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HOW MULTIDIMENSIONAL PROXIMITY AFFECTS COLLABORATIVE INNOVATION PERFORMANCE IN NEW ENERGY VEHICLES

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Annotation. *The collaborative innovation performance in new energy vehicles (NEVs) is significantly affected by such factors as geographical proximity, technological proximity, and organizational proximity among innovation subjects, but the dynamic influence of multidimensional proximity on collaborative innovation performance has been scarcely investigated. To identify the influence of proximal cooperative relationships on the innovation performance in NEVs, this study employed the cooperative patent data of NEVs in China from 2005 to 2022 and applied the social network analysis method and quadratic assignment procedure （QAP）analysis method to verify the influence of multidimensional proximity on collaborative innovation in NEVs in different periods on the basis of transaction cost theory and resource dependence theory. Results show that proximity is an important influencing factor of cooperative relationships, and proximity factors affect cooperation differently in diverse development periods of the NEV industry. Specifically, technological proximity plays a significant positive role in promoting collaborative innovation, while geographical proximity and organizational proximity have a reduced effect on collaborative innovation. The obtained conclusions reveal the influence mechanism of multidimensional proximity on the collaborative innovation in NEVs to some extent, which can provide decision-making references for the deep integration of NEV industry–university–research*.

Keywords: multidimensional proximity, innovation network, new energy vehicles.

JEL classification: O32, O53, P28.

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Introduction

In the context of balancing energy security and achieving the "dual carbon" goals, new energy vehicles (NEVs), as a form of transportation powered by clean energy, have garnered global attention due to their superior energy conversion efficiency and environmental benefits (Lu *et al.*, 2023). As pointed out in the NEV Congress in 2021, NEVs have ushered in a new accelerated development stage because of the expedited integration with relevant technologies in the fields of energy, transportation, information, and communication. For developing the NEV industry, adhering to open cooperation and further promoting cooperation in policy coordination and technological innovation are necessary. Under the background of economic globalization, the innovation environment is changing rapidly, and an increasing number of NEV enterprises have begun to seek for external available innovation resources. Given the uncertainty of the market environment and the scarcity of innovative resources, the network cooperation of heterogeneous subjects, such as enterprises, universities, and scientific research institutions, becomes inevitable. Industry–university–research cooperation, with NEV enterprises as the technology demanders and scientific research institutes or universities as the technology suppliers, has promoted the combination of various production factors required for technological innovation. An innovation network with common technological innovation goals has been gradually formed, helping NEV enterprises utilize external superior resources to strengthen core technologies. One of the key indicators for measuring the technological innovation effect of NEVs is collaborative innovation performance, which also reflects the ability and efficiency of NEV innovation organizations in absorbing and utilizing their internal and external resources.

The current research on collaborative innovation performance in NEVs mainly focuses on network structures, including network location (Choe *et al.*, 2016; Wang *et al.*, 2020), relationship strength (Guan *et al.*, 2016; Yang *et al.*, 2021), and network characteristics (Phelps, 2010; Wang, Yu, 2019; Suo, Li, 2023). The effects of partner selection, knowledge spillover, and innovation performance have been seldom studied from the perspectives of cooperation scenarios between network organizations, such as geographical distance and technological distance. Nevertheless, the proximity dynamic school represented by Shaw (2000), Torre, Rallet (2005), and other EU scholars represented by Boschma (2005) have begun to explore the role of multidimensional proximity, including geographical proximity, organizational proximity, institutional proximity, and social proximity, in organizational cooperation. Among them, geographical proximity is considered the primary factor driving innovation, which can adjust the influence of the innovation network on knowledge novelty and knowledge transfer (D' Este *et al.*, 2012; Wu *et al.*, 2020). According to resource dependence theory, the knowledge base of an organization determines its absorptive capacity and then decides its cooperation prospects. Therefore, a cooperative network can be built with other organizations of technological proximity, and cooperative links can be utilized to efficiently absorb and utilize the knowledge of partners to improve technological innovation performance. Based on transaction cost theory, organizational proximity endows organizations with common cognition, reduces conflicts and uncertainties in collaborative innovation, and lowers the cost of labor division and coordination and the information cost. Thus, the partner selection for NEV technological innovation and the collaborative innovation performance can be investigated from the angle of proximal cooperative relationships. The static influence of multidimensional proximity on collaborative innovation has been surveyed mainly from the levels of enterprise and region in most of the existing studies (Yu *et al.*, 2018; Zhang, Qian, 2021), while the dynamic effect of multidimensional proximity in different periods of time has been less involved. On this basis, the influence of multidimensional proximity on NEV industry–university–research collaborative innovation performance in different periods was investigated using the cooperative patent data of NEVs in China during 2005–2022.

The possible marginal contributions of this study are depicted as follows. (1) Theoretical level: The effects of geographical proximity, technological proximity, and organizational proximity on innovation performance in NEVs were studied from the perspective of multidimensional proximity. This work deepens the research on the internal mechanism affecting the output of collaborative innovation and provides theoretical guidance for the behavioral decision-making of NEV innovation members. (2) Practical level: On the basis of the sample data of cooperative NEV patents in China, the relationship between multidimensional proximity and collaborative innovation performance in NEVs in different periods was empirically tested. This evaluation could provide operational references for innovative organizations to implement dynamic adjustment of proximal cooperation and improve innovation efficiency and offer empirical evidence support for the government to enhance the innovation policy for the NEV industry.

The remainder of this study is organized as follows: In Section II, research hypotheses are proposed on the basis of the theoretical analysis. Specifically, the relevant literature documents regarding the influences of geographical proximity, technological proximity, and organizational proximity on collaborative NEV innovation performance are consolidated, and research hypotheses are put forward. In Section III, the research methods are introduced, and the methods for sample selection and variable measurement are explained. In Section IV, the empirical results are analyzed, and the evolutionary characteristics of the whole NEV collaborative innovation network structure and the regression results with regard to the influence of multidimensional proximity on collaborative innovation performance are discussed. In Section V, a discussion based on the empirical analysis results is provided. In Section VI, the conclusions and suggestions are raised. To be specific, the research conclusions are presented on the basis of the discussion section, and the policy implications, limitations, and future research directions are proposed accordingly.

1. Literature Review and Hypothesis Development

1.1 Influence of Geographical Proximity on Innovation Performance

Amin (1999) defined proximity as the spatial proximity of each subject in a cluster on the basis of external economic theory and believed that the knowledge diffusion among subjects had obvious geographical characteristics, which explained the important position of geographical proximity in innovation activities. Afterward, numerous scholars began to focus on the influence of geographical distance on innovation activities and stated that geographical distance between organizations would affect their ability to absorb and integrate technical information and then influence their innovation output (Capaldo, Petruzzelli, 2014; Rassenfosse *et al.*, 2016). Petruzzellii (2011) found that the longer the geographical distance, i.e., the lower the geographical proximity value, the higher the cost of knowledge diffusion. With the improvement in geographical proximity, the geographical distance between organizations is shortened, which is conducive to face-to-face communication. Anne, Wal (2014) believed that geographical proximity is beneficial to frequent communication and exchange, establishing a good cooperative relationship between organizations and then reaching a consensus and increasing the frequency of resource information exchange between cooperative scientific research institutions. These merits are not only good for the transfer of tacit knowledge but also for the exchange of resource information in the process of innovation activities. However, with the development of communication technology, the role of geographical proximity in collaborative innovation has no longer been recognized, and there is a saying that "geography is dead." Some scholars deem that the innovation in communication technology and transportation mode can offset the adverse effects caused by spatial distance (Liu *et al.*, 2020; Li *et al.*, 2022). NEV technology is a cutting-edge subversive technology, and its R&D is highly complex and uncertain. In practice, various innovative subjects have tried to break the physical distance limit and seek for cross-regional technical cooperation. Therefore, the following hypothesis is put forward.

Hypothesis 1*: Geographical proximity positively influences collaborative innovation performance in NEVs, but the effect is weakened somehow.*

1.2 Influence of Technological Proximity on Innovation Performance

According to resource dependence theory, no organization can completely own all the resources it needs, and it will acquire complementary resources through interactive learning with the outside world (Pfeffer, Salancik, 1978). Innovation itself is characterized by high risk and uncertainty, and the probability of generating new knowledge through complementary knowledge combinations under different technological environments will also vary. Therefore, partners should be carefully chosen through considering interorganizational gaps in the field of technology to reduce the risk of network collaborative innovation. In the 1990s, the economist Griliches (1990) indicated that "Having similar technological knowledge among cooperative subjects is helpful for both parties to acquire knowledge and transform technology to promote R&D and innovation output." Milani (2020) thought that the premise of collaborative innovation is that both partners need to possess a certain similar technological foundation, especially the emerging technological breakthroughs, which contain tacit knowledge. Strong technological similarities are conducive to the effective digestion and absorption of relevant technological knowledge by both partners. On the contrary, excessive technological distance will lead to increased communication cost between the two partners, taking considerable time and energy to improve the ability of knowledge transfer and absorption, adversely affecting cooperative technological innovation. At present, NEVs are in the stage of high-quality development, the core technologies remain to be broken through, and the key components are facing the problem of "clutch at the throat." Under the influence of a new round of scientific and technological revolution, such as information and communication, big data, and Internet, only by insisting on open cooperation, deep cultivation of technologies, and integrated development can innovative subjects form their own technological advantages. Hence, this study supposes that cooperation under the same knowledge base can promote the output of innovation results, and the following hypothesis is raised.

Hypothesis 2*: Technological proximity positively influences the collaborative innovation performance in NEVs.*

1.3 Influence of Organizational Proximity on Innovation Performance

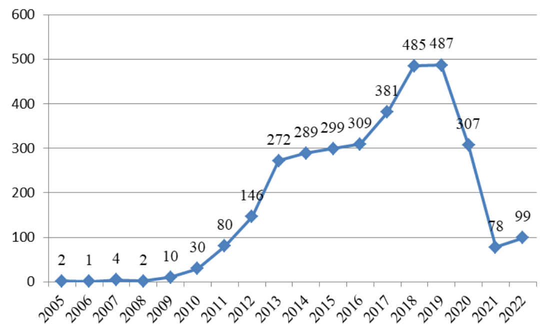
According to transaction cost theory, organizational proximity enables members to have common cognition, reduces conflicts and uncertainties in collaborative innovation, and decreases the cost of labor division and coordination and the information cost, thus achieving the purpose of reducing transaction costs and enhancing trust. Maskell, Malmberg (1999) stated that under the background of similar cultures and languages, information spreads fast, which is conducive to promoting learning and innovation. Therefore, organizational proximity provides a stable environment for subject interaction and knowledge learning. In case of great organizational proximity, the incentive policies and communication and coordination practices among cooperative organizations tend to be consistent, which is good for facilitating knowledge exchange and learning among organizations. In the meantime, organizational proximity encourages both cooperative partners to establish a set of common behavior and value norms, mobilizes members' commitment and investment in collaborative innovation activities under certain spirit of restraint, relieves the alertness of innovative organizations to knowledge exchange, enhances mutual trust and mutual assistance, and promotes the virtuous cyclic development of collaborative innovation activities. On the contrary, low organizational proximity is unconducive to the common cognition of organizations, which increases the information cost, uncertainty, and the transaction cost. With the development of the NEV industry, the industrial chain and innovation chain, which are dominated by leading enterprises and group enterprises, have been continuously extended. Organizational proximity strengthens the interaction among innovation subjects, promotes the emergence of cooperative relationships, and contributes to an open NEV industry–university–research innovation network (Cao *et al.*, 2020). Therefore, the following hypothesis is proposed.

Hypothesis 3: *Organizational proximity positively influences the collaborative innovation performance in NEVs.*

2. Methodology

2.1 Sample Selection

In this study, the "Patent Retrieval and Analysis System" developed by the Intellectual Property Publishing House of the China National Intellectual Property Administration was selected as the patent retrieval tool, and the keyword method was used for retrieval. With reference to the existing literature, the keyword search formula "electric vehicle or pure electric vehicle or plug-in hybrid vehicle or fuel cell vehicle or hybrid vehicle" was prepared, and the scope of retrieval was determined as "title, abstract, and claim" to reduce omissions. Data retrieval was performed on January 31, 2023. Excluding patents involving single institutions and foreign institutions and using Excel for statistical analysis, this study found that from 2005 to 2022, the total number of joint patent applications for NEVs in China was 3,281, including 1,707 cooperative organizations.



Source: created by the authors.

Figure 1. **Number of Joint NEV Patent Applications in China, 2005–2022**

From *Figure 1*, the collaborative innovation in NEVs in China during 2005–2022 could be divided into four stages: In Stage I (2005–2011), which was the budding stage, the number of cooperative patents every year did not exceed 100. In Stage II (2012–2016), which was the rapid growth stage, the number of cooperative patents rapidly grew from 146 in 2012 to about 300 every year. In Stage III (2017–2019), which was the steady development stage, the annual number of cooperative patents reached over 350 and peaked (487) in 2020. In Stage IV (2020–2022), which was the sharp decline stage, the patent research plummeted because of such unforeseeable factors as COVID-19. On the whole, the number of cooperative NEV patents in China showed a growth trend during 2005–2022, and the research on NEV technology gradually warmed up.

2.2 Variable Measurement

A. Dependent variable

The dependent variable was collaborative innovation performance, which was measured by the number of cooperative invention patents between different organizations. Specifically, the cross-organizational collaborative innovation performance was measured by the ratio of the number of joint invention patents between two organizations to the total number of cross-organizational cooperative patents between the two parties, as follows:

$$COOP_{ij} = \frac{P_{ij}}{P_i + P_j} \tag{1}$$

$COOP_{ij}$ is the collaborative innovation performance between organizations i and j, which is a continuous variable within the interval of 0–1; P_{ij} denotes the number of joint invention patents between organizations i and j; P_i and P_j represent the total number of cross-organizational cooperative patents of organizations i and j, respectively. The collaborative innovation performance of each sampled organization in different stages was calculated step by step to acquire the cross-organizational collaborative innovation performance matrix. In accordance with the collaborative innovation degree between innovation subjects, a collaborative innovation proximity matrix $COOP$ was established as

$$COOP = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ g_{i1} & g_{i2} & \cdots & g_{in} \end{bmatrix} \tag{2}$$

B. Independent variables

Geographical proximity is one of the important indicators for measuring the degree of interorganizational communication and cooperation. It is measured mainly through train running time, train running distance between regions, spherical distance, and the distance between provinces and cities where the organization is located. In this study, the actual distance between innovation subjects of the NEV industry was reflected by the spherical distance more appropriately (Reuer and Lahiri, 2014). The spherical distance is obtained by calculating the distance between two latitudes and longitudes, as shown in Formula (3), where $long_i$ and lat_i represent the longitude and latitude of member i, respectively; $long_j$ and lat_j stand for the longitude and latitude of subject j, respectively; and the radius of the Earth is *C*=6371 km (Hong and Su, 2013). The latitude and longitude data of each cooperative subject can be acquired using the pick-up coordinate system of Baidu Map.

$$GP_{ij} = C * \arccos\left[\sin(lat_i)\sin(lat_j) + \cos(lat_i)\cos(lat_j)\cos(long_i - long_j)\right] \tag{3}$$

For eliminating the possible adverse effects of the measuring unit, the geographical distance between two cooperative parties was evaluated using the reciprocal square root $GP_{ij}' = 1/\sqrt{GP_{ij}}$ of the geographical distance (Liu *et al.*, 2014). Meanwhile, given that the innovation subject i owns multiple partners j

within the same time window, i.e., one subject i corresponds to multiple geographical distances $GP_{ij}^{'}$, the geographical distance between subject i and all other cooperative organizations j was calculated using aggregate average GP_{ij} as per formula $GP_{ij} = \sum^{\infty} GP_{ij}^{'} / n_{ij}$. n_{ij} is the number of cooperative invention patents between subjects i and j, and the closer the value is to 1, the closer the relative geographical distance between cooperative members; if this value approaches 0, the geographical distance is great. A geographical proximity matrix GP was constructed on the basis of the geographical proximity value between innovation subjects.

Technological proximity is measured through such indicators as the similarity of patent technologies and the number of patent applications. With reference to Jaffe (1986) who calculated technological distance with the technological similarity between two parties, the following formula for technological proximity was proposed in this study:

$$TP_{ij} = \frac{f_i f_j^{'}}{\sqrt{(f_i f_i^{'})(f_j f_j^{'})}} = \frac{\sum_k F_{ik} F_{jk}}{\sqrt{(\sum_k F_{ik}^2)(\sum_k F_{jk}^2)}} \tag{4}$$

TP_{ij} is the technological distance between subject i and each partner j, and k is the IPC technology category, i.e., the technological fields with the same first 4 bits of patent IPC code (Zhang *et al.*, 2020), which is obtained mainly in accordance with the patent IPC classification involved by the patent applied by subject i and partner j in each stage. F_{ik} and F_{jk} represent the number of invention patents applied by subjects i and j for the k-th patent in the current year, respectively. The data were then standardized, i.e., taking their ensemble average, to obtain the technological distance TP_i to subject i. TP_i ranges from 0 to 1. If the value is closer to 1, the technological basis between cooperative members is more similar, and the technological proximity is higher; if the value is closer to 0, the technological proximity between cooperative members is lower. A technological proximity matrix TP was built on the basis of the technological proximity value between innovation subjects.

Organizational proximity is mainly measured through knowledge sharing and the differences in goal and expected benefit between two organizations when applying for patents. From the perspective of similarity theory proposed by Torre *et al.* (2005), organizational proximity was quantified using the measurement method of dichotomous variables. First, 1 represents the collaborative innovation between organizations of the same type, and 0 denotes that between different types of organizations (Zeng *et al.*, 2014). Hence, the value of OP_{ij} is 0 or 1. Then, data were averaged for standardization, i.e., calculating the ensemble average between organization i and all other partners j to obtain OP_i to organization i; thus, OP_i ranges from 0 to 1. When OP_i is closer to 1, subject i cooperates more frequently with organizations of the same type; if the value is closer to 0, subject i cooperates more frequently with other types of organizations. An organizational proximity matrix OP was established on the basis of the organizational proximity value between innovation subjects.

C. Control Variables

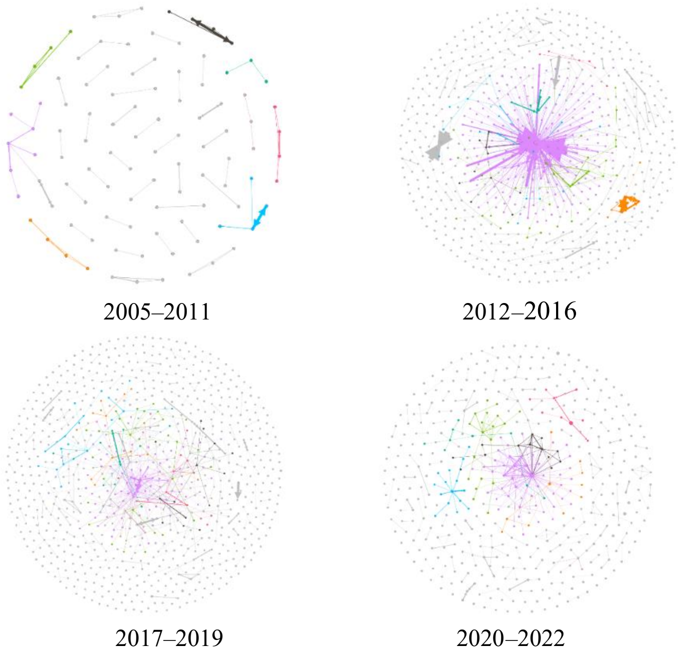
Degree centrality is one of the best indicators for measuring the ability of a single network subject to acquire external information and knowledge, which reflects the resource control of enterprises in cooperative networks. Specifically, it refers to the number of other subjects directly associated with a subject in the network, i.e., the close relationship between the subject and other subjects. If a subject is in direct contact with a large number of other subjects, the subject has a high degree centrality, meaning that it is very able to obtain external information and knowledge. In the enterprise cooperation network, the subject with high degree centrality can usually obtain the cooperation resources, technical knowledge, and market information of other enterprises effectively. The acquisition of these resources is important for the development of enterprises, which can help enterprises improve their innovation ability, speed up product research and development, and expand the market share.

The innovation ability of an enterprise refers to the ability and resources that an enterprise has in technological innovation and their influence on the innovation ability and competitiveness of an enterprise. A high level of technological innovation means that enterprises invest considerably in R&D resources and knowledge reserves, enabling enterprises to comprehensively understand, absorb, and integrate external knowledge, thus providing support for technological innovation. Invention patent, as a high-tech innovation product, can well represent the technological innovation level and independent innovation ability of enterprises. In this study, the innovation ability of enterprises was reflected mainly through the number of patent applications (Yu, Yan, 2017). The technological innovation ability between every combination of two organizations was calculated stepwise and standardized to obtain the technological innovation ability matrix IN in each stage.

3. Result Analysis

3.1 Innovative Network Structure

On the basis of the patent application data of China's NEV industry in four stages (2005–2011, 2012–2016, 2017–2019, and 2020–2022), the patent cooperation network was constructed using UCINET 6 software, and the visual evolution map of the cooperation network in each stage was drawn via Gephi software, as shown in *Figure 2*. Each node in *Figure 2* represents an innovation subject. The network scale is reflected by the number of nodes in the network. The more the nodes, the larger the network scale. The thickness of the connection line represents the number of patent cooperation between nodes; the thicker the sideline, the more frequent the cooperation between nodes in the network. In accordance with the connection relationship in the graph, the nodes were classified, and the nodes of the same type were marked with the same color, which intuitively depicted the set of nodes with close cooperation. On this basis, the topological structure index data of the cooperative NEV innovation network were obtained through UCINET software (*Table 1*).



Source: created by the authors.

Figure 2. **Evolution Map of China's NEV Collaborative Innovation Network During 2005–2022**

Table 1. Topology Analysis of China's NEV Collaborative Innovation Network During 2005–2022

	2005–2011	2012–2016	2017–2019	2020–2022
Sustained connection	—	15	65	30
New connection	—	625	438	361
Disappearing connection	—	55	575	473
Number of incumbents	—	54	234	179
Number of newly added cooperators	—	658	627	307
Number of quitters	—	47	478	682
Network scale (nodes)	101	712	861	486
Number of lines (edges)	70	640	503	391
Number of connections	149	1836	933	657
Network density	0.014	0.002	0.001	0.003
Network diameter	4	7	7	9
Average path length	1.568	2.47	2.742	2.946
Network density	0.014	0.002	0.001	0.003
Average degree	1.386	1.187	0.728	1.28
Average weighting degree	2.95	3.6	1.388	2.16
Average cluster coefficient	0.191	0.171	0.06	0.14

Source: created by the authors.

Table 1 indicates that from Stage I to Stage III, the cooperation network scale increased from 101 to 861, expanding by over 7 times. The number of network edges increased from 70 to 503, and the cooperation between nodes gradually increased. Especially in Stage II, the number of new cooperative connections was 625, accounting for 97.66% of the total cooperation in that year, indicating explosive cooperation and exchange between nodes in this stage. In Stage IV, under the trend of a sharp decline in cooperative patents, the network scale did not shrink significantly, and the number of incumbents remained at 179. Meanwhile, more nodes withdrew from cooperation, and 361 new contacts were added. Based on the data of the four stages, the network scale showed an increasing trend. The continuous connections ranged from 15 in Stage II to 65 in Stage III and then to 30 in Stage IV, and the new connections ranged from 625 in Stage II to 361 in Stage IV. The continuous connections were considerably less than the new connections and disappearing connections, and the number of incumbents was remarkably less than the number of new partners, manifesting that the nodes in the cooperative network were very mobile. Some fixed cooperative relationships were only established between individual nodes, just involving 4–5 nodes. The cooperation between other nodes was rare, not forming a specific scale.

For the average degree and average weighting degree of nodes, each node in the network had at least about two partners on average. However, owing to the dilution of the network, no stable cooperative relationship was established between nodes, and the cooperation breadth did not expand. From Stage I to Stage IV, the average weighting degree of nodes was greater than the average degree, the number of edge connections was greater than the number of edges, and the gap was narrowing, indicating that the cooperation depth between nodes was decreasing. At the same time, the average cluster coefficient showed a decreasing trend, the interaction between nodes in the network was gradually weakened, and the characteristics of cooperative agglomeration were insignificant, meaning that the cooperation depth between nodes in China's NEV patent cooperation network remained to be improved.

3.2 Collaborative Innovation Performance

A. Correlation Analysis

In this study, QAP regression analysis was performed to demonstrate the influence of geographical proximity, technological proximity, organizational proximity, degree centrality, and enterprises' innovation ability on the collaborative innovation performance in NEVs. QAP regression analysis is a social network analysis method for studying the regression relationship between independent matrices. On the basis of the routine analysis of each variable, this method is supplemented by multiple random permutations, including the row and column data of the matrix, to avoid the analysis errors caused by the correlation of observed values and the inaccurate results induced by invalid model construction. In UCINET software, operation was implemented along the path of Tools → Testing Hypothesis → Dyadic (QAP) → QAP Correlation. The correlation between the above five variable matrices and the patent cooperation network matrix in each stage from 2005 to 2022 was analyzed. The QAP correlation analysis results are shown in *Table 2*.

Table 2 presents that geographical proximity was the only variable with a negative correlation coefficient. Except for the positive value in Stage I, the correlation coefficient was negative in the other three stages, and the significance was at the confidence level of 1%. That is, the greater the geographical proximity between regions, the less frequent the interorganizational cooperation. Despite the relatively low coefficient, the collaborative innovation performance was not that significantly influenced. The correlation coefficients of technological proximity and organizational proximity with the NEV cooperative patent innovation network were positive, and the significance level was mostly within 1% in the other stages, except Stage I. That is, in the last three stages, technological proximity and organizational proximity were positively correlated with the patent cooperation network. Compared with those of geographical proximity and organizational proximity, the coefficient of technological proximity was great, preliminarily reflecting that the established collaborative innovation network relationship was greatly influenced by the technological structure possessed by each organization and the empirical correlation.

The last two columns in *Table 2* show the occurrence probability results of random permutation correlation coefficients. Hanneman *et al.* (2005) indicated that if the occurrence probability of $P \geq 0$ is close to 0 and that of P≤0 is close to 1, a real correlation exists between two matrix variables, which, moreover, is strong. Therefore, the research results in Table 2 imply that the correlation coefficient between the selected proximity-related independent variables and the cooperative NEV innovation network matrix is not merely caused by random permutation but is a real strong correlation. To sum up, in the four stages from 2005 to 2022, geographical proximity, technological proximity, organizational proximity, and enterprise resource control have a significant positive effect on the formation and development of collaborative innovation network relationship in NEV patents in China.

Table 2. QAP Correlation Analysis Results

Stage	Variable	Correlation coefficient	P value	Minimum value	Maximum value	Standard deviation	P≥0	P≤0
2005–2011	Geographical proximity	0.001	1	−0.0008	0.001	0.0002	0.399	0.602
	Technological proximity	34.8116	0.0005***	−0.6899	34.8116	1.1338	0.001	1
	Organizational proximity	0.1844	1	−1.0675	0.7355	0.2711	0.503	0.498
	Degree centrality	0.2337	0.0005	−0.3094	0.2337	0.0785	0.13	0.871
	Enterprises' innovation ability	1.9551	1	−3.4851	2.3387	0.8133	0.29	0.711
2012–2016	Geographical proximity	−0.0014	0.0005***	−0.0014	0.0005	0.0002	1	0.001
	Technological proximity	10.5248	0.0005***	−0.8948	10.5248	0.4187	0.001	1
	Organizational proximity	0.5848	0.0145**	−0.4997	0.6182	0.2009	0.024	0.977
	Degree centrality	15.728	0.003**	−4.8767	27.0594	2.5002	0.015	0.986
	Enterprises' innovation ability	2.3002	0.008***	−3.2215	2.3002	0.6262	0.001	1
2017–2019	Geographical proximity	−0.0016	0.0005***	−0.0016	0.0005	0.0001	1	0.001
	Technological proximity	1.8146	0.0005***	−0.5471	1.8146	0.1451	0.001	1
	Organizational proximity	0.746	0.0035***	−0.4006	0.746	0.1437	0.001	1
	Degree centrality	12.2976	0.0005***	−6.0894	12.2976	1.4556	0.005	0.996
	Enterprises' innovation ability	0.7331	0.062*	−2.8983	2.2254	0.7964	0.085	0.916
2020–2022	Geographical proximity	−0.0017	0.0005***	−0.0017	0.0005	0.0002	1	0.001
	Technological proximity	9.5549	0.0005***	−0.8333	9.5549	0.3697	0.001	1
	Organizational proximity	0.3785	0.3223*	−0.6405	0.667	0.1664	0.063	0.938
	Degree centrality	2.3821	0.7795	−2.7635	6.37	1.183	0.106	0.895
	Enterprises' innovation ability	2.7504	0.0005***	−4.991	2.7504	0.8906	0.001	1

Notes: * means the significance level of 10% (bilateral); ** indicates the significance level of 5% (bilateral); *** denotes the significance level of 1% (bilateral).

Source: authors' own calculations.

B. Regression Results

The data on variables in the four stages were imported using UCINET 6 software. After 2000 random permutations, the correlation coefficients of geographical proximity, technological proximity, organizational proximity, degree centrality, and enterprises' innovation ability all passed the significance level test, indicating that these variables have a significant effect on the collaborative innovation in China's NEV patents. Along the path of "Tools → Testing Hypotaxis → Dyadic (QAP) → QAP regression → Double Dekker SemiPartialling (MRQAP)," the QAP regression analysis results were obtained, as shown in *Table 3*. From the coefficient of determination (R^2) fitted by the four-stage model in Table 3, the fitting effect achieved by this model from Stage II to Stage IV was relatively significant, and the hypotheses were accepted mostly under the significance level of 0.1%. Hence, the established model has certain explanatory power, and the three proximity-related independent variables affect the output of the cooperative NEV patent innovation network.

Table 3. QAP Regression Analysis Results

Stage	Variable	Nonstandardized coefficient	Standardized coefficient	P value	Standard deviation	R^2	Adjusted R^2	Observable term
2005–2011	Geographical proximity	0	0	1	0	1	1	2126
	Technological proximity	1	1	0.0005***	0.0268			
	Organizational proximity	0	0	1	0			
	Degree central-ity	0.0005	0	0.0005	0			
	Enterprises' innovation ability	0	0	1	0			
2012–2016	Geographical proximity	0	-0.0402	0.0005***	0	0.0118	0.0118	102116
	Technological proximity	0.0058	0.1002	0.0005***	0.0002			
	Organizational proximity	0.0003	0.0071	0.0145**	0.0001			
	Degree central-ity	−0.0423	0.0118	0.003**	0.0159			
	Enterprises' innovation ability	0.0017	0.0124	0.008***	0.0007			
2017–2019	Geographical proximity	0	−0.0416	0.0005***	0	0.0106	0.0105	188432
	Technological proximity	0.0043	0.0971	0.0005***	0.0001			
	Organizational proximity	0.0002	0.0064	0.0035***	0.0001			
	Degree central-ity	−0.0726	0.0165	0.0005***	0.0144			
	Enterprises' innovation ability	0.001	0.0053	0.062*	0.0007			
2020–2022	Geographical proximity	0	−0.0539	0.0005***	0	0.0232	0.0231	46700
	Technological proximity	0.0107	0.1425	0.0005***	0.0003			
	Organizational proximity	0.0001	0.0023	0.3223*	0.0002			
	Degree central-ity	−0.0612	0.0103	0.7795	0.0002			
	Enterprises' innovation ability	0.0081	0.028	0.0005***	0.0015			

Notes: * means the significance level of 10% (bilateral); ** indicates the significance level of 5% (bilateral); *** denotes the significance level of 1% (bilateral).

Source: authors' own calculations.

4. Discussions

From the perspective of single-dimensional proximity, technological proximity was the only variable that was significant in four stages, i.e., technological proximity played an important role in collaborative innovation, which coincides with the conclusion drawn by Nepelski and Prato (2018). The standardized regression coefficient of technological proximity was 1, 0.1002, 0.0971, and 0.1425 in Stages I–IV, respectively, and the P value was 0.0005, all of which were significant at the level of 0.1%. Hence, technological proximity could promote the cooperative NEV patent innovation performance in China. The effect was first weakened and then enhanced, showing a U-shaped development trend, thus verifying Hypothesis 2. In the initial stage of NEV technology, because of the difficulty in obtaining technical knowledge, several organizations tended to carry out innovation cooperation with established fixed partners or organizations with the same knowledge structure and similar technical foundation among internal networks, aiming to achieve enhanced cross-organizational cooperation and innovation performance. Afterward, with the technological update and progress and the development of the NEV industry, the collaborative innovation network attracted considerable external organizations to join in, increased the frequency of information exchange, and stimulated the production of innovation results via the complementarity of resources, greatly weakening the role of technological proximity. In recent years, NEVs in China have been in need of breaking through core technologies and been stuck in the supply of key parts, making it necessary for innovation organizations to restudy the key technological fields. Consequently, the regression coefficient in Stage IV grew by a small margin.

The standardized regression coefficient of geographical proximity was 0, −0.0402, −0.0416, and −0.0539 in Stages I–IV, respectively, and the P value was 0.0005. The results in the last three stages were significant at the level of 0.1%. Therefore, geographical proximity exerted a negative effect on collaborative innovation, and Hypothesis 1 was rejected. The main reason was that in the initial stage of cooperation, the transportation convenience between cities was relatively poor, and the NEV innovation organizations depended on geographical proximity to some extent, mainly concentrated in the eastern coastal areas. Then, as the regional development level was elevated, interregional innovation factors flowed at an accelerated speed, and cross-regional long-distance technology transfer was faster on the contrary (Wen *et al.*, 2024). The interorganizational cooperation started to be launched in such regions as the Yangtze River Delta and circum-Bohai Sea region. The resistance formed by the geographical distance against the collaborative innovation between two organizations was increasingly weakened, and the geographical scope of cooperation objects was continuously expanded, gradually radiating to the whole country. Especially as new organizations in Mainland China joined in, the diameter of the cooperation network increased, then the new organizations actively cooperated with those in coastal areas possessing relatively mature resource information technologies, aiming to acquire rich information or knowledge.

Compared with geographical proximity and technical proximity, organizational proximity exerted the least influence, and the standard regression coefficient was 0, 0.0071, 0.0064, and 0.0023 in Stages I–IV, respectively. Except that in Stage I, the significance level was 5% in the other stages. Organizational proximity could promote the NEV patent cooperation in China, but its effect was gradually weakened. Hence, Hypothesis 3 held true, which coincides with the conclusion drawn by Lazzeretti and Capone (2016). From Stage II, the regression coefficient of organizational proximity was significantly positive, proving that organizational proximity will positively affect the performance of collaborative innovation and that knowledge information is easy to spread in similar cultural and organizational environments. Because organizations and individuals represented by the State Grid Corporation of China and Tsinghua

University exert a prominent “bridging” effect in the cooperative network, the scope of industry–university–research is increasingly widened. Organizational characteristics are no longer the factors that hinder interorganizational cooperation, and the influence of organizational proximity on collaborative innovation performance is gradually weakened.

The regression coefficient of the control variable—degree centrality—in each stage was positive, being 0, 0.0118, 0.0165, and 0.0103 in Stages I–IV, respectively. In particular, the significance levels in Stages II and III were 5% and 1%, respectively. Degree centrality thus plays a positive role in collaborative innovation performance. In other words, the greater the degree centrality, the closer the direct connection with other network nodes, and the stronger the ability to control such resources as information, knowledge, and technologies, which can substantially improve the cooperative NEV innovation performance (Su and Cao, 2022). The regression coefficient of enterprises' innovation ability was 0.0124, 0.0053, and 0.028 in the last three stages, respectively, all of which were significant at the level of 1%, indicating that collaborative innovation performance is positively affected by enterprises' innovation ability. That is, organizations tend to cooperate with those with strong technological R&D capability to break through their own technical bottlenecks and solve technical difficulties.

Conclusions and Managerial Implications

Main Findings

In this study, the effects of geographical proximity, technological proximity, and organizational proximity on collaborative innovation performance in NEVs were analyzed theoretically, and corresponding hypotheses were put forward. Taking the data on joint NEV invention patent applications in China during 2005–2022 as samples, this study verified the action mechanism of multidimensional proximity on collaborative innovation performance in NEVs via the social network analysis method and QAP regression model. The main research conclusions are as follows: First, technological proximity greatly promotes the collaborative innovation in NEVs. Organizations with relatively high technological proximity are extremely capable of mutual learning and joint innovation. Second, geographical proximity impedes the collaborative innovation between NEV enterprises, and it significantly negatively affects the collaborative innovation performance in NEVs. Third, organizational proximity has a minor positive effect on NEV collaborative innovation, and the effect is gradually weakened.

Managerial Implications

The research conclusions present the following insights: (1) Through paying attention to the core areas of technological innovation in NEVs in China, efforts should be made to seek for organizations in similar technological fields or those prone to cross-absorption of knowledge and technology to build cooperative alliances to promote breakthroughs in key areas of the NEV industry. For example, seminars may be held on NEV technology on a regular basis to strengthen exchanges and communication between enterprises and relevant industry representatives, enhance the flow and absorption of knowledge, and promote the development of NEV technology. (2) Resources can be gathered to develop cross-regional and transnational collaborative innovation. NEV innovation organizations should seize the geographical advantages and introduce regional knowledge capital to improve their own innovation ability, as well as pay attention to the “regional lock-in” problem induced by excessive geographical proximity. The NEV industry is an international industry, in which many countries have rich experience and technical advantages. By strengthening international exchanges and cooperation, enterprises can learn from foreign advanced experience, learn advanced technology, and expand the international market. The government can actively promote enterprises to participate in international cooperation projects and exhibitions and provide corresponding support and services. (3) The mode of school–enterprise R&D alliance can be explored to deepen the integration of industry–university–research. First, enterprises need to focus on collaborative innovation in key technologies in the NEV industry, actively formulate external cooperative R&D strategies, and promote the construction of collaborative innovation networks for NEVs between enterprises and research institutes in universities. Second, the management of school–enterprise R&D alliances should be strengthened, such as through the formulation of cooperative R&D agreements, the organization of R&D lectures and training, the development of cooperative R&D projects, and the publicity and promotion of R&D achievements, to enhance the efficiency of the alliances.

Research Limitations and Future Directions

This study enriches the theoretical research on the influencing factors of innovation networks and provides references for the deep integration of industry–university–research in NEVs in China. However, this study also has the following limitations: First, the awareness of intellectual property protection remains weak in China, and patents may not be applied for owing to the miscellaneous and toilsome patent application process and the protection of commercial secrets. Consequently, limitations exist when collaborative innovation performance is measured using patent data. In the follow-up study, such research methods as scales may be considered. Second, in addition to the three-dimensional proximity variables introduced in this study, other proximities should be introduced in the future to investigate collaborative innovation.

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KAIP DAUGIALYPIS ARTUMAS VEIKIA BENDRADARBIAVIMU GRINDŽIAMŲ INOVACIJŲ VEIKSMINGUMĄ NAUJOSE ENERGIJOS TRANSPORTO PRIEMONĖSE

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Santrauka. Bendradarbiavimu grindžiamų inovacijų veiksmingumą naujose energijos transporto priemonėse (NEV) lemia artumas tarp inovacijų subjektų – geografinis, technologinis ir organizacinis. Tačiau dinamiška daugialypio artumo įtaka bendradarbiavimu grindžiamų inovacijų rezultatams tirta mažai. Siekiant nustatyti proksimalinių bendradarbiavimo santykių įtaką NEV inovacijų rezultatams, šio tyrimo metu buvo naudojami Kinijos nevų (ang. NEV) bendradarbiavimo patentų duomenys nuo 2005 iki 2022 m. Buvo taikomi šie metodai – socialinių tinklų analizės ir kvadratinės priskyrimo procedūros (QAP) analizės siekiant patikrinti daugialypio artumo poveikį bendradarbiavimo inovacijoms NEV skirtingais laikotarpiais, remiantis sandorių sąnaudų teorija ir priklausomybės nuo išteklių teorija. Rezultatai atskleidė, kad artumas yra svarbus veiksnys bendradarbiavimo santykiams, o artumo veiksniai skirtingai veikia bendradarbiavimą įvairiais NEV pramonės vystymosi laikotarpiais. Technologinis artumas itin reikšmingas skatinant bendradarbiavimu grindžiamas inovacijas, o geografinis artumas ir organizacinis artumas mažiau paveikus bendradarbiavimu grindžiamoms inovacijoms. Išvados atskleidžia daugialypio artumo įtakos mechanizmą bendradarbiavimo inovacijoms NEV tam tikru mastu. Tai gali padėti priimti sprendimus siekiant glaudžios NEV pramonės, universiteto ir mokslinių tyrimų integracijos.

Reikšminiai žodžiai: daugialypis artumas; inovacijų tinklas; naujos energijos transporto priemonės.