains a challenge. Although pretrained language models such as BERT have improved in the area of general patent classification, their performance in the specialized NEV domain is still limited, and the risk of model hallucinations remains a significant concern [2–5].

To overcome these challenges, this study introduces an industry-specific patent classification methodology (ISPCM) that integrates expert knowledge with large language models (LLMs). Specifically, we first construct a multilayer classification system—an NEV industry knowledge graph—and design rule-based matching patterns to identify patents across industry segments. These patterns are incorporated into LLM prompts. This approach becomes further enhanced by the reasoning and question-answering capabilities of LLMs, improving classification efficiency while reducing the risk of hallucinations.

In parallel, complex network theory provides powerful tools for analyzing relationships and dynamics in large-scale systems [6,7]. We combine this framework with the ISPCM to examine the evolution of China's NEV patent collaboration network across temporal, industrial, and spatial dimensions, uncovering the mechanisms underlying the country's global leadership [8].

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

2. Literature Review

In recent years, technology identification and patent analysis in the NEV industry have attracted significant attention in both academic and industrial circles. Existing studies have explored various perspectives, including technological trajectories, cooperation networks, and evolutionary dynamics [13,14].

Yuan et al. [13] reported a gradual recovery in fuel cell electric vehicle (FCEV) technologies that has been occurring since 2014. The United States, Japan, Germany, China, and South Korea remain core contributors, although the sources of FCEV innovation are undergoing restructuring. Leading firms, particularly major automakers and component suppliers, play pivotal roles in advancing hydrogen fuel cell technologies. Liu et al. [14] reported that electric vehicle charging technologies are concentrated in areas such as line arrangement, batteries, safety devices, and charging stations. However, large institutions exhibit weak collaborations, and competition is focused on traction power, line arrangement, system control, and charging stations.

Complex network theory has proven highly effective for analyzing international cooperation patterns and synergistic effects, which often occur through the construction of multidimensional patent collaboration networks [15–17]. For example, 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 patent networks in the Yangtze River Delta at the national and regional levels, highlighting distinct cooperation patterns across regions. Hu et al. [20] applied social network analysis to reveal the core–periphery structure and regional disparities in China's charging station patent collaborations. Chen et al. [21] integrated the S-curve model using social network analysis and time series methods and identified the development phases for electric vehicle (EV) technologies and sustainable directions. Their findings suggest that EV technologies have reached saturation both globally and in South Korea, with South 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 is likely to evolve toward electrification, intelligence, lighter weights, and sustainability. However, their study was limited by overly generalized predictions, and it may lack actionable insights for national or corporate technology roadmaps.

In summary, while existing research has made significant progress in analyzing the new energy vehicle innovation network using patent data, it still suffers from two core limitations.

First, at the data level, a heavy reliance on IPC codes or keyword searches for patent identification leads to insufficient accuracy in cross-disciplinary fields such as NEVs, making it difficult to support fine-grained industrial chain analysis.

Second, from an analytical perspective, most studies either focus on macrolevel trend descriptions or are confined to static analyses of network topology, lacking an integrated framework that combines temporal evolution, the industrial chain structure, and the dynamics of collaboration networks.

This study aims to address these challenges by introducing the ISPCM to construct a more accurate CNEVIP dataset. Building on this foundation, we systematically characterize the evolutionary trajectory and structural mechanisms of China's NEV patent collaboration network across temporal, industrial, and actor dimensions, providing new analytical perspectives and empirical evidence for understanding China's rapid rise in this field. We highlight how our study, which focuses on the structural collaboration network, provides a complementary perspective to technology-focused approaches (e.g., energy scheduling in smart grids [23] and IoT perception [24]). Doing so enriches the overall understanding of the NEV innovation ecosystem.

3. Materials and Methods

3.1. Research Framework

As shown in Figure 1, this study adopts a four-stage analytical framework.

Stage 1—Construction of the NEV patent dataset: All the patent data were obtained from the China National Intellectual Property Administration (CNIPA), which provides comprehensive datasets that are widely used in innovation and technology studies [25]. The data were stored and managed in the HDFS of the Cloudera big data platform [26]. To identify NEV-related patents, the ISPCM was developed by integrating an NEV industry knowledge graph with the Qwen LLM [27], which enabled hierarchical multilabel classification across the NEV industrial chain, thereby constructing the China new energy vehicle industry patent (CNEVIP) dataset in Elasticsearch [28].

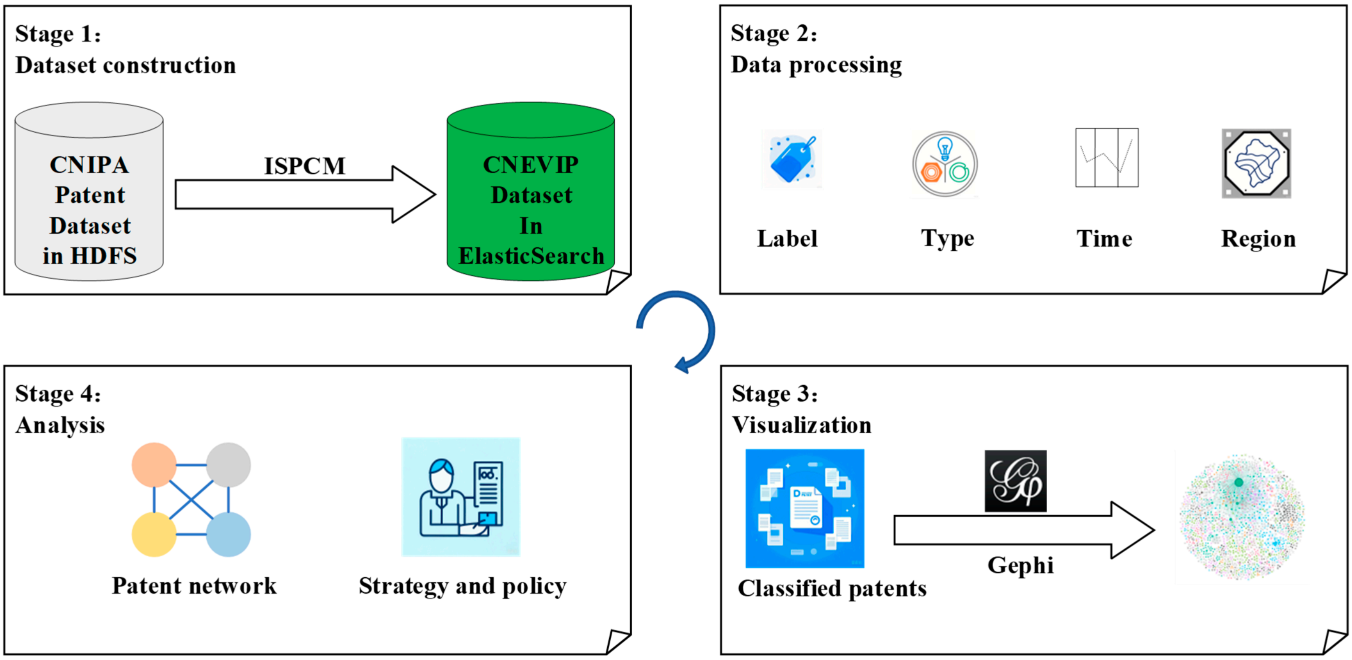


Figure 1. Research framework.

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

Stage 3—Extraction of relational data and the construction of patent collaboration networks: Collaborative patents were defined as those with two or more applicants and were further categorized as domestic or foreign. Gephi (version: 0.10.1 202301172018) was used to construct undirected collaboration networks on the basis of these extracted relationships.

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

3.2. Dataset Constructed Using the ISPCM

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, these methods fail to fully capture newly emerging NEV technologies and tend to yield numerous irrelevant matches. To overcome these limitations, this study employs the ISPCM, which combines a domain-specific knowledge graph with LLMs. Following a comparison of multiple open-source models, including Baichuan [29], ChatGLM [30], ChatGPT [31], and Qwen [27], Qwen was selected as the base model because of its classification performance and cost effectiveness.

The NEV knowledge graph comprises seven hierarchical layers, as shown in Table 1. Owing to its large scale, the full graph is not included in this paper but is available on Gitee at https://gitee.com/LyuXiaozhong/NEV (accessed on 9 November 2025). The ISPCM model (using Qwen-14b-chat with default parameters after three-step training) was parallelized on a server (manufacturer: SITONHOLY (Tianjin) Technology Co., Ltd., Tianjin, China) equipped with eight NVIDIA A40 GPUs to efficiently extract and classify NEV-related patents from the CNIPA dataset, which resulted in the construction of the CNEVIP dataset. Comprehensive details regarding the ISPCM are provided in our granted patent (patent number: CN118798188B) [32]. All patents can be categorized across the various layers of China's NEV industrial chain. Since this method supports multilabel classification, a single patent can be assigned multiple labels. Compared with conventional IPC- or keyword-based filtering approaches, the ISPCM significantly reduces noise and improves accuracy, thereby providing a more robust foundation for subsequent network analysis.

Table 1. The label counts per layer in the NEV knowledge graph.

Layer	Label Counts
1	1
2	3
3	21
4	96
5	134
6	127
7	51
total	433

All patents can be categorized across the various layers of China's NEV industrial chain. Since this method supports multilabel classification, a single patent can be assigned multiple labels. Compared with conventional IPC- or keyword-based filtering approaches, the ISPCM significantly reduces noise and improves accuracy, thereby providing a more robust foundation for subsequent network analysis. A set of 700 samples was independently labeled by three experts. By employing a majority rule, a classification was deemed correct if it was agreed upon by at least two experts. The final results show that the ISPCM achieved an accuracy of 92%, while that of the traditional method reached 61%.

3.3. Data Processing

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

Complex network analysis, which is a graph-theoretical tool that is widely used to study complex systems, was employed to characterize the relationships and collaboration patterns in the network [33]. Network metrics, such as degree centrality and betweenness centrality, were used to identify the key applicants, while topological properties, including small-world characteristics and community structures, were used to reveal the distribution of innovation resources and collaboration patterns. This approach also facilitated the analysis of network evolution and technology diffusion and offered potential guidance for innovation policy and corporate strategy. To systematically characterize the NEV patent collaboration network, we conducted structural, centrality, and cohesion analyses as follows.

3.4. Network Structural Analysis

Network density (D) measures the overall connectivity among nodes and reflects the intensity of node interactions. A higher network density indicates more frequent interactions, leading to faster and more efficient knowledge dissemination [34]. Network density is defined as the ratio of the actual number of edges to the maximum possible number of edges in the network and has a range of [0, 1]. Higher values indicate tighter connections between nodes.

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

The average degree (K) describes the average number of connections per node and reflects the overall connectivity of 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 N is the number of nodes in Formulas (1) and (2).

The network diameter (R) indicates the expansiveness of the network and is a measure of the shortest path between any pair of nodes. It is used to analyze information propagation efficiency and network scale.

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

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

The average clustering coefficient (C) describes the average level of local connectivity among nodes, reflecting the modularity and community structure of the network [35]. It is the mean of the clustering coefficients of all nodes, where the clustering coefficient of a node measures the connectivity among its neighbors.

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

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.

The average path length (L) is the mean shortest distance between any two nodes in the network and is used to evaluate the overall efficiency of the network. Shorter path lengths generally indicate higher efficiency [36].

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

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

3.5. Network Centrality Analysis

Centrality reflects the importance of a node within the network [37,38]. 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 that a node has to other nodes.

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

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.

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

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) is 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.

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

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 [39]. A node is considered important if it is connected to other important nodes.

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

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 of A.

3.6. Network Cohesion Analysis

Network cohesion is generally measured through network density, the average path length, and cohesiveness [40]. A higher network density implies tighter connections between nodes, enhancing the network's overall influence on individual nodes. Cohesion 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 formation of subgraphs is influenced by collaboration types, regional preferences, and technological biases, reflecting certain connection preferences and clique phenomena.

4. Results

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

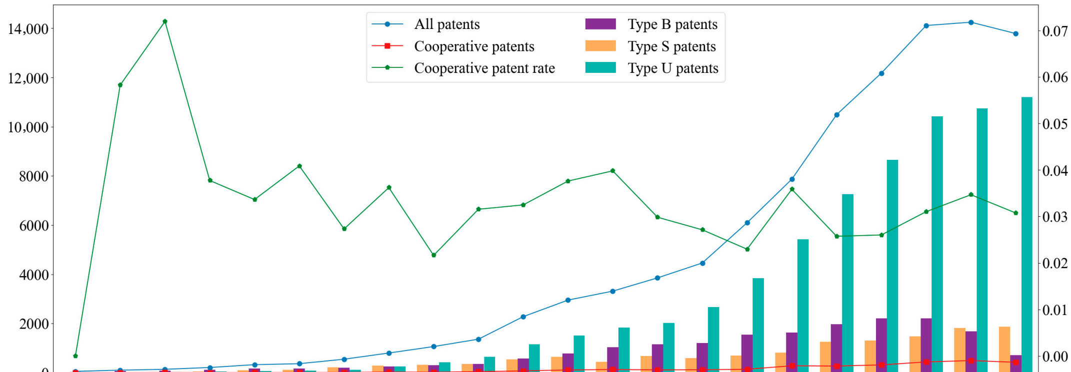
4.1. Patent Temporal Analysis

4.1.1. Overview of Patent Data

Using the ISPCM, we extracted 188,989 NEV-related patents that had been filed and granted in China between 1985 and 2022 from the CNIPA dataset. Since China officially entered the NEV R&D phase in 2001 and the average patent authorization time is approximately 2.9 years [17], this study focuses on patents filed between 2001 and 2022 to ensure completeness and analytical validity. Furthermore, the ISPCM results were manually validated by domain experts. We collaborated with specialists from the Office of the Leading Group for Building the New Energy Vehicle Industry Cluster in Anhui Province to verify the classification outcomes, thereby enhancing the factual accuracy of the patent categorization.

4.1.2. Overall Temporal Evolution

As shown in Figure 2, a total of 100,614 authorized NEV patents were identified, including 3078 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 show a sustained upward trajectory. The number of NEV patents in China that were retrieved through conventional IPC and keyword-based methods reached 13,000 in 2012 and 7.058 million in 2022 [18]; in comparison, the ISPCM method proposed in this study was used to identify 2951 and 13,786 relevant patents, respectively. This substantial reduction in patent counts and the increased focus on relevant results demonstrate that the use of the ISPCM effectively excludes unrelated patents, thereby enhancing the reliability and accuracy of the findings.



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
All	55	103	139	212	327	367	549	801	1063	1363	2278
Type B	40	63	83	121	169	172	211	262	308	357	582
Type S	8	21	30	48	95	115	213	281	331	352	542
Type U	7	19	26	43	63	80	125	258	424	654	1154
Co. patents	0	6	10	8	11	15	15	29	23	43	74
Co. rate(%)	0.00	5.83	7.19	3.77	3.36	4.09	2.73	3.62	2.16	3.15	3.25

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
All	2951	3316	3854	4460	6096	7867	10,489	12,179	14,113	14,246	13,786
Type B	785	1038	1152	1206	1552	1637	1964	2207	2212	1687	709
Type S	646	450	682	591	701	809	1262	1317	1478	1817	1872
Type U	1520	1828	2020	2663	3843	5421	7263	8655	10,423	10,742	11,205
Co. patents	111	132	115	121	140	282	270	317	438	494	424
Co. rate(%)	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 the Chinese NEV industry. The first column lists the different patent types analyzed: 'All' represents the total number of authorized NEV patents, 'Co. Patents and Co. Rate (%)' indicates the number and rate of authorized patents with multiple applicants, followed by counts for authorized invention (Type B), design (Type S), and utility model (Type U) patents.

The temporal evolution of patents can be divided into three periods on the basis of development indicators and product life cycle theory [41]:

Initial Development Period (2001–2008): Annual authorizations remained below 1000 during this period, which reflects an exploratory phase with limited patenting activity. Invention patents accounted for a relatively high proportion, which indicates a focus on fundamental research and core technological breakthroughs.

Rapid Growth Period (2009–2017): Annual authorizations rose sharply to the range of 1000–10,000. This phase commenced shortly after two key industry events: BYD's launch of a mass-produced NEV in December 2008 and the initiation of the "Ten Cities, Thousand Vehicles" demonstration program in 2009. During this period, the proportion of utility model patents increased markedly and consistently exceeded the volume of invention patents, indicating a shift in the focus of innovation toward application-driven development.

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

Although the number of collaborative patents increased in absolute terms, their share remained at approximately 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 composed the majority, followed by invention patents, while design patents were the least numerous. This distribution 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.

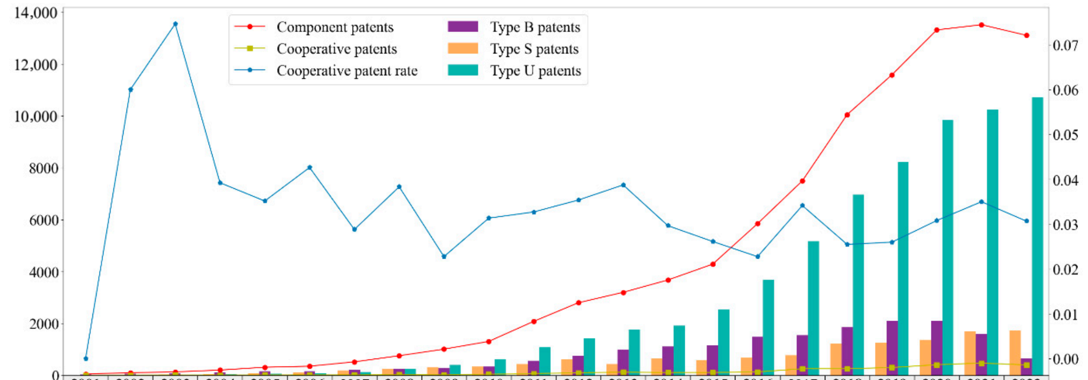
Notably, the high proportion of utility model patents and the prevalence of single corporate structures in China may indeed suppress formal co-application rates. Utility models typically involve incremental innovations, where the need for collaboration may be lower. More importantly, in China, technical collaboration between parent and subsidiary companies or among different entities within the same group is often managed through internal governance mechanisms and does not necessarily manifest as legal co-applications. Consequently, a substantial amount of de facto collaboration is not captured by our method. Therefore, we emphasize that the approximately 3% collaboration rate revealed in this study should be interpreted as a baseline measure of "formal, cross-institutional, equally shared" collaboration within the Chinese innovation system.

4.1.3. Temporal Evolution of Patents in Three Industry Segments

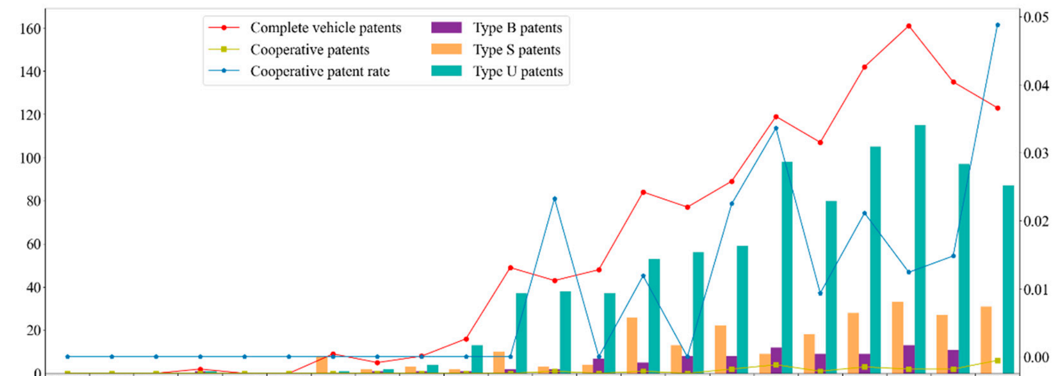
As shown in Figure 3, the component segment holds the largest share of patents, with a total of 95,748, including 17,661 invention patents, 12,821 design patents, 65,266 utility model patents, and 2901 collaborative patents (for a collaboration rate of 3%). In contrast, the complete vehicle sector has significantly fewer patents (1217), including 90 invention patents, 239 design patents, 883 utility model patents, and only 22 collaborative patents (for a collaboration rate of 1.8%). The aftermarket sector accounts for 4310 patents, including 851 invention patents, 733 design patents, 2726 utility model patents, and 152 collaborative patents (for a collaboration rate of 3.5%). Overall, China's NEV patent landscape is heavily concentrated in components and supplemented by the aftermarket, while the complete vehicle segment accounts for the smallest share. This finding indicates that patent activity emphasizes critical components and supporting technologies rather than complete vehicles. Notably, the distribution of patent types varies significantly: both components and the aftermarket are dominated by utility model and invention patents, whereas the complete vehicle sector emphasizes utility model and design patents, thereby reflecting a stronger focus on exterior protection and structural modifications.

The temporal distribution displayed in Figure 3 shows that the number of patent filings across all three segments has increased over time, although the share of collaborative patents remains persistently low and has not significantly improved. This finding suggests that relatively stable cooperation communities have emerged within each segment; however, collaborative innovation is not the primary driver. Furthermore, the component segment began the earliest and maintained long-term dominance, whereas the complete vehicle and aftermarket segments lagged behind. This pattern reveals a "component breakthroughs—complete vehicle integration—aftermarket" innovation trajectory. In the early period, aftermarket patents were primarily low-barrier design patents related to decoration and customization, whereas patents for charging, battery swapping, and cascade utilization technologies, which require higher R&D input and longer cycles, gained momentum only in the mid- to late-development periods.

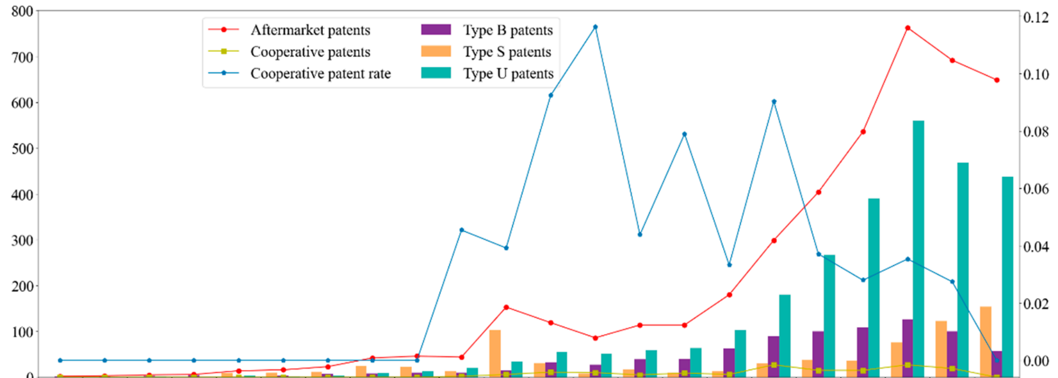
In summary, the temporal evolution and distribution of patents across NEV industry segments demonstrate that innovation was initially reliant on component breakthroughs, which subsequently stimulated advances in complete vehicles and aftermarket technologies. Components and aftermarket innovation are mainly utility model driven, which reflects an application- and engineering-oriented approach, whereas the complete vehicle segment has a 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, thereby highlighting the transition from rapid, profit-oriented innovation to 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	10,054	11,589	13,320	13,520	13,112
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	10,237	10,734
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

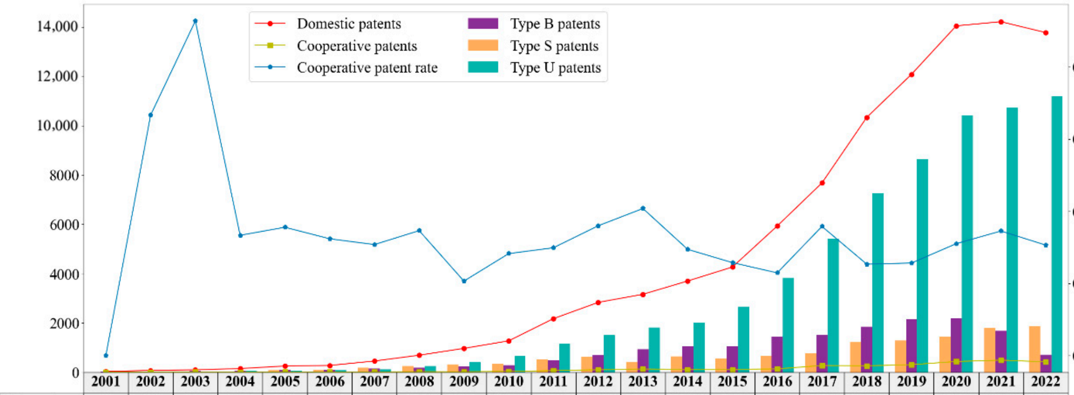


	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Aftermarket	2	3	5	6	14	16	23	42	46	44	153	119	86	114	114	180	299	404	536	763	692	649
Type B	2	2	3	5	1	4	7	8	10	10	15	33	27	39	40	63	89	100	109	127	100	57
Type S	0	1	0	1	9	10	12	25	23	14	103	31	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

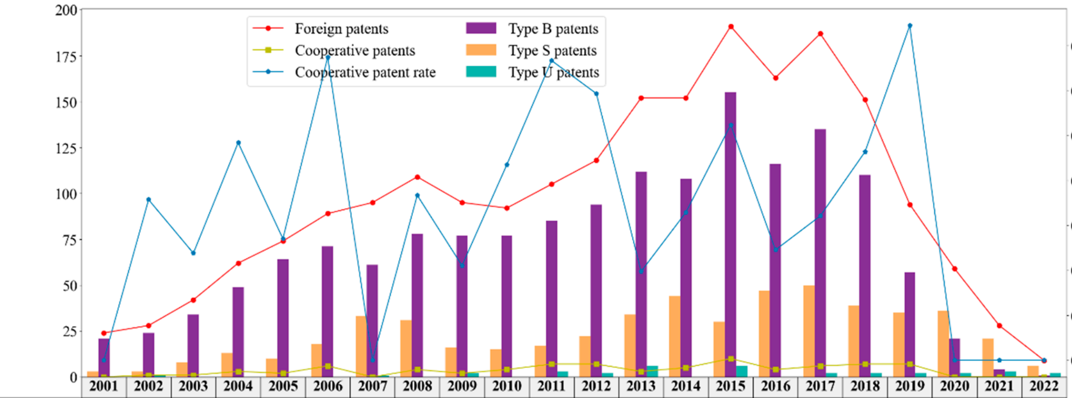
Figure 3. Patent statistics across three segments of the Chinese NEV industry.

4.1.4. Temporal Evolution of Patents for Both Domestic and Foreign Applicants

As shown in Figure 4, China's NEV patents have been 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 2978 collaborative patents, for a collaboration rate of only 3%. Since 2001, domestic patent filings have grown steadily, and they accelerated sharply after 2015, when the number of 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; this finding underscores the focus on engineering applicability and rapid commercialization. The short application cycles and fast approval processes for utility model patents enable rapid iterations, reflecting a "large-scale, wide-coverage" innovation model that has characterized the expansion phase of China's NEV industry.



	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	10,339	12,087	14,054	14,221	13,780
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	10,421	10,741	11,205
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 the NEV industry by domestic and foreign applicants.

In contrast, only 2119 patents in China are from foreign applicants, representing 1554 invention patents (over 70% of the total), 531 design patents, and just 34 utility model patents. Among them, 79 patents are collaborative patents, for a collaboration rate of 3.7%, which is slightly higher than that of domestic applicants. The temporal trend shows that foreign patents peaked in 2015 but declined steadily thereafter, forming a clear "peak-shaped" distribution. Unlike domestic applicants, foreign applicants are focused primarily on invention patents, highlighting original innovation and stronger technological barriers. However, their declining patent presence indicates a reduction in 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 finding 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, namely, application-driven versus originality-driven strategies. With respect to collaboration, domestic applicants maintain a relatively stable collaboration rate (3%), whereas foreign entities exhibit a slightly higher but more volatile rate, which indicates weaker sustainability.

We attribute these differences to several factors. (1) Tesla's 2014 patent pledge reduced entry barriers and weakened foreign incentives to file in China; (2) the rapid expansion of China's NEV market involved intense competition that prompted domestic firms to secure market share through utility model patents; (3) as a result of a divergence in innovation orientation, domestic firms pursued application-driven protection, whereas foreign firms emphasized original inventions; and (4) strong government support in China included policy incentives and R&D subsidies, driving 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. The presence of foreign applicants has been declining since 2015, which reflects their diminishing competitive advantage in the Chinese NEV market.

4.2. Patent Cooperation Network

4.2.1. Overall Cooperation Network

On the basis of the Gephi analysis of 21,347 applicants from 2001 to 2022, Figure 5 illustrates the patent cooperation network, with each node representing an applicant. Node size reflects degree centrality and relative importance, whereas the edges indicate collaborative patent relationships, where edge thickness is proportional to cooperation frequency (the count of co-applications between two entities). Different colors indicate distinct cooperation communities; for clarity, only the six largest communities are presented.

Table 2 and Figure 5 highlight the highly unequal distribution of power. 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 principal collaborator with other authoritative institutions. Thus, the SGCC forms the only "superhub" in the network. Combined with the analysis presented in Table 3, the patent collaboration network can be seen to exhibit the characteristics of a heavy-tailed network [42]. Other leading communities are centered on the Zhejiang Geely Holding Group (Hangzhou, China), 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, which reflects the decisive role of state-owned capital and policy support in shaping China's NEV innovation ecosystem. Except for SJTU, the hubs are all enterprises, confirming that firms, particularly SOEs, are the core drivers and organizers of industry–university–research collaboration. Interestingly, Sinopec Zhuhai Dongfang Gas Station has the highest closeness centrality, making it the most efficient information hub despite having weaker resource control than the SGCC does. This finding likely reflects its unique position at the market interface as a link among upstream component R&D, midstream complete vehicle manufacturing, and downstream services.

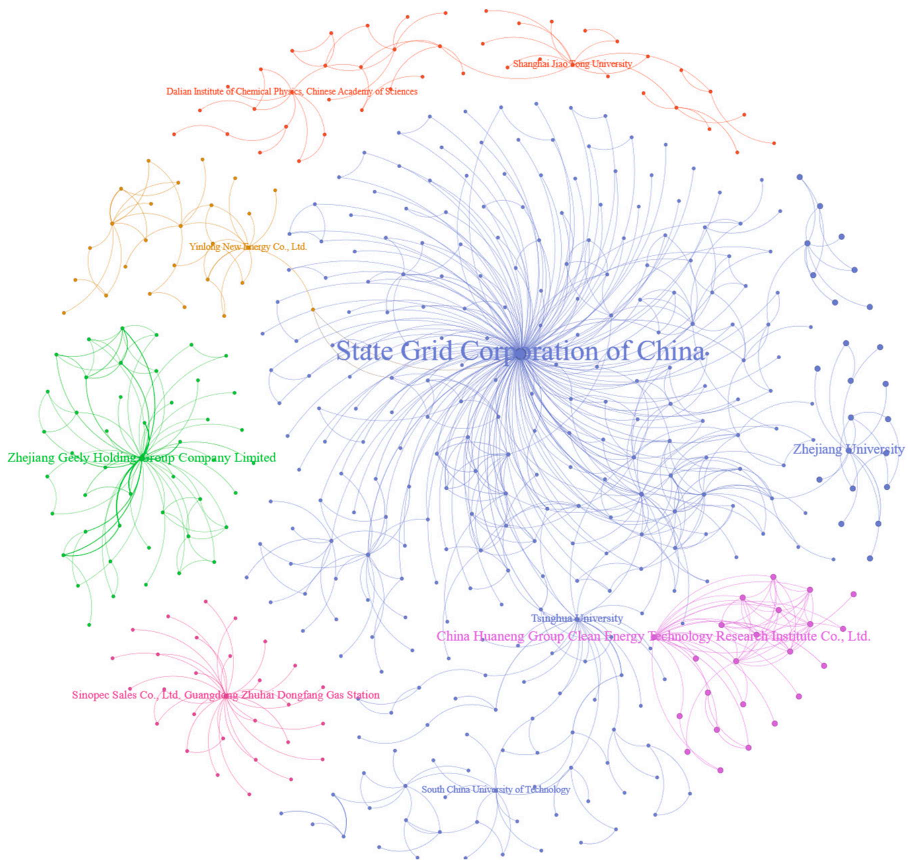


Figure 5. Major communities in the NEV patent cooperation network.

Table 2. Key nodes in the cooperation network.

Centrality	2001–2022
C_D	State Grid Corporation of China Zhejiang Geely Holding Group Co., Ltd. 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 Co., Ltd. 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 3. Structural characteristics of the cooperation network.

Structural Characteristics	2001–2022
Network density	0.0000087
Number of network nodes	21,347
Number of network connections	1983
Connecting times	6314
Average clustering coefficient	0.711
Average path length	3.738
Number of connected subgraphs	19,885
Number of nodes in the maximal connected subgraphs	300 (1.41%)
Number of connections in the maximal connected subgraphs	514 (25.92%)
Connecting times of the maximal connected subgraphs	1276

As shown in Table 3, the cooperation network of China's NEV industry exhibits the 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 that 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 the connections and 20.21% of the cooperative ties. These findings indicate that more than 93% of the applicants exist in isolated small groups and that their innovation activity is 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), which may indicate a "small-world" structure [43]. Locally, there are dense clusters of tightly connected innovation groups, 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.

A comparison of Tables 2 and 4 reveals a mismatch between innovation productivity and network influence. Firms such as Chery, CATL, and JAC lead in terms of patent output (over 1000 grants each) but do not occupy central positions in the cooperation network. Conversely, the SGCC, with only 658 granted patents (ranked 13th), holds unmatched influence as a network hub. This dichotomy suggests that two distinct innovation models are in play.

Table 4. 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 Co., Ltd.	956
Aodong New Energy Co., Ltd.	949
Guangzhou Automobile Group Co., Ltd.	866
Zhejiang Geely Holding Group Co., Ltd.	847
Honeycomb Energy Technology Co., Ltd.	790
Pan Asia Technical Automotive Center Co., Ltd.	729

Table 4. *Cont.*

Applicant	Num.
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 Co., Ltd.	517
Huating (Hefei) Hybrid Technology Co., Ltd.	483
Sinotruk Jinan Power Co., Ltd.	473

4.2.2. Temporal Evolution of the Patent Collaboration Network

For the 2001–2008 period, Figure 6 and the structural characteristics in Table 5 clearly reflect the nascent period of the industry, which includes small-scale, sparse collaboration and simple structures. The network contained only 936 nodes, with the highest density occurring across the three periods (0.0001577), while the absolute value remained extremely low, indicating merely sporadic cooperation. There were as many as 870 connected subgraphs, but 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 6 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 finding indicates that the early-period patent collaboration network followed a typical pattern of foreign technological leadership and academic research dominance. In contrast, Table 7 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 and lacked the ability to organize or lead collaborative networks, indicating an "island-type" innovation model. The policy initiatives at the time, such as "863 Program" EV projects, primarily stimulated basic research and early technology exploration while failing to generate large-scale collaborative innovation. Overall, the patent collaboration network during this period can be characterized as being in a fragmented embryonic phase that was driven by foreign leadership and academic exploration.

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

Structural Characteristic	2001–2008	2009–2017	2018–2022
Network density	0.0001577	0.0000208	0.0000102
Number of network nodes	936	8423	16,011
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	15,041
Number of nodes in the maximal connected subgraph	6 (0.64%)	86 (1.02%)	188 (1.17%)
Number of connections in the maximal connected subgraph	6 (8.7%)	171 (23.2%)	310 (23.68%)
Connecting times of the maximal connected subgraph	6	393	708

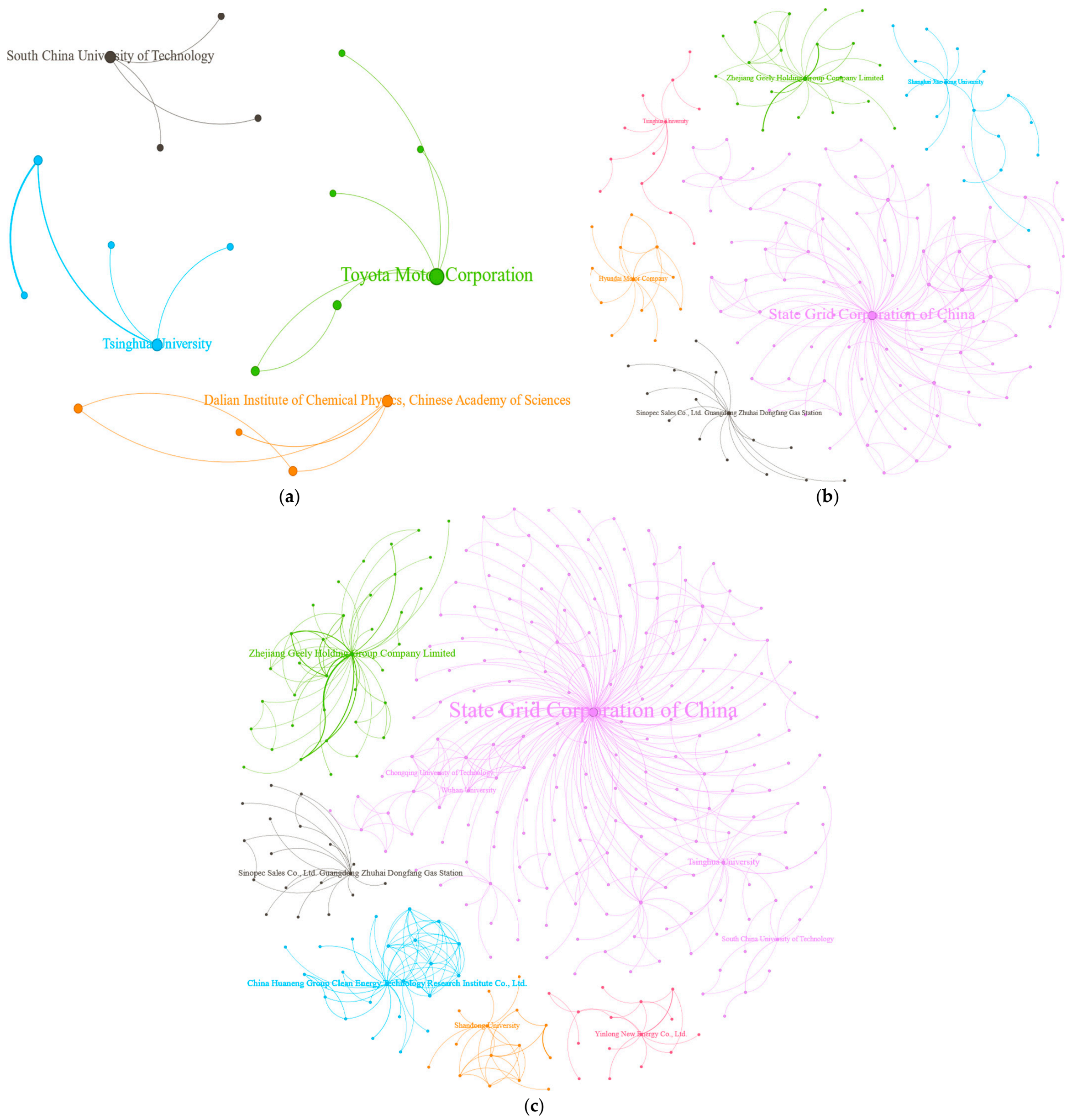


Figure 6. Patent collaboration networks across three periods: (**a**) 2001 to 2008, (**b**) 2009 to 2017, and (**c**) 2018 to 2022.

Table 6. Key nodes of the collaboration network across the 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 Co., Ltd.	Zhejiang Geely Holding Group Co., Ltd.
	Tsinghua University	Sinopec Sales Co., Ltd. Guangdong Zhuhai Dongfang Gas Station	China Huaneng Group Clean Energy Technology Research Institute Co., Ltd.
	Dalian Institute of Chemical Physics, Chinese Academy of Sciences	Xj Power Co., Ltd.	Tsinghua University

Table 6. *Cont.*

Centrality	2001–2008	2009–2017	2018–2022
C_C	Toyota Motor Corporation	Zhejiang Geely Holding Group Co., Ltd.	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 Co., Ltd.
	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 7. Top 20 applicants by granted patents across the 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 Co., Ltd.	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
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 Co., Ltd.	321	Hefei Gotion High-Tech Power Energy Co., Ltd.	778
Anhui Jianghuai Automobile Group Corp., Ltd.	56	Zhejiang Geely Holding Group Co., Ltd.	305	Guangzhou Automobile Group Co., Ltd.	582

Table 7. *Cont.*

2001–2008		2009–2017		2018–2022	
Applicant	Num.	Applicant	Num.	Applicant	Num.
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 Co., Ltd.	540
Pan Asia Technical Automotive Center Co., Ltd.	45	Ford Global Technologies, LLC	277	BYD Co., Ltd.	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 Co., Ltd.	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 Ltd.	163	Jiangsu Zenergy Battery Technologies Co., Ltd.	300

The years 2009–2017 represented a period of explosive growth and structural reshaping of the network. The number of nodes increased by nearly ninefold (to 8423), with both connections and collaboration frequency increasing sharply (by 737 and 1828, respectively). However, network density sharply declined to 0.0000208, reflecting the influx of many new participants without a proportionate increase in cooperation, which resulted in a "large but sparse" structure. As illustrated in Figure 6 and Table 6, 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 to become the sole superhub of the network. The largest collaboration community expanded significantly around the SGCC, 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. Moreover, foreign enterprises such as Toyota and Hyundai experienced a relative decline in influence. This phase of transformation coincided with China's accelerating industrialization and the rollout of large-scale demonstration projects, notably the "Ten Cities, Thousand Vehicles" initiative. During this period, state-owned enterprises leveraged policy support and infrastructure deployments (e.g., charging stations), a context that aligned with the observed reshaping of the collaborative ecosystem toward a structure characterized by a dominant core and several significant participants. Table 7 further confirms this trend by showing that domestic automakers and battery suppliers such as JAC Motors, Chery, and CATL experienced an explosive increase in patent output, which became the backbone of innovation. Therefore, this period represents the formation period of an industrialization-driven, state-owned-enterprise-led core–periphery patent collaboration network.

From 2018 to 2022, the network continued to expand (16,011 nodes), and collaborations continued to deepen (4382 connections), but density decreased to its lowest level (0.0000102), thereby reinforcing the "large but sparse" pattern with a vast number of peripheral participants (15,041 subgraphs). Nevertheless, the data presented in Figure 6 and Table 6 reveal that the network core underwent accelerated integration and consolidation. SGCC further strengthened its dominance and expanded 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, for 1.17%). This finding 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. Moreover, the ecosystem became more diversified; Geely retained its importance, while new actors such as the China Huaneng Group and Gree Altairnano emerged as community hubs. Notably, Table 7 shows that specialized battery manufacturers, namely, CATL and Eve Energy, monopolized the top two positions in granted patents, which far surpassed automakers. This finding 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 emerged: despite CATL's dominant patent output, it does not rank among the top centrality nodes (Table 6). This finding 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 the SGCC, while technology-driven private firms emphasize internal R&D and patent generation. These two models, namely, resource integration-led innovation and technology-independent breakthrough-driven innovation, coexist and jointly drive 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 first shifted from foreign firms and academic institutions to SOEs and then to the coexistence of SOEs and private firms. Structurally, the network 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 engines driving 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 plays a central role in all three segments of the NEV industry, which underscores its status as a key innovation orchestrator in the industrial chain. In contrast, patent collaboration in the complete vehicle segment is extremely limited. Distinct collaboration communities emerged in the aftermarket, 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. also established a notable collaboration community.

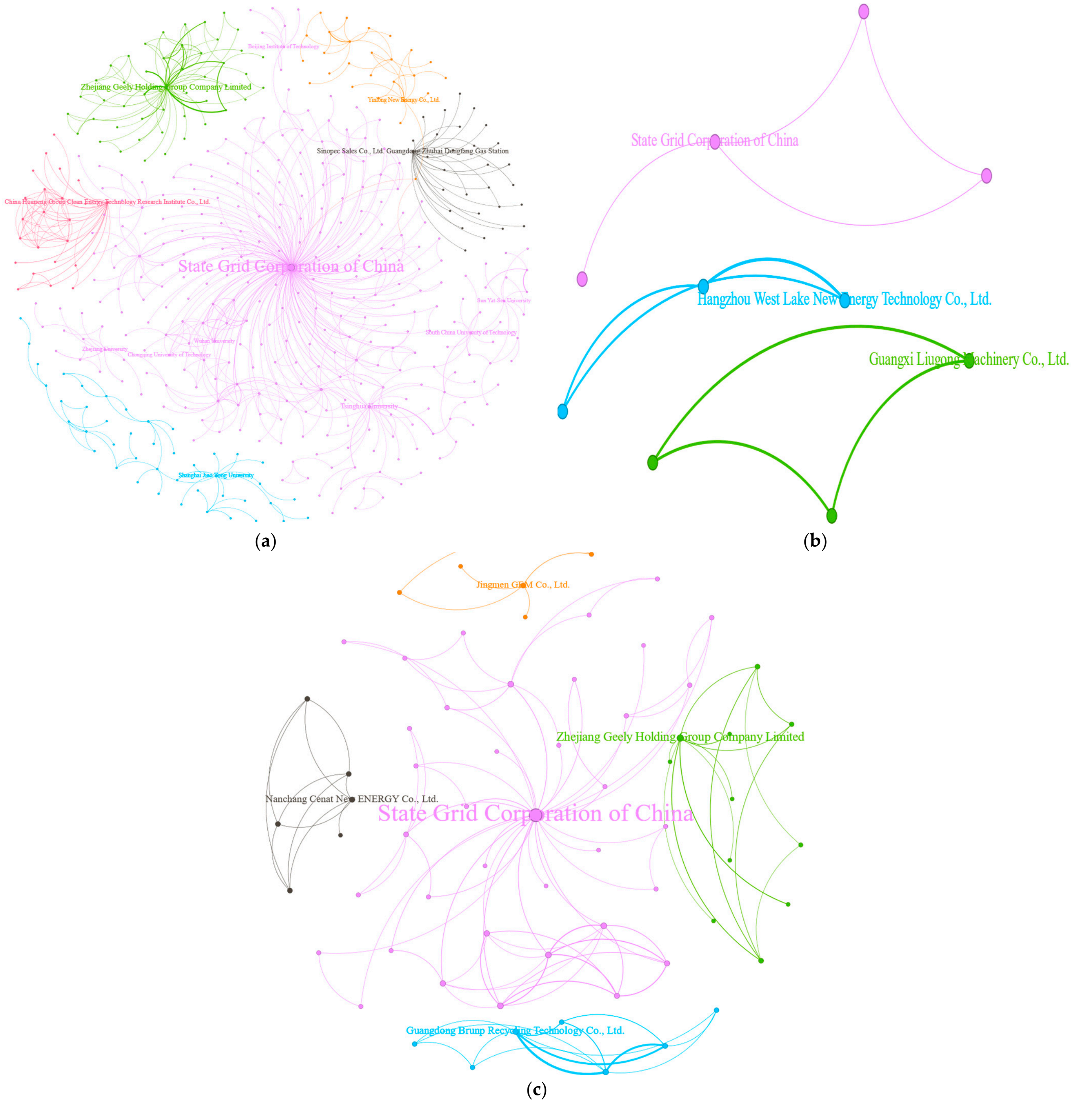


Figure 7. Patent collaboration networks across three segments: (**a**) the component segment network; (**b**) the complete vehicle segment network; and (**c**) the aftermarket segment network.

The first chart in Figure 8 shows the patent distribution across NEV components. Batteries (29.8%) and body systems (29.0%) dominate, accounting for nearly 59% of patents. Other major areas include general parts (11.9%), chassis systems (9.8%), and intelligent connected technologies (8.7%). Segments such as environmental perception (7.0%) and electronic control (1.9%) are relatively small, and those related to motor (1.6%) and power systems (0.2%) are very limited.

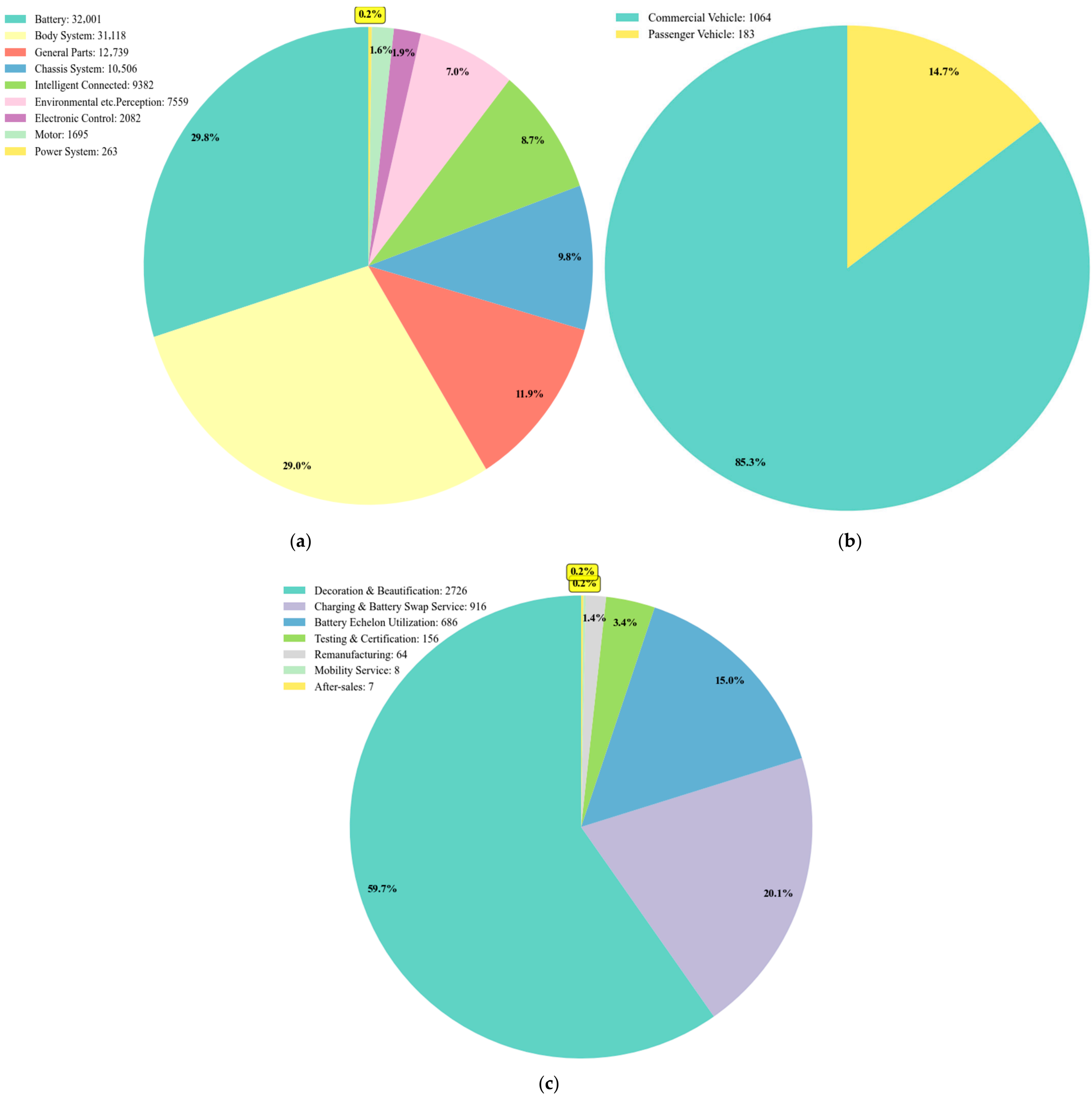


Figure 8. Proportion and number of patents in sublevel links of the three segments: (**a**) the component segment; (**b**) the complete vehicle segment; (**c**) the aftermarket segment.

These findings indicate that the patenting efforts in the component segment of the NEV industry chain are heavily concentrated in batteries and body systems, which reflects their central roles in technological innovation and the cost structure. The lower patent activity for motors and power systems, despite their crucial role, can be attributed to the field's established technological maturity and dependencies on the global supply chain for foundational materials (e.g., high-grade silicon steel) and core semiconductors (e.g., advanced IGBT/SiC chips).

The second chart compares the patents between commercial vehicles (85.3%) and passenger vehicles (14.7%).

Patent activity in the complete-vehicle segment is heavily skewed toward commercial vehicles. This finding may be due to government policies that prompt electric buses, logistics vehicles, and fleet electrification, as such policies drive more R&D and patenting compared to the passenger car segment.

The third chart in Figure 8 highlights those patents related to NEV aftermarket services. Decoration and beautification (59.7%) overwhelmingly dominate, suggesting that service-oriented patents are still highly concentrated in noncore innovation areas. Battery-related services such as battery echelon utilization (20.1%) and charging and swapping services (15.0%) are important but secondary. Testing and certification (3.4%), remanufacturing (1.4%), and mobility services (0.2%) have a very limited patent presence.

Compared with the component layer, aftermarket innovation appears less technologically intensive, with its patents concentrated in user experience improvements and second-life battery usage. This finding reflects a still-developing aftermarket ecosystem for NEVs in China.

In the component segment, innovation is concentrated in batteries and body systems, which constitute the technological core of NEVs. In the complete-vehicle segment, commercial vehicles lead in patenting activity, which reflects policy-driven industrial priorities. In the aftermarket segment, patents are less balanced, with a dominance of noncore services (decoration) and emerging importance for battery recycling and charging infrastructure.

This layered view reveals that China's NEV industry chain patents are core heavy at the component level, policy driven at the vehicle level, and experience focused in the aftermarket.

As shown in Table 8, the component segment, with 20,484 nodes and 1900 connections, represents the largest and most active network. However, its extremely low density (0.0000091) reflects a "large but fragmented" structure. The presence of 19,076 disconnected subgraphs shows that most innovators operate independently or in small, isolated clusters. Nonetheless, the largest connected subgraph accounts for 25.11% of all ties, and the relatively high clustering coefficient (0.708) points to the existence of a tightly knit core. As shown in Table 9, within this core, the State Grid Corporation of China is dominant in terms of degree, betweenness, and eigenvector centralities, positioning it as the undisputed "innovation orchestrator" and "resource allocator" in the component layer. Its dominance stems from its extensive patenting in charging infrastructure, smart grids, and battery-swapping technologies. Tsinghua University plays a crucial bridging role through its high betweenness centrality, while Sinopec's Zhuhai Dongfang Gas Station achieves the highest closeness centrality, serving as a unique information hub.

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

Structural Characteristic	Component	Complete Vehicle	Aftermarket
Network density	0.0000091	0.0001996	0.0000851
Number of network nodes	20,484	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	19,076	451	1873
Number of nodes in the maximal connected subgraph	290 (1.42%)	4 (0.85%)	37 (1.86%)
Number of connections in the maximal connected subgraph	477 (25.11%)	4 (18.18%)	68 (40.48%)
Connecting times of the maximal connected subgraph	1110	4	141

Table 9. Key nodes of collaboration networks across the 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 Co., Ltd.	Guangxi Liugong Machinery Co., Ltd.	Zhejiang Geely Holding Group Co., Ltd.
	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 Co., Ltd.	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 Co., Ltd.
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.
	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

As further illustrated in Figure 8a, patenting within the component segment is highly concentrated in batteries (29.8%) and body systems (29.0%), which together account for nearly 60% of all patents. This technological focus aligns with the key actors in the collaboration network; the leading patent producers listed in Table 10, such as CATL, Chery Automobile, Jianghuai Automobile, Gotion High-Tech, and EVE Energy, are predominantly battery and NEV manufacturers. However, this situation is in sharp contrast to the cooperation-centered network orchestrated by State Grid, thereby reflecting a clear separation between “technological output” and “ecosystem coordination.” The component segment therefore has a dual structure: (1) a state capital-driven collaboration ecosystem centered on State Grid and (2) market-driven, R&D-intensive innovation dominated by battery and NEV manufacturers. Together, these dynamics define the upstream innovation landscape.

Table 10. Top 20 applicants by granted patents across the 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
FAW Group Co., Ltd.	1088	China Dragon Development Holdings, Ltd.	20	Shanghai Dianba New Energy Technology Co., Ltd.	76
BYD Co., Ltd.	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 Co., Ltd.	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 Co., Ltd.	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 is the weakest network, with only 470 nodes and 22 connections. Although it has a slightly higher density (0.0001996), its largest connected subgraph remains extremely small (4 nodes, 0.85%), and collaboration is virtually absent. Nevertheless, the clustering coefficient reaches 0.926, suggesting that the limited collaborations that exist occur in tight, closed circles—primarily intragroup subsidiaries or restricted university–industry partnerships. Here, central actors such as the State Grid and Guangxi Liugong Machinery emerge through mainly cross-industry activities involving specialized vehicles (e.g., forklifts and sanitation vehicles) rather than mainstream passenger or commercial vehicles. This structural isolation is mirrored in the patent distribution shown in Figure 8b, which reveals a pronounced skew toward commercial vehicles (85.3%), reflecting policy-driven electrification in public and utility transport. Notably, Anhui Heli, a forklift producer, ranks first with only 267 patents, which is far below the thousand-level counts observed in the component segment. This finding further underscores the insularity and fragmentation of the segment. The complete vehicle segment thus exemplifies an "exclusive club" model, where collaboration is confined to a small circle of leading firms that prioritize closed, independent R&D and erect strong technological barriers, reflecting both the integration complexity and the competitive market pressures of vehicle systems.

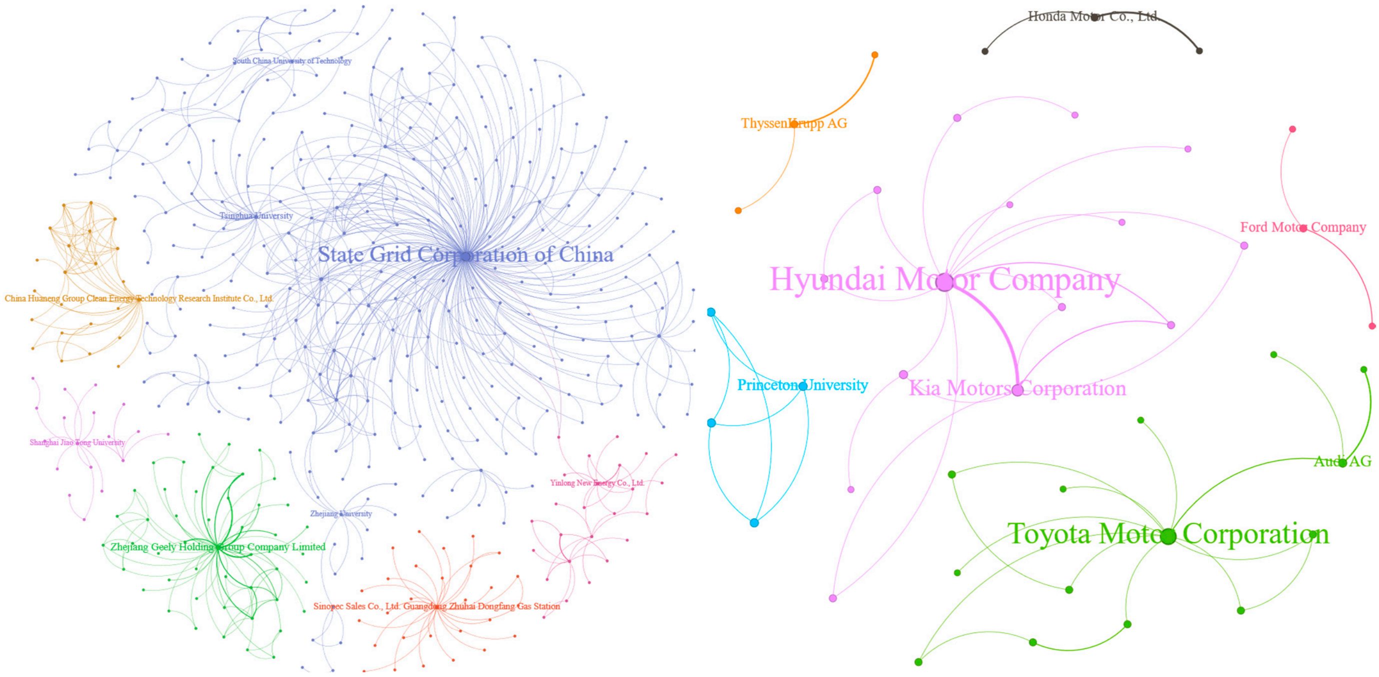
The aftermarket segment is more moderate in scale (1987 nodes) but comparatively active in collaboration, with 168 connections. Its largest connected subgraph accounts for 40.48% of the ties, supported by a high clustering coefficient (0.82), which indicates the formation of specialized innovation communities with dense internal linkages. In this segment, the power balance has shifted significantly. While the State Grid remains influential, firms specializing in battery recycling and material regeneration, such as Brunp, GEM, and Cenat, rise to prominence in terms of closeness centrality rankings. The Zhejiang Geely Holding Group also appears across multiple measures, reflecting its diversified strategic deployment. As depicted in Figure 8c, patenting activity in the aftermarket is overwhelmingly dominated by decoration and beautification (59.7%), followed by battery echelon utilization (20.1%) and charging and swapping services (15.0%). This distribution highlights both the user experience orientation of current aftermarket innovation and the growing importance of battery-related circular economy technologies. Patent data further confirm this shift: Aodong New Energy, which specializes in battery swapping, tops the list, along with Brunp and GEM. These findings demonstrate that as the stock of NEVs increases, end-of-life battery management, second-life applications, and circular economy solutions emerge as new innovation frontiers, attracting substantial patenting activity. Therefore, the aftermarket exemplifies a cluster-oriented innovation model that is led by specialized firms and driven by emerging market demand.

Overall, innovation in China's NEV industry chain is characterized by pronounced segmentation, which includes the dual structure of state-driven coordination and market-driven R&D for components; a closed, insular model for complete vehicles, which reflects high barriers to collaboration; and a cluster-based, demand-driven ecosystem in the aftermarket, in which battery recycling and circular economy firms are emerging as new hubs.

Bridging these segments remains a critical challenge for future industrial policy. Although the State Grid strongly influences both the component and aftermarket segments, its presence has yet to meaningfully extend into the complete vehicle core, which underscores the difficulty of achieving full-chain collaboration in the NEV industry.

4.2.4. Patent Collaboration Networks for Domestic and Foreign Applicants

The patent collaboration communities for domestic and foreign applicants in China's NEV industry are shown in Figure 9. Compared with domestic collaboration communities, the communities that are formed by foreign applicants are significantly smaller in scale, and their central nodes are primarily occupied by automobile manufacturers. The two largest foreign applicant communities are led by entities from South Korea and Japan, and the Japanese cluster also integrates German applicants. In contrast, the domestic collaboration communities largely mirror the structure shown in Figure 1.



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

Figure 9. Patent collaboration networks of domestic and foreign applicants: (**a**) domestic applicant network; (**b**) foreign applicant network.

Table 11 presents the key nodes of the domestic and foreign collaboration networks. The structural characteristics are summarized in Table 12. 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 more than 93% of the innovation actors remain isolated or at the periphery. However, the largest connected subgraph aggregates 27.17% of all connections, coupled with a high clustering coefficient (0.726), thereby demonstrating the existence of a tightly integrated core power circle. Consistent with the overall network analysis, the degree, betweenness, and eigenvector centralities of the SGCC dominate, confirming its role as the absolute hub and gatekeeper of innovation resources. This core circle comprises state-owned enterprises (e.g., State Grid and Sinopec), large private firms (e.g., Geely and Gree), and elite universities (e.g., Tsinghua University), forming a relatively closed cooperation system that is 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 11. Key nodes of the collaboration network for domestic and foreign applicants.

Centrality	Domestic	Foreign
C_D	State Grid Corporation of China	Hyundai Motor Company
	Zhejiang Geely Holding Group Co., Ltd.	Toyota Motor Corporation
	Sinopec Sales Co., Ltd. Guangdong Zhuhai Dongfang Gas Station	Kia Motors Corporation
	Tsinghua University	Audi AG

Table 11. *Cont.*

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

Table 12. Structural characteristics of the collaboration network for domestic and foreign applicants.

Structural Characteristic	Domestic	Foreign
Network density	0.0000088	0.0003949
Number of network nodes	20,716	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	19,342	563
Number of nodes in the maximal connected subgraph	299 (1.44%)	15 (2.38%)
Number of connections in the maximal connected subgraph	511 (27.17%)	20 (25.64%)
Connecting times of the maximal connected subgraph	1273	28

The patent output data displayed in Table 13 highlight the vitality of the domestic network. Leading firms such as Chery, CATL, and JAC hold more than 1000 granted patents each, far surpassing any single foreign applicant. This finding 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 with a powerful yet relatively closed core that orchestrates resource flows, surrounded by a vast periphery of marginalized small and medium-sized actors. Overall, the number of patents has undergone explosive growth.

In contrast, the foreign collaboration network is much smaller (629 nodes) but considerably denser (density = 0.0003949), which suggests the occurrence of 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 11, network power is highly concentrated among traditional automotive giants such as Hyundai, Toyota, Kia, and Audi. Importantly, the Korea Advanced Institute of Science and Technology (KAIST) ranks high in terms of both betweenness centrality and eigenvector centrality, 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, which constitutes a tightly knit, technology- and supply chain-based exclusive club.

Table 13. 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 Co., Ltd.	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 Co., Ltd.	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

The patent output comparisons shown in Table 13 further reinforce this contrast. The top foreign applicant, Ford (629 granted patents), holds fewer patents than China's 13th-ranked applicant does, which underscores the scale gap. This finding may be related to the more selective patenting strategies of multinational corporations in the Chinese market. In summary, 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, thereby constituting an ecological separation that reflects limited embeddedness.

Notably, cross-ecosystem collaboration remains minimal. As shown in Tables 2 and 11, there are only 24 collaboration links and 29 collaboration events between the domestic and foreign applicants, which is an extremely low level given the vast sizes of the two networks (20,716 vs. 629 nodes). This finding provides quantitative evidence of the community segregation shown in Figure 9.

These findings indicate that, despite the active foreign patent deployment in China, the innovation activities of foreign firms remain largely detached from the domestically dominated ecosystem. The result is a form of parallel development, with deep and strategic technological exchange of limited effectiveness. Such weak connectivity highlights the 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 will require greater openness, higher-level international collaboration mechanisms, and the integration of global innovators into the core ecosystem. Strengthening such crossboundary innovation loops is essential for enhancing the global competitiveness and resilience of China's NEV industry.

5. Discussion and Conclusions

This study introduces the ISPCM for China's NEV sector, integrating expert knowledge with LLMs to enhance the accuracy and relevance of patent screening. Applying this method, we systematically identified and analyzed NEV patents filed between 2001 and 2022, constructing for the first time a comprehensive patent collaboration network that examines temporal evolution, the industrial chain structure, and applicant nationality. The analysis provides novel insights into the structural mechanisms driving China's global leadership in NEVs, offering significant theoretical contributions to innovation ecosystem research and substantive policy implications for sustainable industrial development. The key findings are as follows:

NEV patent filings in China have grown rapidly and continuously, evolving through three stages: initial development (2001–2008), accelerated growth (2009–2017), and maturity (2018–2022). Policy initiatives, such as the "Ten Cities, Thousand Vehicles" program, were implemented alongside market expansion during the observed period. The observed correlations could be influenced by other co-evolving factors, such as technological maturation and market development. Analysis of patent filings reveals that domestic applicants dominate throughout, with invention patents being more prevalent during the technology accumulation phase, while utility model patents become more common during the subsequent industrialization stage. This pattern in patent types is consistent with a transition from foundational R&D toward more application-oriented, iterative innovation.

The collaboration network is large yet sparse, exhibiting a heavy-tailed characteristic. A "one-super, many-strong" oligopolistic structure is predominant, with the SGCC serving as the core hub. State-owned capital orchestrates infrastructure development, such as charging networks, and integrates industry–academia–research resources to serve as the central innovation coordinator. This finding highlights the decisive role of state strategy, complemented by market-driven private sector R&D, in shaping the innovation landscape.

During its initial development (2001–2008), collaboration was sparse and led by universities and foreign firms (e.g., Toyota). This was followed by rapid growth (2009–2017): During this period, state-owned enterprises (e.g., SGCC) reshaped the network into a core–periphery structure through policy leverage and infrastructure dominance. Maturity was reached (2018–2022): In this period, the core continued to consolidate, absorbing key academic clusters, while private firms (e.g., CATL) emerged as major technology contributors. This resulted in a dual innovation model in which SOEs coordinate the ecosystem and private firms drive specialized technological advancement.

In terms of the divergent innovation patterns across the industrial chain segments, the component segment exhibits a dual structure that combines state-led collaboration and market-driven R&D. The complete vehicle segment persists as a tightly knit "exclusive club," a structure defined by limited collaboration and intense internal competition. The aftermarket segment (e.g., battery recycling and reuse) forms specialized innovation clusters that are led by firms such as Brunp Recycling and GEM. Notably, the influence of the SGCC does not extend deeply into vehicle manufacturing, thereby revealing challenges in achieving full value chain integration.

Domestic and foreign applicants operate largely in parallel, with domestic networks forming a policy-shaped mega-ecosystem with quantitative dominance and foreign networks forming exclusive "elite clubs" focused on high-value invention patents. The number of cross-ecosystem ties is minimal (with only 24 collaborative links), which indicates limited deep technological exchange and a potential decoupling risk. This study relies exclusively on patent data from the CNIPA. Consequently, our analysis does not capture cross-border collaborations that resulted only in patent filings in other jurisdictions (e.g., EPO, USPTO, WIPO). This may introduce a 'home jurisdiction bias', indicating that our findings regarding international 'decoupling' are primarily reflective of the collaboration dynamics within the Chinese domestic innovation system. Future research incorporating international patent families would provide a more global perspective.

In summary, China's NEV leadership stems not from isolated technological breakthroughs but from a state-orchestrated, market-supported dual-circulation model that enables rapid scaling, efficient resource integration, and iterative application development. However, challenges remain in terms of original innovation, cross-chain coordination, and international collaboration.

On the basis of this study's findings and limitations, we suggest several promising research directions:

The three-phase evolution model proposed in this study is primarily based on the observation of time series macrolevel network metrics (e.g., number of nodes and number of links). While the model is heuristic, future research could validate and refine this model by employing more granular dynamic network analysis methods, such as introducing overlapping time windows and calculating community persistence indices. Future studies could also employ temporal network analysis or exponential random graph models to better capture the dynamics of collaboration formation and network evolution.

The causal mechanisms between network position (e.g., centrality) and innovation outcomes (e.g., patent quality and product commercialization) remain underexplored. Panel data regression or case-based longitudinal analysis could offer deeper insights in this area.

Extending the network analysis to include major NEV markets such as the U.S., Germany, and Japan would enable comparative studies of innovation structures, core players, and policy impacts, thereby helping to identify the competitive advantages and strategic reference points.

The incorporation of R&D investment, government subsidies, talent mobility, and market data could lead to the development of a more comprehensive analytical framework. For example, how do subsidies affect network connectivity? Does university talent cultivation increase corporate innovation?

Beyond classification, future research could apply natural language processing to enable the semantic mining of patent texts, such as the identification of emerging technical themes, the tracing of technology trajectories, and the detection of innovation gaps, and integrate these insights into a network analysis to improve strategic forecasting.

While these research directions cannot advance the theoretical understanding of innovation networks, they can provide actionable insights for policymakers and corporate strategists aiming to enhance ecosystem collaboration, guide technology planning, and foster international cooperation within the global NEV industry.

6. Patents

A Chinese patent (patent number: CN118798188B) resulted from the work reported in this manuscript.

Author Contributions: Conceptualization, X.L. and Y.Y.; methodology, X.L. and Z.H.; software, H.L. and J.W.; validation, X.L. and M.J.; formal analysis, X.L.; investigation, X.L.; resources, X.L.; data curation, X.L.; writing—original draft preparation, X.L. and Q.W.; writing—review and editing, X.L.; visualization, X.L.; supervision, X.L.; project administration, X.L. and Q.W.; funding acquisition, X.L. and Q.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the University-level Scientific Research Startup Project (grant number: KYQD-2024035), the Hefei City Project (grant number: No. 2023SGJ014), the Anhui Provincial University Outstanding Research and Innovation Team Program (grant number: No. 2024AH010022) and the Joint Research Project of the National Natural Science Foundation of China (grant number: U23B2031).

Data Availability Statement: All the data and code used in this research are shared at https://gitee.com/LyuXiaozhong/NEV (accessed on 9 November 2025).

Acknowledgments: We acknowledge the support given by the Office of the Leading Group for Building the New Energy Vehicle Industry Cluster in Anhui Province, China, to verify the classification outcomes.

Conflicts of Interest: Authors Jian Wang, Xiaozhong Lyu, and Hao Li are inventors of the awarded patent (CN118798188B, "Enterprise attribution method and attribution system of industrial nodes"), assigned to the Institute of Data Space, Hefei Comprehensive National Science Center. Author Hao Li is also an employee of Quectel Wireless Solutions Co., Ltd. The patented method was utilized in this study exclusively as a data preprocessing tool to construct the analytical dataset. The core research focus remains on investigating the evolution and structural mechanisms of China's new energy vehicle patent collaboration network. All authors affirm that the disclosed affiliations have not influenced the research design, methodology, analysis, or conclusions presented in this manuscript. Authors Yu Yao, Zanjie Huang, Mingxing Jiang, and Qilin Wu declare that they have no conflicts of interest. The funders played no role in the design of the study; in the collection, analyses, or interpretation of the data; in the writing of the manuscript; or in the decision to publish the results.

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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