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The Impact of Technology Convergence on the Sustainable Innovation of China's Modern Manufacturing Enterprises: The Mediating Role of the Knowledge Base

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Abstract: Against the backdrop of swiftly changing industrial environments, this study aims to investigate the influence of technology convergence on the sustainable innovation of manufacturing enterprises. The purpose of this research is to determine the future competitiveness and expansion potential of industries by evaluating the impact of technological convergence on innovation performance, which serves as a significant metric for assessing the sustainability of corporate innovation practices. Specifically, the relationships among three characteristics of technological convergence and enterprise innovation performance—betweenness, closeness, and clustering—are analyzed. Using the financial, property, and patent data of listed companies in China's automotive manufacturing industry, an empirical study is conducted using a negative binomial regression model. Enhancing all three technology convergence characteristics is found to be conducive to enhancing sustainable innovation. Meanwhile, the corporate knowledge base plays a mediating role in which the effect of knowledge base width on clustering technology integration is more strongly mediated by the effect of knowledge base depth on approaching technology integration. The results of this study are useful for policymakers, corporate strategists, and innovation managers who are looking to enhance sustainable innovation practices within their organizations. By understanding the critical roles of betweenness, closeness, and clustering in technological convergence, stakeholders can better position their firms to leverage these attributes for improved innovation performance and competitive advantage.

Keywords: technology convergence; knowledge base; sustainable innovation; modern manufacturing enterprise



Citation: Li, C.; Gong, J.; Luo, J.; Qiu, Z. The Impact of Technology Convergence on the Sustainable Innovation of China's Modern Manufacturing Enterprises: The Mediating Role of the Knowledge Base. *Sustainability* **2024**, *16*, 5307. <https://doi.org/10.3390/su16135307>

Academic Editor: Davide Settembre-Blundo

Received: 30 April 2024

Revised: 15 June 2024

Accepted: 18 June 2024

Published: 21 June 2024



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1. Introduction

Technology convergence represents the amalgamation of diverse technological elements to forge novel technological domains, playing a vital role in generating new value and launching innovative products and services [1]. As the digital economy flourishes, identifying opportunities for the transformation and advancement of the modern manufacturing sector towards high-quality, innovative development has become an especially critical issue in the current landscape [2,3]. Recently, digital transformation has successfully contributed to enhancing the sustainable innovation of China's manufacturing enterprises, particularly within the automotive manufacturing sector [4,5]. The automotive manufacturing industry plays a pivotal role in contemporary manufacturing, with its state of advancement reflecting the overall caliber of the nation's manufacturing sector [6,7]. Data from the China National Bureau of Statistics reveals that in 2021, China's automotive manufacturing industry experienced a 5.5% year-on-year increase in industrial value added for enterprises above a designated size. These enterprises within the automotive manufacturing sector reported operating revenues of CNY 8.67 trillion, representing 6.7%

year-on-year growth, and total profits of CNY 530.57 billion, representing a 1.7% increase from the previous year. Nevertheless, the automotive manufacturing industry's extensive connections to a wide array of upstream and downstream sectors mean that corporate performance is significantly impacted by the cost of materials from suppliers. This situation, coupled with the rise of new business models experiencing diminishing profits, is driving automotive manufacturers to explore new avenues for growth [8]. Sustainable innovation is generally recognized as the updating or enhancement of technology, products, and processes, aimed at achieving continuous improvements in productivity and reinforcing competitive advantages. It promotes environmental protection and actively contributes to the sustainable development of society [9,10]. In the digital era, cutting-edge digital technologies such as artificial intelligence (AI), digital twins, and the Internet of Things (IoT) have become the core drivers of sustainable innovation and development potential within enterprises through their synergistic effects and deep integration. The integrated application of these technologies not only optimizes production processes, increasing efficiency and quality, but also provides strong support for the green transformation and intelligent upgrading of the automotive industry [11]. In China's 14th Five-Year Plan, the government set forth a strategy to amplify the exploration of various technological avenues and encourage the cross-fertilization and dissemination of disruptive technologies, and the strategy highlighted that fusion innovation has become a pivotal approach for the development of critical core technologies and for seizing future industrial development opportunities. Technology convergence is instrumental to assisting automotive manufacturing enterprises in uncovering technological opportunities through the restructuring and merging of various technological sectors, consequently enhancing innovation performance and strengthening sustainability [1,12,13]. Additionally, convergence aids these enterprises in acquiring complementary innovation capabilities, improving R&D efficiency, and facilitating the sharing of risks and costs [14]. Therefore, it is necessary to understand the technological connections based on knowledge sharing within and outside an organization, at the firm level, to predict trends in technological change and evolution and to explore strategies for enhancing sustainable innovation in the automotive manufacturing industry, thus grasping the subtle to foresee the significant.

Existing research on technology convergence has focused on the perspectives of technology trajectories [15,16] and technology composition [17,18], revealing the importance of technology opportunity discovery, technology evolution paths, future emerging technologies, and the ability of enterprises to respond to dynamic technological change. However, technological diversity, complex technology convergence networks, and ambiguous technological boundaries in emerging industries pose serious challenges to the previous similarity-based prediction of technology convergence directions and direct utility evaluation [19,20]. Knowledge, serving as a crucial foundational resource for sustainable innovation, facilitates the foundational elements of technology convergence through the reconstruction and reengineering of knowledge across disparate domains [21]. Concurrently, the interactions derived between core knowledge and ancillary knowledge offer a network topology perspective, enabling the characterization of technology convergence amid intricate network relationships [22,23]. Scholars have begun to focus on technology convergence characteristics and knowledge flow, integration, and creation to analyze the impact of knowledge flow in heterogeneous technology domains on technology convergence opportunities, dual innovation capabilities, and enterprise performance through different intra-organizational and extra-organizational knowledge integration strategies [16,24]. Given that distinct characteristics of technology convergence determine knowledge heterogeneity and that knowledge heterogeneity in turn dictates the variability in corporate innovation performance [25], this paper explores the role that technology convergence characteristics and knowledge heterogeneity play in the context of technology convergence and corporate innovation performance. Incorporating a knowledge base into this study facilitates an examination of the links between heterogeneous knowledge combinations, the integration process, and corporate innovation performance [26]. By using objective

data on an enterprise's own technological resources and knowledge (patents), this research delves into the evolution of single-technology integration at the firm level. It dynamically measures the enterprise's own conditions and the integration methods of knowledge resources to deeply investigate the impact of technology integration on corporate innovation performance and to uncover effective patterns through which technological integration drives sustainable innovation.

This paper selected listed enterprises in the automobile manufacturing industry in the Shanghai and Shenzhen stock markets in China as samples, extracted enterprise-related data from the WIND database from 2009 to 2020, identified industries using the International Patent Classification (IPC) table, constructed a technology integration network for the whole automobile manufacturing industry, measured enterprise technology integration characteristics using network analysis methods, and used negative binomial regression models to empirically test the impact of convergence characteristics on the enterprises' innovation performances. The mediating role of the knowledge base was empirically tested using a negative binomial regression model. Network topology analysis enriches the research methodology used in the field of technology convergence, and the analysis of the role of knowledge bases also provides useful references for the patent restructuring strategy of enterprise technology convergence.

2. Literature Review and Research Hypotheses

2.1. Technology Convergence and Innovation Performance

Technology convergence is considered a major source of innovation—an innovative activity in which knowledge interacts and reorganizes across boundaries [14,27,28]. Curran and Leker [29] argued that technology convergence is characterized by the creation of new subdomains, which can trigger synergistic overlapping effects of cross-domain knowledge flows and thus lead to new enterprise growth opportunities. Enterprises use technology convergence to integrate knowledge from different technology tracks into existing innovation processes, where diverse technology convergence characteristics reflect the breadth of the fused technologies, while the uniformity of technology distribution reflects the depth of the fused technologies, laying the foundation for a knowledge network of technology convergence [30]. A technology convergence network with knowledge as the node, technology convergence as the edge, and technology breakthrough as the strength of the relationship, conditional on the synergistic interaction of knowledge flow inside and outside the technology domain, has gradually become a trending topic for academic research [31]. Thus, the network embedding approach and structural topology provide technology convergence characteristics for analysis based on a large amount of patent data [32]. Network centrality embodies the characteristics of technology convergence, as delineated by the processes of knowledge creation, transfer, accumulation, and utilization within enterprises [32–34]. Variations in network centrality have diverse effects on innovation performance, thereby highlighting the significant role of network attributes in determining innovation outcomes from both structural and relational perspectives [34]. Related studies tend to consider the impact of knowledge networks on knowledge transfer, absorption, and innovation activities in terms of both structural and relational embedding, with structural holes being particularly prominent in structural embedding studies [15,35].

2.1.1. Betweenness Technology Convergence and Innovation Performance

Betweenness technology convergence reflects the depth of convergence that occurs across multiple domains of knowledge in technology fusion networks [16]. These characteristics describe the strategy of enterprises to seek opportunities to increase their knowledge base based on existing technologies and to search externally for fungible knowledge [15]. Enterprises, having initiated a tiered open selection model, regard technologies poised for integration as core technologies, with any technology that interacts knowledgeably with these core technologies as subject to attempts at technology convergence [36]. The knowledge flow interactions under this feature are heterogeneous and multilevel, and are

attempted in descending order of betweenness centrality values until technological breakthroughs are achieved [37]. Betweenness technology convergence facilitates an increase in the knowledge base; strengthens the ability to acquire, integrate, and create heterogeneous resources; helps enterprises identify scarce and valuable fusible technologies, as well as highly mediated irreplaceable knowledge; and then integrates a firm's own technologies to achieve technological innovation breakthroughs and improve innovation performance [32]. At the same time, the convergence of key technologies is equivalent to occupying the key "gatekeeper" position, which not only provides enterprises with an information advantage but also makes it easy to obtain scarce information, grasp rich knowledge resources, and acquire stronger autonomy in technology convergence activities to gain insight into the intensity of knowledge flow and further grasp technology convergence opportunities [15]. The betweenness technology convergence feature is more conducive to knowledge reorganization in heterogeneous technology domains, strengthening the understanding of previously less-connected technologies in different domains, promoting new technologies created by multidomain convergence, and ensuring the overall growth of multilink technology convergence innovation performance [38]. Therefore, we propose the following hypothesis:

Hypothesis H1a. *Betweenness technology convergence has a positive effect on enterprise innovation performance.*

2.1.2. Closeness Technology Convergence and Innovation Performance

Closeness technology convergence reflects the breadth of knowledge integration of enterprises in technology integration networks [15,27,32]. Such characteristics describe the strategy of rapid integration of similar knowledge within an enterprise and an external search for knowledge with greater impact on closeness and convergence, also known as the short-path strategy [32]. Enterprises prioritize engagement, amalgamation, and innovation with neighboring and compatible knowledge, alongside their targeted technologies for fusion [39]. By employing link prediction, they pinpoint opportunities for convergence across each segment of the knowledge flow during the fusion process, thereby enabling the identification and selection of critical technologies [40]. Thus, enterprises have a faster technology convergence rate [19]. Technologies with greater closeness to the center in a technology convergence network tend to be basic, generic technologies in an industry, and enterprises thus choose less-risky technology routes [15,27,32]. Conversely, enterprises that cover fewer areas within a knowledge network or identify fewer potential opportunities for technological convergence are not only less likely to succeed in finding convergence opportunities within the existing stock of technological knowledge but may also engage in the redundant creation of knowledge due to similarities with existing technological convergences, thereby incurring unnecessary expenditures of time, money, and human capital [41]. Consequently, an enterprise's limited proximity to technology convergence hampers the integration of pertinent knowledge with existing technologies within a convergence network, adversely impacting the advancement of innovation performance [15,32]. Therefore, the following hypothesis is proposed:

Hypothesis H1b. *Closeness technology convergence has a positive effect on enterprise innovation performance.*

2.1.3. Clustered Technology Convergence and Innovation Performance

Clustered technology convergence indicates the recurrent emergence of similar technology convergence forms, representing the degree of closeness within a specific technology domain [37,38]. In this approach, enterprises appraise convergence opportunities for each of their R&D technologies, proceeding to explore technological integration once a synergistic effect with technology units from alternate domains is detected [19]. The focus then shifts to attempting technology convergence with groups of technology units that demonstrate a

substantial flow density of technological knowledge; essentially, those with a pronounced clustering coefficient [38]. Variations in local clustering coefficients within technology convergence networks signal the velocity of technological knowledge flow, serving as benchmarks for assessing fusion opportunities and potential added value [42]. A network-wide escalation in clustering coefficients signifies enhanced information exchange capabilities across a network, fostering improved innovation performance [37]. Furthermore, elevated clustering coefficients aid in the dissemination of innovation resources, increasing the likelihood of possessing transferable knowledge or learnable experiences [32,37]. However, this could also lead to confusion from an excess of technological directions or choices and the negative impact of a large volume of similar or redundant knowledge on the effectiveness of technology integration. In such situations, enterprises can boost innovation performance by incorporating external knowledge bases [35,43]. When the clustering of technology convergence is low, enterprises tend to explore the combinations among related technology units less or fail to sufficiently investigate their potential applications and opportunities [32]. Hence, a higher degree of clustering in technology fusion enables enterprises to pursue alternative technology integration within similar domains, magnifying the effects of knowledge acquisition, integration, and creation and thereby enhancing innovation performance. Therefore, we propose the following hypothesis:

Hypothesis H1c. *Clustering technology convergence has a positive effect on enterprise innovation performance.*

2.2. The Mediating Role of the Knowledge Base

The formation of a knowledge base depends on the accumulation of knowledge and can be characterized by the collection of knowledge domains by its owner as well as the relationships established among them [44–47]. An enterprise's existing knowledge base comprises internal knowledge resources, alongside the information, inputs, expertise, and capabilities that support technological innovation [46]. Knowledge is frequently viewed as a crucial unit for technology transfer; however, the breadth and intricacy of the technology domain within the technology convergence process transform it into a collection of knowledge domains that firms actively identify and engage with [16]. The characteristics of technology convergence influence the interaction and reorganization of knowledge domains via dynamic shifts in network structure, thereby imbuing the knowledge base with complex and dynamic social relations in the context of technology convergence activities [48]. These social relationships within knowledge bases emerge as knowledge networks created through multidomain knowledge associations embedded across inter- and intra-organizational contexts [29,47]. These networks align with the requirements for analyzing knowledge domain interactions influenced by technology convergence knowledge networks and their structural dynamics [45,48].

A knowledge base is considered a key criterion for judging the breadth and depth of an enterprise's knowledge, and knowledge breadth and depth are also seen as two different dimensions of the knowledge base [49]. The breadth of the knowledge base encompasses the extensive scope of knowledge, incorporating diverse and multidomain expertise [45]. This characteristic signifies a horizontal dimension, capturing the varied content of heterogeneous knowledge [47,48]. Conversely, the depth of the knowledge base pertains to the intricacy of critical domain knowledge, representing a vertical dimension that delves into unique, complex, and domain-specific expertise [45,49]. Together, these dimensions elucidate the structure and substance of the knowledge held by an enterprise, exerting a considerable positive influence on the enterprise's innovation performance [46]. Network-based knowledge organizations can gather knowledge resources more effectively, and different knowledge-based dimensions play a mediating role in the effect of knowledge network embeddedness on innovativeness [50].

2.2.1. Knowledge Base, Betweenness Technology Convergence, and Innovation Performance

Drawing from the theory of knowledge bases, innovation output is conceptualized as the reconfiguration of existing knowledge components or the integration of both new and existing knowledge domains [44]. Mediated technology convergence is particularly favorable for the reorganization of knowledge across diverse technological domains [38], with the knowledge flow interactions under this characteristic being heterogeneous and multilevel [37]. In this context, betweenness centrality influences the capacity for knowledge interaction, integration, and generation within firms, subsequently impacting the breadth and depth of the knowledge base [45]. Both of these dimensions of the knowledge base contribute to the identification of new knowledge and are intrinsically linked to knowledge reorganization mechanisms, such as knowledge sharing, acquisition, and integration [47]. Both expanding the search range for heterogeneous knowledge and deepening the understanding of multilevel expertise areas enable firms to bolster their technological integration and innovation capabilities, thereby enhancing innovation performance [23,30]. Specifically, mediated technology fusion promotes the expansion of the knowledge base, enhancing the acquisition, amalgamation, and generation of heterogeneous resources [47]. This process aids firms in pinpointing rare and valuable interchangeable technologies, as well as knowledge that is both highly mediated and challenging to replace [50]. Consequently, the breadth and depth of the knowledge base serve as intermediaries in the nexus between mediated technology integration and innovation performance. Therefore, the following hypotheses are proposed:

Hypothesis H2a. *Knowledge base breadth plays a mediating role in the relationship between betweenness technology convergence and innovation performance.*

Hypothesis H3a. *Knowledge base depth plays a mediating role in the relationship between betweenness technology convergence and innovation performance.*

2.2.2. Knowledge Base, Closeness Technology Convergence, and Innovation Performance

Considering the significance of information superiority in boosting enterprise innovation performance during technology convergence [15], closeness technology convergence illustrates a strategy of swiftly integrating similar knowledge within firms in technology convergence networks and externally sourcing knowledge with greater proximity and convergent impact [25]. Here, closeness centrality signifies a firm's capability for technology convergence and knowledge interaction. Organizations with greater closeness convergence are better positioned to avoid being misled by distorted or incomplete information due to multichannel information vetting [45]. Since the depth of the knowledge base can assure knowledge homogeneity, utilizing homogeneous information can effectively diminish communication mismatches and boost the capacity to pinpoint technology convergence knowledge domains. This leads to swifter technology convergence and enhanced innovation performance, influenced by the 'shortest path' approach to technology convergence [35,37]. As the breadth of the knowledge base expands, firms gain access to a more diverse range of information, favoring the emergence of novel ideas, thoughts, and perspectives. This expansion leads to improved knowledge comprehension and information processing capabilities, facilitating the identification of opportunities and knowledge integration for adjacent technology convergence, thus enhancing innovation performance [50]. Therefore, the breadth and depth of the knowledge base act as mediators in the relationship between closeness technology convergence and innovation performance [36]. Therefore, we propose the following hypotheses:

Hypothesis H2b. *Knowledge base breadth plays a mediating role in the relationship between closeness technology convergence and innovation performance.*

Hypothesis H3b. *Knowledge base depth plays a mediating role in the relationship between closeness technology convergence and innovation performance.*

2.2.3. Knowledge Base, Clustering Technology Convergence, and Innovation Performance

Cohesion within knowledge networks is a hallmark characteristic, with the level of clustering within these networks indicating an enterprise's adeptness at reorganizing internal knowledge resources and assimilating knowledge from beyond its boundaries [45]. The concept of clustered technology convergence, gauged by the density of knowledge exchange, signifies the proximity of convergence within specific technology domains [32,37]. In this context, the occurrence of knowledge interaction may not necessarily successfully achieve technological integration and requires effective recombination [48]. Wang and Nie [45] referred to this phenomenon as technical domain coupling. From a knowledge base standpoint, coupling assesses the capacity of firms to amalgamate knowledge from disparate domains in pursuit of novel technologies. This process is bifurcated into adjustments in the coupling among existing knowledge domains and the coupling between new and incumbent knowledge domains [33]. The effectiveness of this coupling in resource transformation is crucial for the innovation efficacy of technology convergence initiatives [41]. A wider knowledge base translates to increased knowledge heterogeneity, offering diverse avenues for resource identification and convergence. This heterogeneity enhances the chances of successfully reorganizing both existing and novel knowledge, thereby fostering technological synergy and elevating innovation performance [38]. An enriched depth of the knowledge base, indicative of a wealth of domain-specific knowledge accrued over time, amplifies the imperative to broaden existing knowledge bases and the competency to unearth novel, valuable knowledge [42,46]. This enrichment facilitates the segmentation of technological innovation into several R&D subdomains, enabling a more structured and systematic approach to exploring subdomain technology convergence opportunities, consequently augmenting the efficiency of technology convergence and boosting innovation performance [46,50]. Consequently, the breadth and depth of the knowledge base serve as critical mediators in the dynamic between clustered technology convergence and innovation performance. We therefore propose the following hypotheses:

Hypothesis H2c. *Knowledge base breadth plays a mediating role in the relationship between clustering technology convergence and innovation performance.*

Hypothesis H3c. *Knowledge base depth plays a mediating role in the relationship between clustering technology convergence and innovation performance.*

Based on the above hypotheses, the conceptual model of this study is shown in Figure 1.

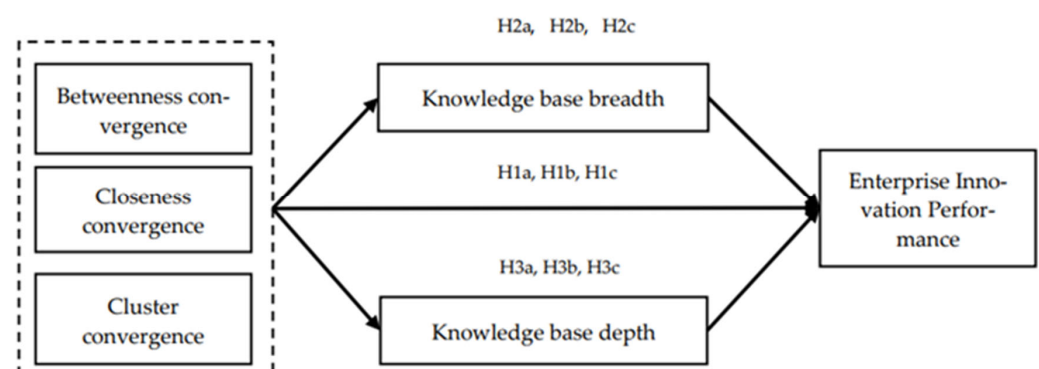


Figure 1. The conceptual model of this study. Source: Authors.

Figure 1 illustrates the relationships among the three characteristics of technological convergence—betweenness, closeness, and clustering—and their impact on enterprise innovation performance. The empirical analysis reveals the following key findings: (i) Betweenness technology convergence: This metric represents the extent to which a knowledge base acts as a bridge within the network, facilitating access to diverse and non-redundant knowledge resources. This position enhances innovation performance by leveraging information asymmetries, consistent with the structural holes concept in social capital theory. (ii) Closeness technology convergence: This characteristic indicates the average shortest path between knowledge nodes within the network, which accelerates information dissemination and knowledge acquisition. Firms with higher closeness technology convergence can more efficiently integrate new knowledge and adapt to technological changes, boosting their innovation capabilities. (iii) Clustering technology convergence: This measure reflects the tendency of firms to seek convergence opportunities among their technologies. Higher clustering technology convergence indicates a greater familiarity with relevant technology areas, leading to more effective use of social capital within tightly knit clusters and higher innovation performance. These findings underscore the importance of enhancing all three technology convergence characteristics to boost sustainable innovation. Additionally, the corporate knowledge base plays a mediating role, where the effect of knowledge base width on clustering technology integration is more strongly mediated by the effect of knowledge base depth on approaching technology integration. This analysis provides valuable insights for policymakers, corporate strategists, and innovation managers aiming to enhance their organizations' sustainable innovation practices and competitive advantages.

3. Research Design

3.1. Sample Selection and Data Sources

The automobile manufacturing industry is a knowledge- and technology-intensive industry, and automobiles are complex products involving multiple materials, processes, components, and systems in the manufacturing process; therefore, innovation in the automobile field often requires the crossover or introduction of multiple technologies. In this study, 139 automotive manufacturing enterprises in the Shanghai and Shenzhen stock markets (A-share markets) were selected as research samples according to the industry classification of listed companies of the China Securities Regulatory Commission (CSRC). Considering the impact of the COVID-19 pandemic-induced patent outliers in 2021 and 2022 on the analysis results, data on the R&D investment, scale, and operation time of these enterprises from 2009 to 2020 were collected from the WIND database. Then, from the patent information publicly available at the State Intellectual Property Office, we collected invention and utility model patent data from the 139 sample companies and the automotive manufacturing industry (as comprehensively as possible) from 1985–2020.

The design of the patent data analysis is as follows: First, based on the classification features of China's invention and utility model patents and the IPC international patent classification guidelines, this paper uses the complete hierarchical classification system of IPC classification numbers to divide the collected patent data into ministries, major categories, minor categories, major groups, and subgroups. Second, this study refers to the practice of most scholars in the literature review to determine how to apply technology to large groups. For example, if we take the classification number B60L8/00 (electric traction with electricity provided by natural forces, such as solar energy and wind power) as an example, if we focus solely on the small category B60L electric vehicle power device, it may reflect only the integration relationship between components, while the division of large groups can better account for the technology involved in realizing the components or methods. Again, the patents of the automotive manufacturing industry and patents under corporate control (Patents under the control of the company are those held by the listed company itself and its publicly disclosed equity participation or controlling subsidiaries and grandchildren) are collated and formed into a dataset applicable to the analysis. In the dataset, industry is used as the limiting boundary for patent search in this paper,

i.e., patents related to the automobile manufacturing industry are delineated, and the industry cross-reference table in the International Patent Classification (IPC) is used for further analysis.

Notably, the common methods used by scholars to define boundaries include using the IPC classification number and technology and industry field cross-reference tables to identify industry-related patents or a set of search terms for emerging industries. Although some scholars have suggested that the existing classification cross-reference tables are still subjective and time-sensitive, this paper adopts the IPC industry cross-reference table for the sake of consistency and the stability of the research. At present, several national and institutional organizations have compiled similar cross-references, including the “ISI-OST-INPI” classification system issued by the World Intellectual Property Organization and the “Concordance IPC V8 NACE REV.2” issued by the European Industry Agency in 2014 after several iterations. However, all these cross-references emphasize the comparison between IPC classification numbers and technical fields; considering that industry, as the main basis for classification, can avoid endogeneity and guarantee the consistency of data retrieval to a certain extent, this paper finally selects the “KSIC-IPC” cross-reference prepared by the Korean Patent Office based on the international industry standard of the United Nations. The “KSIC-IPC” comparison table is used. The “KSIC-IPC” table is one of the classification standards developed by the Korean Patent Office for industries, goods, science and technology, and industrial technology (Other standards include the HSK-IPC correlation table based on the World Customs Organization’s Harmonized Commodity Description and Coding System, the National Science and Technology Standard Classification–IPC correlation table based on the regulations of the Ministry of Science, Technology and Communications of Korea, and the Industrial Technology Classification–IPC correlation table based on the business plan of the Ministry of Industry and Energy of Korea). This standard has a high degree of distinction between the industrial field and the technical field. The corresponding IPC numbers for the automotive industry are B60B, B60D, B60F, B60G, B60H, B60J, B60K, B60L (except B60L13), B60N, B60P, B60R, B60S (except B60S3), B60T, B60W, B62D, E05F, F02M, F02N, F02P, F16J, G05G, F16J, and G05G. In addition, many companies will make all patent applications in the name of the parent company based on the overall corporate IP strategy (e.g., National Grid, etc.), but there are also patent applications by subsidiaries due to business (product line) separation, equity mergers and acquisitions, asset allocation, risk sharing, qualification restrictions, and tax benefits. The patents applied for by either the parent company or its subsidiaries reflect the innovation performance of the parent company and cannot be hastily divested from the performance of the subsidiaries. Therefore, this paper selects patents under corporate control as the research object to enhance the robustness of the study.

This study uses the co-occurrence relationship of knowledge elements in patent documents to construct a technology fusion network. The IPC number is a distillation of the components, functions, and technical topics involved in the patent application content. An invention often relies on several different technologies to achieve a function, method, or constituent component, so an inventive activity is an innovation across technical fields, and the multiple classification numbers corresponding to a patent mark the fusion of its corresponding technologies. The research data processing process is shown in Figure 2.

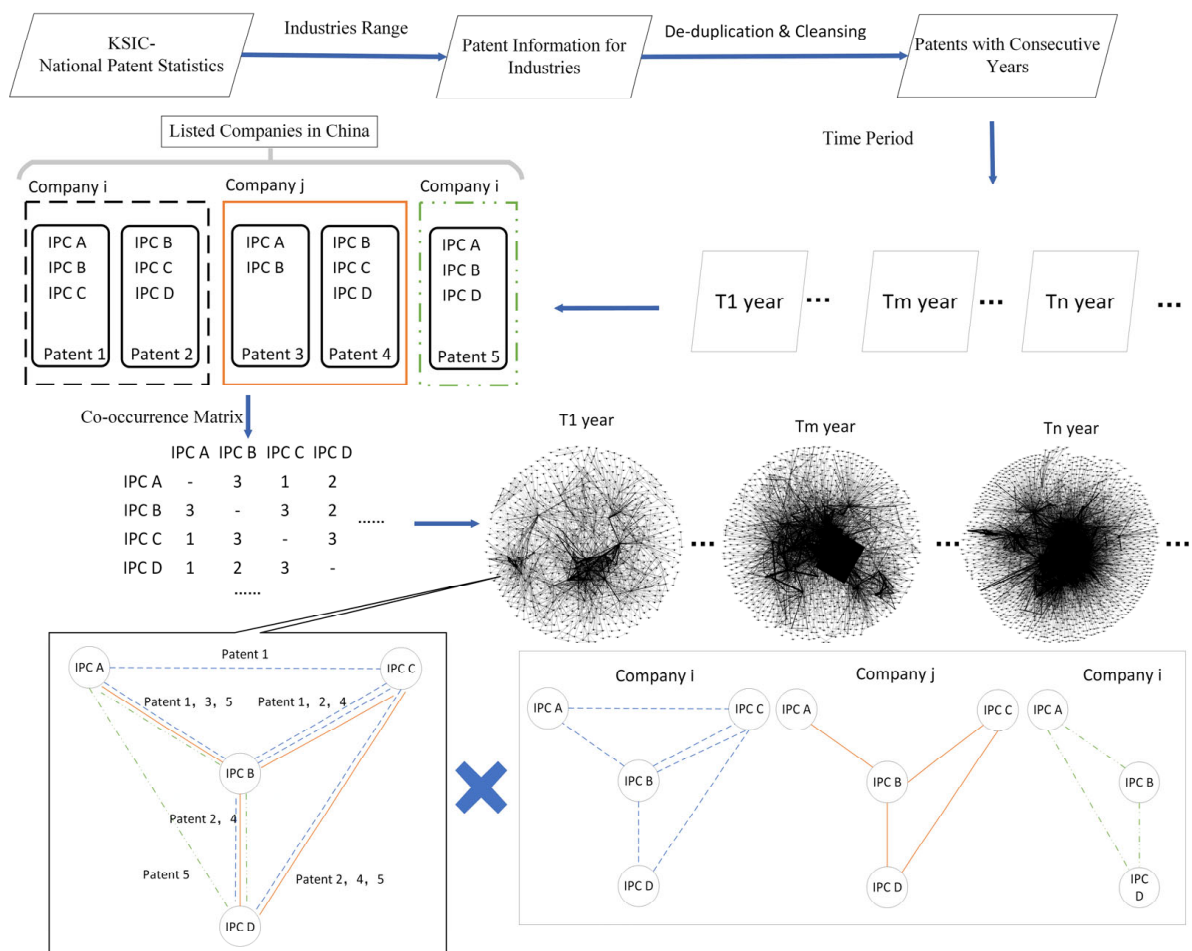


Figure 2. Schematic diagram of the data processing.

3.2. Variables and Measurement

1. **Innovation performance.** Innovation performance is the outcome of a firm's engagement in a diversified range of sustainable innovation activities [51]. It not only reflects the immediate effects of innovative actions but also indicates the company's intent towards future sustainable innovation. Furthermore, the ongoing optimization of innovation performance transforms into an intrinsic driving force that propels the company to pursue sustainable innovation. The number of patent applications is a commonly used indicator of corporate innovation performance. The automotive industry is highly competitive, intellectual property rights are actively used among companies to expand their advantages, and patent information largely reflects the innovation activities of automotive companies. Therefore, this paper draws on previous research and adopts the number of enterprise patent applications to measure the innovation performance of enterprises [52].
2. **Technology convergence characteristics.** This study draws on three technology convergence characteristics based on network structure characteristics selected as independent variables, namely, mediated technology convergence, proximity technology convergence, and clustering technology convergence. First, the intermediary centrality, proximity centrality, and local clustering coefficients of each IPC number in the technology fusion network are calculated by year. Then, the proportion of each IPC number in the patents under the control of each firm is calculated. Although individual firms holding patents in the same industry often share similar IPC numbers, the proportion of IPC numbers is different and can indicate differences in technology mastery among firms. Then, the three network structure characteristics of each IPC

- number are multiplied by the proportion of the IPC numbers of the enterprises, and the products are summed. Finally, when the structural characteristics of the points tend to follow a skewed distribution, the sum obtained is increased by 1 and then logarithmically processed to obtain the three technology integration characteristics.
3. Knowledge base breadth. In this paper, we use technological diversity to represent knowledge base breadth (breadth) [32] and calculate it using the entropy index method [16], which is calculated as $breadth = \sum_{j \in IPC_i} p_j \ln p_j$ and classified according to the first three digits of the IPC classification number, where P_j is the share of technology unit j in the IPC_i of patents held by enterprise i , i.e., the ratio of IPC number j to the total number of patents of the enterprise.
 4. Knowledge base depth. We use the average number of claims of patents under the control of enterprises to indicate the knowledge base depth. Patent claims are the scope of protection given to a patent application and often require the description of technical features such as the method or function of the patent in scientific terms. The greater the number of claims in a patent, the greater the number of corresponding technical features and the greater the number of patent owner requirements for patent protection and implementation, indicating that the patent is more important or is more cutting-edge.
 5. Control variables. In this study, financial leverage, return on total assets, internal R&D intensity, and enterprise age are selected as control variables. The financial leverage is measured by the gearing ratio, the internal R&D intensity is expressed by the logarithm of the ratio of R&D investment to main business revenue plus one, and the age of the enterprise is measured by the logarithm of the establishment time of the enterprise plus one.

3.3. Model Selection

The dependent variable (number of patent applications) in this study is a nonnegative integer variable, and the counting model is more suitable for its analysis than the general linear regression model is. Negative binomial regression and Poisson regression are commonly used for technological innovation studies, and the variance of the dependent variable is much larger than the mean, which is inconsistent with the assumption that the variance of the Poisson distribution is equal to the mean. In addition, random effects need to rely on a more stringent assumption of equal covariance; therefore, the negative binomial regression fixed effects model is chosen for analysis in this paper.

4. Empirical Analysis

4.1. Descriptive Statistics and Correlation Analysis

The results of the descriptive statistics are shown in Table 1. The data are unbalanced panels due to the different times when companies started to disclose data and carry out patent application activities when they went public. The minimum and maximum values of the dependent variable, innovation performance patent applications, are 0 and 4021, respectively, with a mean value of 141.7644 and a standard deviation of 374.7657, with large inter-individual differences. The independent variables include an intermediary technology fusion maximum value of 12.687, a minimum value of 1.806, a standard deviation of 1.406, and inter-firm variation, while proximity technology fusion has a minimum value of −3.880, a maximum value of −0.717, a mean value of −1.025, a standard deviation of 0.240, a clustering coefficient fusion minimum value of −3.457, a maximum value of 0, and a standard deviation of 0.278. The relatively small gaps between enterprises are due to the logarithmic treatment of proximity technology fusion and clustering technology fusion presenting negative values, probably because the technology fusion network is sparser or enterprises occupy more mediated positions in the technology fusion network, while proximity center and local clustering capture fewer relationships. The mediating variable, knowledge-based breadth, has a mean of 3.381, with a standard deviation of 1.221, and knowledge-based depth has a mean of 4.945, with a standard deviation of 1.770, varying

between firms. The standard deviation of the control variable financial leverage is 3.380 with large individual differences, the standard deviation of internal R&D is 0.696, and the standard deviation of firm age is 0.448, all with relatively small inter-individual differences.

Table 1. Descriptive statistics of variables.

Variable Name	Variable Abbreviation	Number	Average Value	Standard Deviation	Minimum Value	Maximum Value
Innovation performance	<i>pat</i>	1668	141.764	374.766	0	4021
Betweenness convergence	<i>bet</i>	1642	8.954	1.406	1.806	12.687
Closeness convergence	<i>clo</i>	1645	−1.025	0.239	−3.880	−0.717
Cluster convergence	<i>clu</i>	1645	−1.112	0.278	−3.457	0.000
Knowledge base breadth	<i>kbb</i>	1610	3.381	1.221	0.234	6.373
Knowledge base depth	<i>kbd</i>	1650	4.945	1.770	1.000	15.750
Financial leverage	<i>lev</i>	1421	51.476	135.596	4.167	4193.939
Return on total assets	<i>roa</i>	1486	8.956	57.243	664.879	2078.546
Internal R&D	<i>rdi</i>	1290	−17.209	0.696	−24.681	−12.585
Business age	<i>age</i>	1659	2.707	0.448	0.000	3.892

In this study, the Pearson correlation coefficient was used to test the correlation between the selected variables, and the results of the correlation analysis are shown in Table 2. The independent variables ‘betweenness technology convergence’ and ‘closeness technology convergence’, the betweenness variables ‘knowledge base breadth’ and ‘knowledge base depth’, and the control variable ‘firm age’ are significantly correlated with the number of patent applications at the 1% level and have a strong correlation. The correlation coefficients of betweenness technology convergence and closeness technology convergence with the number of patent applications were positive, while the correlation coefficient of clustered betweenness convergence with the number of patent applications was −0.284, which was negatively correlated. The independent variables betweenness technology convergence, closeness technology convergence, and clustering technology convergence are all significantly correlated with the mediating variable knowledge base breadth at the 1% level, and all of them are positively correlated, verifying that the enhancement of technology convergence strengthens enterprises’ expansions of their own knowledge bases to different degrees. Therefore, knowledge base breadth and depth play a positive mediating role in the effects of betweenness technology convergence, closeness technology convergence, and clustering technology convergence on innovation performance. The independent variables are also correlated with each other at the 1% significance level, but the positive and negative correlation coefficients and magnitudes vary, which is partly because the three independent variables are based on betweenness centrality, closeness centrality, and local clustering coefficients; the three types of network characteristics are not mutually exclusive, and the type of correlation depends on the particular technology convergence network. On the other hand, the three variables are calculated using the same summation method, which to some extent enhances the significance of the correlation coefficients.

Since there is a significant linear relationship between some of the variables, to exclude the effect of multiple cointegrations between the variables, cointegration analysis was performed with the help of the variance inflation factor (VIF). Co-collinearity is prevalent among variables, and it is generally considered that a $VIF > 5$ indicates the existence of co-collinearity problems, while a $VIF > 10$ means that serious co-collinearity problems need to be solved. The results of the covariance analysis are also presented in the table, and it is found that the VIFs of the variables are all less than 4, allowing for the next step of the study.

Table 2. Correlation and covariance analysis.

Variable	VIF	<i>pat</i>	<i>bet</i>	<i>clo</i>	<i>clu</i>	<i>kbb</i>	<i>kbd</i>	<i>lev</i>	<i>roa</i>	<i>rdi</i>	<i>age</i>
<i>pat</i>	1.63										
<i>bet</i>	3.56	0.237 ***									
<i>clo</i>	3.04	0.173 ***	0.670 ***								
<i>clu</i>	1.84	−0.037	−0.284 ***	0.245 ***							
<i>kbb</i>	1.95	0.557 ***	0.340 ***	0.268 ***	0.110 ***						
<i>kbd</i>	1.26	0.287 ***	0.214 ***	0.209 ***	0.0240	0.299 ***					
<i>lev</i>	1.29	0.020	0.050 *	0.036	−0.030	−0.023	−0.012				
<i>roa</i>	1.27	−0.022	−0.017	−0.032	−0.018	−0.045 *	−0.046 *	−0.125 ***			
<i>rdi</i>	1.17	−0.007	0.005	0.086 ***	0.152 ***	0.050 *	0.236 ***	−0.187 ***	−0.146 ***		
<i>age</i>	1.18	0.185 ***	0.226 ***	0.248 ***	0.040	0.354 ***	0.190 ***	0.039	−0.028	0.004	

Note: *** and * represent the 1% and 10% significance levels, respectively.

4.2. Regression Analysis

The negative binomial regression results of this study are shown in Table 3. A total of 15 regression models were used according to the research hypotheses. Models (1–3) include betweenness, closeness, and clustering technology convergence in addition to the control variables to test the effects of the three variables on firms' innovation performance. The regression coefficients of betweenness technology convergence, closeness technology convergence, and clustering technology convergence are 0.134, 0.596, and 0.413, respectively (all *p* values are less than 0.01), and all three have a significant positive effect on innovation performance. Higher betweenness technology convergence implies that firms tend to act as bridges between technology areas and have a better chance of capturing the direction of knowledge flows, and firms gain an advantage in generating cutting-edge results by linking different technologies. Closeness technology convergence represents the actual potential for convergence between technology areas, and firms with high closeness technology convergence are more likely to reach other technology areas and undergo technology convergence. Clustered technology convergence implies that firms seek opportunities for convergence among the technologies they hold, as they are more familiar with the relevant technology areas and have a better chance of applying for new patents. The coefficients of closeness technology convergence and cluster technology convergence are greater than that of betweenness technology convergence, indicating that there are greater innovation benefits for firms to enhance their exposure to a wide range of knowledge areas or deepen their intrinsic connection to their own mastery of technology knowledge. Hypotheses H1a, H1b, and H1c are supported by the empirical results.

Table 3. Main effects regression.

Variable	(1) <i>pat</i>	(2) <i>pat</i>	(3) <i>pat</i>
<i>bet</i>	0.134 *** (4.84)		
<i>clo</i>		0.596 *** (3.87)	
<i>clu</i>			0.413 *** (3.82)
<i>lev</i>	−0.001 (−0.34)	−0.000 (−0.00)	0.000 (0.25)
<i>roa</i>	−0.001 (−0.45)	−0.001 (−0.42)	−0.001 (−0.50)
<i>rdi</i>	0.212 *** (5.72)	0.207 *** (5.56)	0.198 *** (5.29)
<i>age</i>	1.281 *** (12.71)	1.299 *** (12.51)	1.481 *** (16.08)
Constant	0.006 (0.01)	1.667 ** (2.13)	0.867 (1.16)
Observations	1286	1286	1286
Number of ID	139	139	139

Note: *** and ** represent 1% and 5% significance levels, respectively, and standard errors are in parentheses.

Models (4–9) explore the mediating effects of knowledge base breadth on the relationships between betweenness, closeness, and clustering technology convergence and firm innovation performance, as shown in Table 4. Models (4–6) show that the three technol-

ogy convergence characteristics have a significant positive effect on firm knowledge base breadth. Models (7~9) add knowledge base breadth regressions to (1~3). The coefficients of betweenness and closeness technology fusion remain significant, but both decrease significantly ($0.088, p < 0.01$; $0.395, p < 0.05$), and the coefficient of clustered technology convergence decreases substantially (0.068 , not significant). The empirical results support Hypotheses H2a, H2b, and H2c. This shows that the broader the knowledge base and the more diverse the mastery of knowledge, the more companies benefit from technology convergence, and companies that achieve innovation by exploring the links between mastered technologies rely on their own diverse knowledge base, particularly for their R&D activities.

Table 4. Mediated effects regression of knowledge base breadth.

Variable	(4)	(5)	(6)	(7)	(8)	(9)
	<i>kbb</i>	<i>kbb</i>	<i>kbb</i>	<i>pat</i>	<i>pat</i>	<i>pat</i>
<i>bet</i>	0.161 *** (8.49)			0.088 *** (2.93)		
<i>clo</i>		0.766 *** (8.38)			0.395 ** (2.52)	
<i>clu</i>			0.597 *** (9.57)			0.068 (0.52)
<i>kbb</i>				0.538 *** (14.67)	0.547 *** (14.87)	0.546 *** (14.74)
<i>lev</i>	−0.004 *** (−4.04)	−0.003 *** (−3.20)	−0.002 ** (−2.11)	−0.001 (−1.00)	−0.001 (−0.78)	−0.001 (−0.69)
<i>roa</i>	−0.007 *** (−4.11)	−0.006 *** (−3.68)	−0.005 *** (−2.93)	0.006 ** (2.33)	0.006 ** (2.37)	0.006 ** (2.12)
<i>rdi</i>	0.091 *** (4.89)	0.103 *** (5.59)	0.113 *** (6.16)	0.196 *** (5.67)	0.189 *** (5.45)	0.193 *** (5.50)
<i>age</i>	1.697 *** (27.95)	1.646 *** (25.57)	1.895 *** (36.33)	0.608 *** (6.23)	0.590 *** (5.76)	0.718 *** (7.75)
Constant	−0.855 ** (−2.13)	1.694 *** (4.01)	1.001 ** (2.58)	0.178 (0.25)	1.262 * (1.75)	0.657 (0.95)
Observations	1275	1275	1275	1275	1275	1275
R-squared	0.697	0.697	0.702			
Number of ID	139	139	139	139	139	139

Note: ***, **, and * represent 1%, 5%, and 10% significance levels, respectively, and standard errors are in parentheses.

As shown in Table 5, models (10~15) explore the mediating role of knowledge base depth on the relationship between betweenness, closeness, and clustering technology convergence and firm innovation performance. Models (10~12) show that the three technology convergence characteristics have a significant positive effect on the firm's knowledge base depth. Models (13~15) add the regression of knowledge base depth to (1~3). The coefficients of betweenness and clustered technology convergence are still significant, but both decrease ($0.115, p < 0.01$; $0.333, p < 0.01$). The coefficient of proximity technology convergence decreases more ($0.285, p < 0.05$), and Hypotheses H3a, H3b, and H3c are verified. This indicates that the technology chosen by the company is more likely to achieve crossover with the new field and requires the company to have a deep enough understanding of the technology it possesses to better achieve innovation.

Table 5. Mediated effects regression of knowledge base depth.

Variable	(10)	(11)	(12)	(13)	(14)	(15)
	<i>kbd</i>	<i>kbd</i>	<i>kbd</i>	<i>pat</i>	<i>pat</i>	<i>pat</i>
<i>bet</i>	0.188 *** (5.11)			0.115 *** (4.09)		
<i>clo</i>		0.434 ** (2.43)			0.285 ** (2.00)	
<i>clu</i>			0.309 ** (2.48)			0.333 *** (3.08)
<i>kbd</i>				0.220 *** (11.88)	0.218 *** (11.59)	0.222 *** (11.93)
<i>lev</i>	−0.007 *** (−3.79)	−0.006 *** (−3.35)	−0.006 *** (−3.22)	0.000 (0.28)	0.001 (0.57)	0.001 (0.75)
<i>roa</i>	−0.015 *** (−4.44)	−0.014 *** (−4.27)	−0.015 *** (−2.98)	0.003 (1.05)	0.002 (0.97)	0.002 (0.95)
<i>rdi</i>	0.011 (0.28)	0.029 (0.78)	0.042 (1.12)	0.172 *** (5.07)	0.170 *** (4.96)	0.159 *** (4.59)
<i>age</i>	2.067 *** (16.95)	2.205 *** (17.07)	2.346 *** (21.94)	0.995 *** (10.14)	1.087 *** (10.83)	1.165 *** (12.97)
Constant	−1.849 ** (−2.30)	0.194 (0.23)	−0.071 (−0.09)	−0.753 (−1.10)	0.291 (0.40)	−0.052 (−0.08)
Observations	1286	1286	1285	1286	1286	1286
R-squared	0.464	0.454	0.454			
Number of ID	139	139	139	139	139	139

Note: *** and ** represent 1% and 5% significance levels, respectively, and standard errors are in parentheses.

4.3. Robustness Tests

The robustness tests conducted in this study include the following: (1) Robustness tests for an alternative model commonly used for count variables, replacement using the Poisson model, as shown in Table 6, which yielded results consistent with those of the baseline model. (2) Robustness tests for the substituted dependent variable. The number of patent applications in the year used in the baseline regression does not account for the differences in importance among patents, so we refer to Sampson [53] and use the number of forwards citations within 3–5 years of patent applications in the year to measure innovation performance, denoted as *cited*, and only the results of replacing the number of forwards citations within 3 years of patent applications as the dependent variable are reported due to space limitations, as shown in Table 7. The conclusions obtained after regression are all consistent with those of the baseline regression. Because of the need for several years of forwards patent citation data, the reporting period is shortened, and the number of observations is reduced.

Table 6. Poisson model robustness test results.

Variable	(1) <i>pat</i>	(2) <i>pat</i>	(3) <i>pat</i>	(4) <i>pat</i>	(5) <i>pat</i>	(6) <i>pat</i>	(7) <i>pat</i>	(8) <i>pat</i>	(9) <i>pat</i>
<i>bet</i>	0.086 *** (4.67)			0.098 *** (4.38)			0.142 *** (7.51)		
<i>clo</i>		1.713 *** (4.82)			2.709 *** (6.49)			2.618 *** (7.15)	
<i>clu</i>			0.994 *** (3.86)			0.326 (1.06)			0.855 *** (3.34)
<i>kbb</i>				0.669 *** (29.80)	0.678 *** (30.07)	0.664 *** (29.60)			
<i>kbd</i>							0.224 *** (20.95)	0.219 *** (20.80)	0.212 *** (19.99)
<i>lev</i>	−0.004 *** (−6.13)	−0.004 *** (−5.94)	−0.004 *** (−5.74)	0.001 (1.11)	0.001 (1.61)	0.001 (1.25)	−0.006 *** (−8.27)	−0.006 *** (−7.89)	−0.005 *** (−7.72)
<i>roa</i>	0.010 *** (7.30)	0.010 *** (7.46)	0.010 *** (7.33)	0.009 *** (6.69)	0.010 *** (7.16)	0.009 *** (6.76)	0.009 *** (6.86)	0.010 *** (7.25)	0.009 *** (6.80)
<i>rdi</i>	0.164 *** (16.93)	0.165 *** (17.01)	0.164 *** (16.93)	0.155 *** (15.85)	0.157 *** (16.06)	0.154 *** (15.80)	0.118 *** (11.85)	0.121 *** (12.19)	0.120 *** (12.05)
<i>age</i>	2.708 *** (44.82)	2.662 *** (40.16)	2.877 *** (64.84)	1.294 *** (15.67)	1.114 *** (12.44)	1.521 *** (23.98)	2.090 *** (31.20)	2.053 *** (28.38)	2.417 *** (48.83)
Observations	597	597	597	582	582	582	595	595	595
Number of ID	125	125	125	125	125	125	125	125	125

Note: *** represent 1% significance levels, respectively, and standard errors are in parentheses.

The results presented in Table 7 confirm the robustness of our findings. By replacing the dependent variable, we demonstrate that the conclusions remain consistent across different specifications. This robustness check reinforces the validity of our empirical results, supporting the hypotheses. This comprehensive analysis underscores the importance of strategic knowledge management and technological integration for enhancing innovation performance, offering valuable implications for industry practitioners and policymakers aiming to drive sustainable growth and competitiveness.

Table 7. Results of robustness tests for replacing the dependent variable.

Variable	(1) <i>cited</i>	(2) <i>cited</i>	(3) <i>cited</i>	(4) <i>cited</i>	(5) <i>cited</i>	(6) <i>cited</i>	(7) <i>cited</i>	(8) <i>cited</i>	(9) <i>cited</i>
<i>bet</i>	0.137 *** (3.75)			0.056 (1.26)			0.135 *** (3.35)		
<i>clo</i>		2.543 *** (2.81)			2.673 *** (2.71)			2.649 *** (2.81)	
<i>clu</i>			2.130 *** (3.43)			1.177 (1.47)			1.827 *** (2.84)
<i>kbb</i>				0.719 *** (14.21)	0.733 *** (14.71)	0.723 *** (14.34)			
<i>kbd</i>							0.222 *** (6.22)	0.226 *** (6.40)	0.214 *** (6.02)
<i>lev</i>	−0.001 (−0.26)	−0.000 (−0.14)	0.000 (0.14)	−0.001 (−0.53)	−0.001 (−0.52)	−0.001 (−0.35)	−0.001 (−0.42)	−0.001 (−0.32)	0.000 (0.02)
<i>roa</i>	−0.001 (−0.18)	0.001 (0.14)	0.005 (0.84)	0.019 *** (3.58)	0.021 *** (3.94)	0.020 *** (3.74)	0.008 (1.30)	0.010 (1.57)	0.012 * (1.88)
<i>rdi</i>	0.174 *** (3.05)	0.167 *** (2.88)	0.175 *** (2.98)	0.188 *** (4.03)	0.174 *** (3.80)	0.185 *** (3.91)	0.150 *** (2.86)	0.141 *** (2.65)	0.149 *** (2.75)
<i>lage</i>	0.761 *** (4.34)	0.799 *** (4.50)	0.918 *** (5.32)	0.087 (0.54)	−0.030 (−0.18)	0.131 (0.83)	0.682 *** (3.87)	0.691 *** (3.88)	0.822 *** (4.72)
Constant	0.650 (0.56)	0.836 (0.72)	0.727 (0.62)	1.153 (1.11)	0.882 (0.88)	1.095 (1.04)	−0.491 (−0.43)	−0.314 (−0.28)	−0.265 (−0.23)
Observations	597	597	597	582	582	582	595	595	595
Number of ID	125	125	125	125	125	125	125	125	125

Note: *** indicates $p < 0.01$, * indicates $p < 0.1$, two-tailed z test.

5. Conclusions and Implications

This paper analyzes the role of technology convergence in innovation performance and its indirect effect on firms through the knowledge base as a mediating variable at both the theoretical and empirical levels, thereby exploring the path to sustainable innovation for enterprises. The results of the study show the following: (i) Betweenness technology convergence, closeness technology convergence, and clustering technology convergence all have significant positive effects on innovation performance. The effect of closeness technology convergence is the largest, and the effect of betweenness technology convergence is the smallest. Mapping the continuous attempts to integrate higher-impact and less-risky technologies in familiar domains has become the main strategy for technology integration. (ii) Corporate knowledge base breadth plays a mediating role in the relationship between technology convergence characteristics and innovation performance. The intervention of knowledge base breadth leads to the direct effect of clustering technology convergence being greatly affected. An increase in knowledge heterogeneity intensifies the pressure of enterprises to identify the fusion opportunities of technologies in familiar fields and contributes positively to the diversification of an enterprise's own knowledge accumulation. (iii) The depth of the enterprise knowledge base plays a mediating role in the relationship between technology convergence characteristics and innovation performance. The intervention of knowledge base depth has a greater impact on the direct effect of approaching technology integration; thus, knowledge complexity and technology accumulation have a positive contribution to the rapid search for intermediary technologies, which has a greater impact on enterprises.

The theoretical contributions of this paper are as follows.

First, this paper integrates the concepts of a technology innovation network, knowledge network, and cooperative innovation network, shifts the research perspective to the technology convergence network, studies the phenomenon and characteristics of technology convergence from the perspective of network microstructure, and deepens the

understanding of technology convergence and the technology innovation process. In this way, we attempt to innovate the perspective of research.

Second, a network topology is used to define the characteristics of technology convergence and deepen the study of technology convergence and its effects. There have been studies on the effect of network centrality on technology convergence [1,15,35]. However, the field also needs to consider the dynamic patterns and evolutionary trajectories of technology convergence based on the static analysis of network structures [15]. In this paper, we start from the role of network connectivity, structural holes and knowledge bases to generalize the mechanisms of action for betweenness, closeness, and clustering technology convergence features and introduce the influence of knowledge bases to explore the changes in the impact of technology convergence features on innovation performance based on a static analysis of degree distribution, centrality, entropy, and gravity.

Third, social capital theory also provides practical explanatory grounds for the findings of this paper. For instance, the influence of the three types of technology convergence on sustainable innovation performance can be explained using this theory [54–56]. Betweenness technology convergence measures the extent to which the knowledge base acts as a bridge within the network. By facilitating access to diverse and non-redundant knowledge resources, it enhances innovation performance. This is consistent with the concept of structural holes in social capital theory, where actors in such roles can exploit information asymmetries to gain innovative benefits [54]. Closeness technology convergence indicates the average shortest path between two different knowledge nodes within the network, helping to accelerate information dissemination and knowledge acquisition, thus fostering a more efficient innovation process. By effectively leveraging their social capital, firms with higher closeness technology convergence can swiftly integrate new knowledge and respond to technological changes, thereby enhancing their innovation capabilities [55]. Clustering technology convergence, which reflects the tendency of firms to seek opportunities for convergence among the technologies they hold, can also be explained through the lens of social capital theory. Firms with high clustering technology convergence are more familiar with their relevant technology areas and have a higher chance of applying for new patents. This familiarity enhances their ability to exploit their social capital within closely knit clusters, leading to more effective innovation performance [56]. The insights from social capital theory not only reinforce the findings on the importance of network microstructure in technology convergence but also deepen the understanding of the mechanisms through which network positions influence innovation performance.

Finally, the antecedents of the utility of the knowledge base are revealed through the role analysis of technology convergence features. The importance of knowledge bases and their positive effects on innovation performance have been discussed [49]. As the cross-structural boundary interactions of knowledge bases in knowledge networks are recognized by most scholars, the study of knowledge bases also needs to clarify the dynamics that influence their own changes. Studying the antecedents of the utility of knowledge bases can help firms improve existing knowledge domains or integrate new knowledge domains to respond to new development needs [45]. In this paper, we further explore the utility of knowledge base breadth and depth through an empirical analysis of the impact of knowledge network centrality on the ‘two-dimensionality’ of knowledge bases inherent in technology convergence and expand the research on knowledge bases in technology innovation.

This paper also offers the following insights into technology convergence management practices. First, at the enterprise level, enterprises play an important role in technology convergence networks, and the flow of knowledge and resources that occurs in the process of technology convergence occurs both through formal relationships, such as industry–university research partnerships, and through informal relationships, such as the exchange and flow of technical personnel. In particular, enterprises in the automotive manufacturing industry pool heterogeneous information, knowledge, and resources through multilevel network relationships. Companies can configure network relationships and select cooperation partners at the technology meta-level, specifically R&D projects and research groups.

Enterprises should formulate development goals and technology strategies that combine their own strengths and weaknesses and competitive environments, tap their advantages in technology links, technology stacks, and industry chains, be clear about the possible risks in future technology development, and not only focus on emerging technologies but also analyze whether they have a greater role in promoting their own sustainable innovation. In addition, the management of knowledge assets should be performed well, including by maintaining the frontier of core technology, crafting a ‘patent fence’, and constructing an enterprise knowledge base. Second, at the industry level, the modern manufacturing industry should be actively guided to establish a sounder R&D mechanism and a healthy market environment and pay attention to the dynamic state of technology integration. For budding converging technologies, this entails enhancing heterogeneous resource sharing for relevant innovation subjects, exploring potential technology convergence opportunities for relatively mature technology fields, and actively cultivating emerging technologies and markets. The international competitiveness of the industry as a whole should be improved, key core technologies protected, the integrity of manufacturing systems maintained, and more authoritative and open standard systems established. Third, at the government level, more precise policy cultivation should be adopted for the state of technology integration and the main body of industry, academia, and research; for example, at the early stage of technology integration, the main body of relevant academia and research often needs more funding, while the relevant enterprises often need more opportunities for knowledge and resource exchange. With respect to achieving a good balance between strategic core technology protection and industrialization, the military has long relied on state support and the enthusiasm of researchers; developed countries tend to have relatively well established civil–military integration mechanisms. Aircraft, automobiles, chips, and other areas of independent and controllable core technology often come from the integration of military research and development results with generated civilian technology; the civilian market can feed back to support subsequent research, and the government should foster a sound system of civil–military integration to avoid brain drain.

The main limitation of this paper’s research is that the main technology convergence trend and the construction of an enterprise knowledge base are long-term gradual processes; the time span selected in this paper is not long enough to fully determine its direct or indirect impact, the sample size is limited to the automotive manufacturing industry, which mainly uses patents to secure intellectual property rights, and further work is thus needed to support the conclusions.

Author Contributions: C.L., Z.Q. and J.G. were involved in the conceptualization, literature review, methodology design, investigation, data analysis, and review. Writing, C.L., Z.Q., J.L. and J.G.; project administration, C.L.; funding acquisition, C.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Humanities and Social Sciences Fund Project of the Ministry of Education of China, grant No. 20YJCZH066. This work was also supported in part by Beijing Natural Science Foundation under grant No. 9222010 and National Social Science Foundation Project of China, grant No. 23BGL055.

Institutional Review Board Statement: This study does not involve any hazards, such as the use of animal or human subjects. This work was approved by the Institutional Review Board of North China University of Technology, Beijing, China.

Informed Consent Statement: The data involved in the research are all publicly available.

Data Availability Statement: Patent data are public data, which can be downloaded from the website of the National Intellectual Property Administration of China at <https://www.cnipa.gov.cn>, accessed on 20 December 2020. The data presented in this study are available on request from the corresponding author. The data are not publicly available due to restrictions of privacy.

Conflicts of Interest: The authors declare no conflicts of interest.

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