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The Impact of Supply Chain Network Embeddedness on Firms' General-Purpose Technology Innovation

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Abstract. With the gradual refinement of the division of labor in the market, suppliers in the upstream of the supply chain and customers in the downstream have become increasingly closely connected, forming a supply chain network among firms. As one of the important components of the social network in which firms are located, the supply chain network also affects the innovation activities of firms. Under the severe situation of "bottlenecking" of key common technologies in the industry, it is especially important to study the innovation effect and mechanism of the embedded position of firms in the supply relationship structure. In this theoretical and practical context, this study focuses on collecting supply chain data of the biopharmaceutical industry, constructing a biopharmaceutical supply chain network, using tools such as UCINET for social network analysis, identifying key core common technologies of the biopharmaceutical industry based on patent data, and finally constructing and validating the research model. The research process mainly explores two key issues: firstly, the impact of firm centrality on firm General-Purpose Technologies (GPTs) innovation; and secondly, the impact of structural holes on firm General-Purpose Technologies.

Keywords: Supply chain network; Complex networks; General purpose technologies; Technological innovation.

1. Introduction

Innovation is widely recognized as the cornerstone of national progress and economic prosperity. In China's *14th Five-Year Plan* and *Vision 2035 Outline*, innovation has been identified as a strategic priority for achieving sustainable development and long-term competitiveness. Over the past decades, China has made remarkable technological advances in fields such as 5G communication and high-speed rail, transforming from a follower to a global leader in several industries. However, dependence on foreign countries for certain core technologies remains a major constraint. Addressing this challenge, the *Report to the 20th National Congress of the Communist Party of China* reaffirmed that "science and technology are the primary productive forces, talent is the primary resource, and innovation is the primary driving force," emphasizing the role of firms as key actors in achieving technological self-reliance and industrial upgrading.

A substantial body of research has examined the determinants of firm performance and innovation outcomes [1][2]. Earlier studies focused mainly on internal organizational factors such as leadership quality, R&D capabilities, knowledge accumulation, and innovation culture. More recently, attention has shifted toward external relational factors, highlighting the importance of interorganizational networks—such as board interlocks, cross-shareholding ties, and venture capital linkages—in shaping firms' strategic and innovative behavior [3][4][5]. With the deepening of market specialization, firms are increasingly embedded in complex supply chain networks that link upstream suppliers and downstream customers. These networks serve as important conduits for resource exchange, information transfer, and knowledge spillovers, thereby influencing firms' innovation capacity.

Despite growing academic interest in the relationship between network structures and innovation, most prior studies have concentrated on product or process innovation. Far less attention has been devoted to General Purpose Technologies (GPTs)—technologies characterized by *pervasiveness, high improvability, and strong complementarities with innovation*. GPTs are foundational technologies that underpin multiple industries and drive broad technological progress. They play a central role in enhancing industrial resilience, advancing productivity, and maintaining national technological sovereignty. However, in the face of persistent "bottleneck" constraints in key industrial sectors, China continues to encounter challenges in achieving breakthroughs in critical GPTs. Understanding how network structures affect the innovation of such technologies is therefore both theoretically significant and practically urgent.

Although previous studies have acknowledged the importance of supply chain networks for innovation, our understanding of how a firm's embeddedness within these networks influences its ability to innovate in GPTs remains limited. In particular, few studies have investigated how different dimensions of embeddedness—such as centrality and structural holes—affect GPTs innovation performance, or how network relationships with upstream and downstream partners exert asymmetric influences. Given that firms operate within interdependent ecosystems rather than in isolation, the position they occupy in a supply chain network may critically determine their access to knowledge flows, collaborative opportunities, and innovation synergies.

To address these gaps, this study empirically examines the relationship between supply chain network embeddedness and focal firms' GPTs innovation performance. Specifically, it investigates how centrality and structural holes influence GPTs innovation, and how upstream supplier and downstream customer embeddedness generate heterogeneous effects. By integrating insights from network theory and innovation studies, this research seeks to clarify the mechanisms through which supply chain structures shape firms' innovation behavior in the context of key GPTs.

This study makes several contributions to both theory and practice. First, it extends the existing literature on interorganizational networks by introducing GPTs innovation as a distinct and strategically critical innovation type, thereby broadening the understanding of how network structures facilitate foundational technological progress. Second, it develops a dual-perspective analytical framework that distinguishes between upstream and downstream embeddedness, revealing differentiated effects on innovation performance. Third, it provides practical implications for both firms and policymakers. For firms, the findings can inform strategies to leverage network positions for strengthening GPTs innovation capability and enhancing competitive advantage. For policymakers, the results offer guidance for designing targeted policies that promote collaboration within supply chain networks, strengthen industrial innovation ecosystems, and accelerate breakthroughs in key GPTs.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature, introduces the conceptual foundations, and develops the research hypotheses. Section 3 presents the methodology, including data and sample selection, variable measurement, and statistical methods. Section 4 reports the empirical results, including descriptive statistics, correlations, regression analyses, and robustness tests. Section 5 discusses the theoretical contributions, practical implications, and limitations, and suggests directions for future research.

2. Literature review and hypotheses

2.1. The impact of network structural embeddedness on firm performance

Social networks are structures in which nodes are connected through relationships, forming a web-like pattern, and structural embeddedness captures a node's position within the network, highlighting the advantages conferred by such positions. Centrality and structural holes are the most commonly used measures of these advantages and are widely applied to examine their impact on firm performance. Centrality reflects the extent to which a node occupies a central position, indicating its importance and influence. In inter-firm collaboration networks, a firm's centrality represents its network position and the scale of its direct connections [6]. Studies show mixed findings: some argue that higher centrality promotes innovation, as central firms access diverse knowledge, share external risks, and leverage extensive information from partners, enhancing innovation potential. Others suggest an inverted U-shaped relationship, where moderate centrality fosters breakthrough innovation, but excessive centrality imposes relational maintenance costs and leads to diminishing returns, constraining innovation [7].

Structural holes, introduced by Burt, refer to gaps between non-redundant contacts in a network, where intermediaries bridging these gaps gain informational and control advantages. Firms occupying structural holes can access unique knowledge and influence information flows, potentially enhancing innovation. Empirical studies present three views: structural holes can promote innovation by providing heterogeneous resources; they can impede innovation by reducing trust and increasing integration costs [8][9][10][11]; or they can differentially affect innovation types, promoting exploratory innovation but hindering exploitative innovation [12][13]. Overall, centrality and structural holes are critical dimensions of network embeddedness, but their effects on firm innovation depend on network position, firm capabilities, and the type of innovation pursued.

2.2. The impact of supply chains on firm innovation

The concept of supply chains emerged in the 1980s and has since attracted attention from both management scholars and practitioners. Ellram (1991) defined supply chains as networks involving suppliers, logistics providers, manufacturers, distributors, and retailers [14]. Scholars have examined supply chains' effects on firm performance from multiple theoretical perspectives. Transaction cost theory suggests that effective integration reduces long-term costs. Organizational learning theory posits that inter-firm learning within supply chains fosters exploratory and exploitative innovation Resource-based theory emphasizes that integrating external complementary resources through the supply chain enhances operational and financial performance. Given firms' limited resources, accessing heterogeneous and complementary resources from supply chain partners is often crucial for long-term innovation.

Empirical studies on supply chains and firm innovation remain inconclusive. Pittaway et al. (2004) argued that networks with suppliers, customers, and intermediaries significantly influence innovation performance and productivity [15]. Due to the complexity and uncertainty of innovation, firms increasingly leverage external knowledge from suppliers, customers, and other stakeholders in the early stages of new product development [16][17]. From the supplier perspective, research shows that R&D collaboration with suppliers can enhance product innovation, as suppliers contribute specialized knowledge and resources [18][19][20][21]. However, some studies indicate that supplier involvement may sometimes inhibit innovation, depending on timing and engagement [22]. From the customer perspective, the impact varies by stage and mode of participation. Early involvement in concept development positively correlates with breakthrough innovation [22][23], while forms of engagement—such as information provision, co-development, or direct innovation—affect outcomes differently depending on contextual factors like technological capability and market heterogeneity[24][25][26][27]. Third-party institutions also play a role, providing valuable knowledge and facilitating innovation through both STI (Science, Technology, and Innovation) and DUI (Doing, Using, Interacting) modes [28]. Overall, supply chain networks, encompassing suppliers, customers, and external institutions, critically influence firm innovation, though effects depend on the nature and structure of these relationships.

2.3. Centrality—Customer Perspective and Firms' GPTs Innovation

The centrality of a firm refers to the number of organizations with which it has direct cooperative relationships. Previous studies have often treated a firm's suppliers and customers as a single integrated network to calculate its centrality, ultimately concluding that centrality has either a positive or negative effect on firm innovation. The divergence—even sometimes the opposite—of these findings, in the author's view, arises from the fact that the impact of firm centrality on innovation differs when viewed from the customer perspective versus the supplier perspective. Therefore, this study separates firm centrality into two perspectives: customer-centric and supplier-centric, and investigates their respective effects on firms' GPTs innovation.

From the customer perspective, customer participation in the early stages of new product or technology development can improve the likelihood of success [23]. Customers can also help firms identify market opportunities [15], as they understand unmet preferences and demands, thereby providing opportunities for creative innovation. Adopting customer suggestions helps companies better understand their needs [20]. Moreover, customers, being aware of their own needs, can provide complementary knowledge to purchasing firms and feedback relevant information to upstream suppliers [23]. According to signaling theory, customers can provide feedback to suppliers, thereby enhancing innovation outcomes [29]. Overall, active customer participation is crucial for the success of supplier innovation. Firms with high centrality are better positioned to grasp customer demands and market trends, and customers may provide technical innovation requirements or directions [22]. Additionally, firms, motivated by the need to meet customer requirements, are more likely to engage in technological innovation.

Based on the above analysis, we propose the following hypothesis:
H1: From the customer perspective, firm centrality is positively associated with firms' GPTs innovation.

2.4. Centrality—Supplier Perspective and Firms' GPTs Innovation

According to Resource Dependence Theory, no organization is self-sufficient; all organizations must engage in exchanges with their environment to survive. Clearly, firms depend on their suppliers for critical resources. The degree of this dependence and the importance of being a preferred customer continue to increase [30]. Meanwhile, suppliers' knowledge exhibits spillover effects, which can facilitate firm innovation [31]. According to the traditional resource-based view, the innovative value of suppliers stems from their superior internal resources and capabilities, which are valuable, rare, inimitable, and non-substitutable. Supplier participation helps firms acquire and utilize suppliers' specialized technical knowledge and capabilities, thereby enhancing product innovation performance [23]. Moreover, since the success of purchasing firms benefits suppliers, suppliers are more willing to share their technology and information [32].

When a firm's centrality is low, it lacks scale and resource advantages, making supplier resources more valuable. In this case, firms can leverage supplier knowledge to promote their own innovation. However, when a firm's centrality is high, it controls more information and resources. High centrality may lead firms to rely excessively on suppliers, reducing their own innovation motivation [33]—a "free-riding" phenomenon. For example, as noted by Gambardella (2010), downstream software firms heavily depended on independent software suppliers for promising application modules; their advantage no longer came from direct R&D, but from their ability in commercialization, marketing, installation, and sales integration [34]. In other words, when specialized companies exist in a market to trade specific technologies, competition among these companies is no longer based on owning unique technologies, but on achieving cost advantages compared to in-house development. This implies that purchasing firms cannot rely solely on possessing unique technology to outperform competitors and must pay more attention to cost-effectiveness.

Based on the above analysis, we propose the following hypothesis:
H2: From the supplier perspective, firm centrality has an inverted U-shaped relationship with firms' GPTs innovation.

2.5. Structural Holes and GPTs Innovation

When two nodes in a network are disconnected, intermediaries are required to establish links. The position occupied by such intermediaries is referred to as a structural hole. Firms occupying structural holes act as "bridges," connecting otherwise independent organizations, facilitating the flow of information and resources, and gaining advantages in controlling resources. Choi et al. (2022) studied the relationship between a country's embeddedness in the global knowledge spillover network and its national innovation performance, finding that structural holes generally have a positive effect on innovation outcomes [35]. Heterogeneous knowledge is crucial for firm innovation [36]; firms in the same industry often lack such heterogeneity. Firms occupying more structural holes can connect with a more diverse set of firms and form alliances.

When a firm's structural holes are low, it has fewer technological and knowledge resources, and its willingness to innovate is stronger. When structural holes are high, the firm has greater control over resources and more opportunities to access technological and knowledge-based innovation resources. Firms with many structural holes can reach non-redundant innovation resources in the network by connecting otherwise disconnected partners, thereby promoting innovation. However, when structural holes are at moderate levels, firms neither possess abundant resources nor strong capabilities, and their innovation motivation is limited. Innovation performance is lowest in this case.

Based on the above analysis, we propose the following hypothesis:
H3: Structural holes have a U-shaped relationship with firms' GPTs innovation.

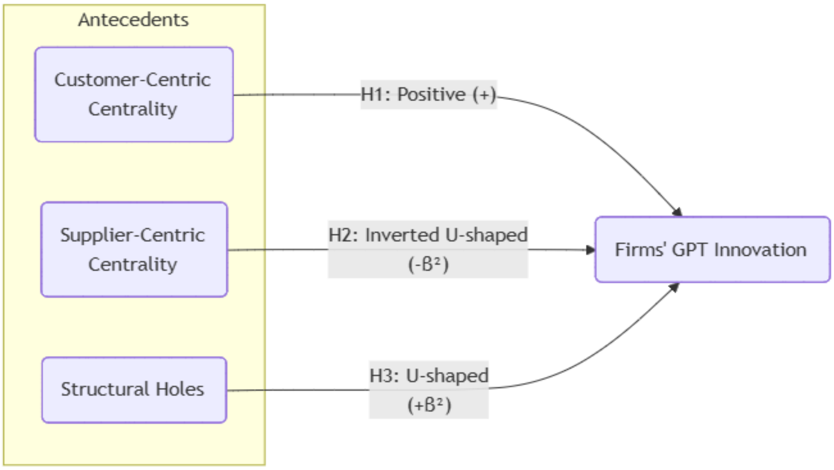

Fig. 1 Research framework

3. Methodology

3.1. Data and samples

This study first screened 145 firms in the biopharmaceutical industry with complete supply chain data from the Compustat database. Then, we collected the firms' GPT invention patent data from 2010 to 2019 from the Derwent Innovations Index Database (DII). After removing missing values, a total of 1,405 observations were obtained.

This study focuses on a single industry because the characteristics of technologies vary across industries, and the tendency to convert innovative outcomes into patents also differs [37]. This approach avoids the heterogeneous effects caused by cross-industry differences and ensures the completeness of supply chain data.

Furthermore, the biopharmaceutical industry was chosen because it involves advanced biotechnology and represents a typical high-tech sector. As a knowledge-intensive industry, its innovative outputs are a critical manifestation of the firms' core capabilities [38]. In addition, to protect intellectual property, firms in the biopharmaceutical industry generally present their innovative achievements in the form of patents whenever possible [39].

3.2. Variables and measurements

3.2.1. Dependent variable

First, for GPT, this study identifies them using the Technology Co-classification Ratio (TCR) method. TCR reflects the co-occurrence relationships between a specific technological field and other technological fields, indicating the relative breadth of application of a given technology across different areas. In calculating TCR, this study follows Donohu's model and sets the threshold for the number of co-occurrence partners in high-frequency technological fields within the biopharmaceutical industry [40]. The threshold is calculated as follows:

$$T = \frac{-1 + \sqrt{1 + 8I_1}}{2} \tag{1}$$

where T is the boundary value between high- and low-frequency technological fields, and I_1 is the total frequency. A co-occurrence matrix is then generated based on the selected high-frequency terms, and TCR is calculated from this matrix. A higher TCR indicates that the technological field has broader penetration into other technological fields within the industry, and thus its "GPT" characteristic is more pronounced. The calculation formula is as follows:

$$Technology\ Co - classification\ Ratio$$
$$= \frac{Number\ of\ Co - classification\ partners}{Number\ of\ all\ high - frequency\ technology\ fields\ except\ itself} \tag{2}$$

Considering cross-industry differences, this study sets the standard for identifying GPT as TCR greater than 30%, following prior studies to select GPT-related patents for each industry.

Second, regarding GPTs innovation, this study measures it by the number of GPT patents (GPT performance). Previous studies have defined technological innovation differently based on various perspectives and standards, including indicators such as the proportion of R&D personnel, employee education level, R&D expenditures, number of patents, and new product releases. Following the approach of Wan Kunyang and Lu Wencong [41], this study uses patents to measure GPTs innovation output. Patents are assigned to the year of their application, which better reflects the timing of firms' technological innovation.

3.2.2. Independent variables

*Centrality***.** Firm centrality refers to the number of partner organizations with which a firm has direct collaborative relationships. A higher centrality indicates that the firm is more important within the innovation network and holds a higher network position. The calculation formula is as follows:

$$C_{D(i)} = \sum_{j-1}^{N} x_{ij} \tag{3}$$

where x_{ij} equals 1 or 0; 1 indicates that node j has a direct collaborative relationship with node i, and 0 indicates no direct relationship. N represents the size of the collaborative innovation network, i.e., the total number of nodes. Using social network analysis software (Ucinet), the calculation path is: Network > Centrality > Degree. In this study, centrality from the supplier perspective is measured as Indegree, while centrality from the customer perspective is measured as Outdegree.

*Structural Hole (SH)***.** This study measures the number of structural holes in a firm's collaborative innovation network using the constraint index [42]. The constraint index reflects the degree to which a firm is constrained by other firms in the network. A higher value indicates greater network closure, stronger constraints on the firm, and fewer structural holes; conversely, a lower value indicates more structural holes. The calculation formula is as follows:

$$C_a = \sum\nolimits_b \left(x_{ab} + \sum\nolimits_c x_{ac} x_{cb}\right)^2 \tag{4}$$

where a represents the sample firm, i.e., the focal firm, b represents other organizations in the network excluding a (firms, universities, research institutes, etc.), and c represents all other organizations excluding a and b. x_{ab} denotes the proportion of time/effort that aaa invests in collaborating with bbb relative to its total time/effort, and x_{ac} and x_{cb} have similar meanings. The constraint index ranges from 0 to 1.125. The calculation path in Ucinet is: Network > Ego Networks > Structural Holes.

3.2.3. Control variables

This study controls for several factors that have been widely confirmed in the literature to affect firm innovation performance. The control variables include: knowledge depth, knowledge breadth, knowledge unrelated diversification, knowledge related diversification, knowledge coherence, firm age, firm size, debt-to-asset ratio, and return on equity.

Knowledge Depth (KD). Patent knowledge depth (calculated at the individual patent level) refers to the depth of technology involved in a patent within its technical field. It can be measured by counting the number of sub-classifications within the patent's assigned technical field (determined by the main classification code). A firm's knowledge depth is a key factor in evaluating its competitive advantage. Lin and Wu (2010) suggested that higher knowledge depth is associated with better firm performance [43], and thus knowledge depth may influence firm innovation.

Knowledge Breadth (KB) represents the range of knowledge elements a firm possesses, which can be measured by the number of distinct (4-digit/6-digit) technological classifications to which the firm's successfully applied patents belong. When both technological breadth and technological distance are high, acquiring firms can identify, recombine, and utilize external knowledge from their supplier networks to generate innovation performance [44]. Research by Triguero et al. (2019) found an inverted U-shaped relationship between the breadth of external knowledge sources and the propensity for eco-innovation, both for product and process eco-innovation, indicating that knowledge breadth may influence firm innovation [45].

Knowledge Unrelated Diversification (KUD) refers to the degree of diversification of a firm's technological capabilities across unrelated technological fields [46]. The aim of pursuing knowledge unrelated diversification is to broaden the knowledge base and increase opportunities for cross-field technological learning. This study draws on the approach of Chen (2012), using the entropy index to measure knowledge unrelated diversification [46]. Based on the characteristics of China's patent classification system, the first 4 digits of the IPC code represent technological subcategories (used for measuring knowledge diversification), while the first 3 digits represent technological main categories (used for measuring knowledge unrelated diversification).

Knowledge Related Diversification (KRD) refers to the degree of diversification of a firm's technological capabilities across related technological fields [46]. Knowledge related diversification primarily involves knowledge search and R&D activities within the scope of the firm's existing technological fields. Increasing knowledge related diversification allows firms to benefit from economies of scale [47]. Firms with high knowledge related diversification possess more specialized knowledge, leading to greater economies of scale associated with knowledge specialization. This study draws on the approach of Chen (2012), using the entropy index to measure knowledge related diversification [46]. Based on the characteristics of China's patent classification system, the first 4 digits of the IPC code represent technological subcategories (used for measuring knowledge diversification), while the first 3 digits represent technological main categories (used for measuring knowledge related diversification).

Knowledge Coherence (KC) measures the strength of relationships between knowledge elements, which significantly impacts knowledge integration capability. Tighter relationships between new knowledge and existing knowledge elements make it easier for firms to integrate new knowledge.

Firm Age (Age). The natural age of a firm refers to the length of time that has passed since its establishment, primarily indicating the duration of the firm's existence.

Firm Size (Size). Firm size refers to the classification of a firm's scale of production, operation, etc. Firm sizes are generally categorized as extra-large, large, medium, small, and micro. This study uses firm market value as the measure.

Debt-to-Asset Ratio (DAR) also known as the debt management ratio, is used to measure a firm's ability to use funds provided by creditors for operational activities and reflects the security level of loans issued by creditors. It is derived by comparing the firm's total liabilities to its total assets, reflecting the ratio of liabilities to total assets.

Return on Equity (ROE) is the ratio of net profit to average shareholders' equity. A higher index indicates higher returns on investment; a lower ROE indicates weaker ability to generate profits from owners' equity.

3.3. Statistical methods

The dependent variable in this study is firms' GPTs innovation performance, measured by the annual number of newly added invention patents in IPC categories. This variable is a non-negative count measure. Since its variance significantly exceeds its mean, displaying over-dispersion, the Poisson regression—which assumes equidispersion—is unsuitable. Instead, a negative binomial regression model is adopted, as it better accommodates the data characteristics and mitigates the impact of heteroscedasticity and outliers. Furthermore, as the dataset is structured as panel data, a Hausman test was conducted to determine the appropriate model form. The test result (p-value < 0.1) supports the use of a fixed-effects negative binomial regression model. The baseline regression model is specified as follows:

$$\begin{pmatrix} \text{GPT performance}_{it} = \beta_0 + \beta_1 \text{Indegree}_{i,t-1} + \beta_2 \text{Indegree}^2{}_{i,t-1} + \\ \beta_3 \text{Outdegree}_{i,t-1} + \beta_5 \text{SH}_{i,t-1} + \beta_6 \text{SH}^2{}_{i,t-1} + \beta_7 KD_{it} + \beta_8 KB_{it} + \beta_9 KUD_{it} + \\ \beta_{10} KRD_{it} + \beta_{11} KC_{it} + \beta_{12} Age_{it} + \beta_{13} Size_{it} + \beta_{14} DAR_{it} + \beta_{15} ROE_{it} + \varepsilon_i \end{pmatrix} \tag{5}$$

4. Results

4.1. Descriptions and correlations

Table 1 presents the descriptive statistical analysis results of the main variables involved in this study. The table shows that among the 1,405 firms, the maximum value of GPTs innovation is 225, the minimum value is 0, with a mean of 7.61 and a standard deviation of 18.04 (variance of 325.442). The mean is substantially smaller than the variance. This indicates that the outcome variable in this study exhibits over-dispersion. Therefore, employing a negative binomial regression model under the Bayesian framework is necessary. Firm age ranges from 0 to 179 years, with a standard deviation of 31.72, indicating that the sample data adequately cover various stages of firm development and meet the research requirements.

Table 1. Descriptive Statistics of the Main Variables

Variable	Obs	Min	Max	Mean	Std. Dev.
GPT performance	1,405	0	225	7.61	18.04
Indegree	1,405	0	31	2.66	5.36
Outdegree	1,405	0	33	2.99	3.49
SH	1,405	1	1.97	1.61	0.32
KD	1,405	0	0.67	0.01	0.04
KB	1,405	0	1	0.05	0.21
KUD	1,405	0	3.33	0.73	1.02
KRD	1,405	0	47.64	3.67	6.38
KC	1,405	-1.84	16.23	0.59	1.53
Age	1,405	0	179	30.64	31.72
Size	1,405	6.04	1.95E+08	1.24E+07	2.98E+07
DAR	1,405	0.02	7.46	0.54	0.52
ROE	1,405	-996.15	409.42	-39.21	118.59

According to the correlation coefficient analysis of various variables in Table 2, it can be observed that firms' GPTs innovation shows a significant positive correlation with supplier quantity ($r=0.568$, $p<0.05$). Although this finding does not contradict Hypothesis 1's proposed inverted U-shaped relationship between firm centrality and GPTs innovation regarding suppliers' impact, further verification is still required. The correlation coefficient between GPTs innovation and customer quantity is relatively low ($r=-0.045$, $p>0.05$), indicating no significant correlation between these two variables. Meanwhile, GPTs innovation demonstrates a significant positive correlation with structural holes ($r=0.288$, $p<0.05$), which aligns with Hypothesis 3's proposed U-shaped relationship between structural holes' impact on GPTs innovation, although additional testing is needed for confirmation.

Table 2. Correlation Analysis Results of the Main Variables in This Study

Variable	GPT performance	Indegree	Outdegree	SH	KD	KB	KUD	KRD	KC	Age	Size	DAR	ROE
GPT performance	——												
Indegree	.568*	——											
Outdegree	-0.045	-.145*	——										
SH	.288*	.394*	.457*	——									
KD	-0.010	0.022	0.022	.058*	——								
KB	-.063*	-.082*	-0.014	-0.044	.065*	——							
KUD	.530*	.483*	-.097*	.307*	.139*	-.058*	——						
KRD	.603*	.579*	-.115*	.320*	0.009	-.099*	.784*	——					
KC	.551*	.492*	-.109*	.257*	0.010	-.071*	.531*	.558*	——				
Age	.323*	.357*	-.150*	.165*	0.031	-.086*	.338*	.360*	.220*	——			
Size	.559*	.880*	-.132*	.348*	0.021	-.080*	.455*	.519*	.418*	.392*	——		
DAR	-0.010	0.031	0.047	0.018	-0.045	0.007	-0.005	-0.009	0.015	-0.03	0.028	——	
ROE	.206*	.233*	-.066*	.142*	0.011	-0.043	.224*	.243*	.219*	.206*	.215*	-.158*	——

Note: Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.2. Regression results

Table 3 presents the results of the panel fixed-effects negative binomial regression. Model 1 is the baseline model containing only the control variables. The significance levels of the control variables indicate that our selection of control variables is appropriate. Model 2 introduces the antecedent variable of supplier count, but the result is not significant. Model 3 incorporates the quadratic term of supplier count. The Bayesian estimated posterior coefficients for the linear and quadratic terms of supplier count on GPTs innovation are positive and negative, respectively, both significant at the 1% level ($\beta=0.037$, $p<0.01$; $\beta=-0.001$, $p<0.01$). This indicates an inverted U-shaped relationship between supplier count and firms' GPTs innovation, supporting Hypothesis 2.Model 4 introduces customer count. The results show that the Bayesian estimated posterior coefficient for customer count on GPTs innovation is positive and significant at the 1% level ($\beta=0.039$, $p<0.01$). However, when both the linear and quadratic terms of customer count are included in Model 5, the results are not significant. Thus, customer count has a positive linear impact on GPTs innovation, supporting Hypothesis 1.Model 6 introduces the antecedent variable of structural holes, but the result is not significant. Model 7 includes both the linear and quadratic terms of structural holes. The Bayesian estimated posterior coefficients for the linear and quadratic terms of structural holes on GPTs innovation are negative and positive, respectively, both significant at the 1% level ($\beta=-2.654$, $p<0.01$; $\beta=0.879$, $p<0.01$). This indicates a U-shaped relationship between structural holes and GPTs innovation, supporting Hypothesis 3.

Table 3. Results of the Panel Fixed-Effects Negative Binomial Regression

VARIABLES	GPT patent number						
	Model1	Model2	Model3	Model4	Model5	Model6	Model7
Indegree		-0.004	0.037***				
		(0.008)	(0.014)				
Indegree_squ			-0.001***				
			(0.000)				
Outdegree				0.039***	0.002		
				(0.012)	(0.038)		
Outdegree_squ					0.003		
					(0.003)		
SH						0.160	-2.654***
						(0.154)	(0.941)
SH_squ							0.879***
							(0.327)
Presamples	-0.002**	0.006***	-0.003**	-0.003**	-0.003**	0.006***	-0.003**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
KD	-0.454	-0.231	-0.494	-0.614	-0.622	-0.261	-0.555
	(0.554)	(0.630)	(0.557)	(0.554)	(0.555)	(0.631)	(0.559)
KB	-0.078	-0.014	-0.082	-0.063	-0.065	-0.010	-0.059
	(0.112)	(0.118)	(0.111)	(0.111)	(0.111)	(0.118)	(0.111)
KUD	-0.003	0.048	0.001	-0.008	-0.007	0.044	0.008
	(0.033)	(0.039)	(0.032)	(0.033)	(0.033)	(0.039)	(0.033)
KRD	0.004	0.012**	0.003	0.006*	0.006*	0.012**	0.003
	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)
KC	0.009	0.019	0.005	0.009	0.009	0.018	0.009
	(0.007)	(0.011)	(0.007)	(0.007)	(0.007)	(0.012)	(0.007)
Age	0.099***	0.011***	0.101***	0.098***	0.098***	0.010***	0.103***
	(0.008)	(0.003)	(0.008)	(0.008)	(0.008)	(0.003)	(0.008)
Size	0.000***	0.000	0.000***	0.000***	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DAR	0.101	0.056	0.086	0.091	0.093	0.055	0.092
	(0.074)	(0.085)	(0.075)	(0.074)	(0.075)	(0.084)	(0.074)
ROE	0.000	0.000	0.000	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year dummies	Included	Included	Included	Included	Included	Included	Included
Constant	0.043	1.131***	0.033	0.004	0.049	0.881***	1.953***
	(0.180)	(0.154)	(0.181)	(0.184)	(0.188)	(0.279)	(0.674)
Observations	1,055	1,055	1,055	1,055	1,055	1,055	1,055
Log likelihood	-1915.29	-1909.31	-1910.84	-1909.98	-1909.48	-1908.86	-1910.91
Wald chi2 test	529.81***	227.27***	557.58***	534.49***	537.53***	.226.91***	552.96***

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

4.3. Robustness tests

To ensure the validity of our findings against potential influences from different variable measurement methods, this study conducts robustness checks by adopting an alternative methodological approach. First, we apply the natural logarithm transformation to the dependent variable and use Ordinary Least Squares (OLS) regression to examine whether the significance of the variables remains consistent. Should the significance of the independent variables remain unchanged after this transformation, the results are considered robust. Table 4 presents the OLS regression analysis results.

Analysis of Table 4 shows that in Model OLS2, the relationship between supplier count and the dependent variable remains significant. The coefficient of the linear term is positive and the coefficient of the quadratic term is negative, both significant at the 1% level ($\beta = 0.063$, $p < 0.01$; $\beta = -0.002$, $p < 0.01$). In Model OLS3, the relationship between customer count and the dependent variable is significant at the 5% level ($\beta = 0.023$, $p < 0.05$), indicating a positive correlation between the two variables. In Model OLS4, the linear term of structural holes shows no significant relationship with the dependent variable, while the quadratic term of structural holes is significant at the 10% level ($\beta = 0.440$, $p < 0.10$).

According to Lind and Mehlum (2010), determining U-shaped or inverted U-shaped relationships based solely on the significance of the quadratic term of the core explanatory variable is not sufficiently rigorous [48]. If the sample data exhibit monotonic convexity only over a specific interval, the quadratic term of the explanatory variable may still appear significant, potentially leading to spurious U-shaped or inverted U-shaped relationships. Furthermore, relying exclusively on the significance of the quadratic term cannot rule out the possibility of cubic or higher-order polynomial relationships. Drawing on the methodology of Lind and Mehlum, this study applies a more stringent U-test to verify U-shaped and inverted U-shaped relationships, thereby addressing potential biases in identifying nonlinear relationships based solely on the coefficients of the linear and quadratic terms of the core explanatory variables.

The test results indicate that the extreme point for supplier count is calculated as 14.4620, which falls within the range of supplier count values [8.1894, 20.6177]. The null hypothesis can be rejected at the 5% significance level. Additionally, the slope within this interval shows a negative sign, thereby confirming an inverted U-shaped relationship between supplier count and firms' GPTs innovation and ruling out the possibility of cubic or higher-order polynomial relationships. The extreme point for structural holes is calculated as 1.5100, which lies within the range of structural holes values [1.3843, 1.8226]. The null hypothesis can be rejected at the 5% significance level. Moreover, the slope within this interval shows a negative sign, thus verifying a U-shaped relationship between structural holes and firms' GPTs innovation and excluding the possibility of cubic or higher-order polynomial relationships.

In summary, the inverted U-shaped relationship between supplier count and GPTs innovation, the positive correlation between customer count and GPTs innovation, and the U-shaped relationship between structural holes and GPTs innovation are all confirmed and consistent with the previous conclusions. Therefore, the findings of this study are robust.

Table 4. Panel Fixed-Effects OLS Regression Results

VARIABLES	Ln GPT patent number			
	OLS1	OLS2	OLS3	OLS4
Indegree		0.063***		
		(0.018)		
Indegree_squ		-0.002***		
		(0.001)		
Outdegree			0.023**	
			(0.009)	
Structural hole				-1.039
				(0.686)
Structural hole_squ				0.440*
				(0.249)
Presamples	0.006**	0.005*	0.005*	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
KD	-0.548	-0.502	-0.552	-0.536
	(0.349)	(0.348)	(0.348)	(0.348)
KB	0.007	0.007	0.009	0.010
	(0.055)	(0.055)	(0.055)	(0.055)
KUD	0.009	0.010	0.006	0.005
	(0.025)	(0.025)	(0.025)	(0.025)
KRD	0.014***	0.013***	0.014***	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)
KC	0.015	0.006	0.016	0.014
	(0.014)	(0.014)	(0.014)	(0.014)
Age	0.061***	0.060***	0.060***	0.060***
	(0.006)	(0.006)	(0.006)	(0.006)
Size	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
DAR	0.007	0.006	0.012	0.012
	(0.027)	(0.027)	(0.027)	(0.027)
ROE	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Year dummies	Included	Included	Included	Included
Constant	-0.865***	-0.893***	-0.918***	-0.323
	(0.175)	(0.175)	(0.176)	(0.486)
Observations	1,405	1,405	1,405	1,405
R-squared	0.207	0.216	0.211	0.213
F	20.314	18.985	19.572	18.649

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

5. Discussion and conclusions

5.1. Theoretical Contributions

This study focuses on firm-level General-Purpose Technology (GPT) innovation and, drawing on social network theory, decomposes structural embeddedness into two dimensions: centrality and structural holes. Centrality is further examined from both supplier and customer perspectives to investigate how supply chain network embeddedness affects firms' breakthrough innovation performance. The key theoretical contributions are twofold:

First, it extends research on the drivers of GPTs innovation. Existing literature has explored factors affecting breakthrough innovation performance from perspectives such as alliance networks, human capital and resource endowments, and knowledge learning. However, few studies have examined how network structural embeddedness influences GPTs innovation. By investigating the relationship between supply chain network embeddedness and firm GPTs innovation, this study provides a new perspective on how network structures shape technological innovation outcomes.

Second, it refines and deepens the conceptualization of structural embeddedness. By distinguishing between centrality and structural holes, and further differentiating the influence of suppliers versus customers on focal firm innovation, this study adds granularity to prior research that treated structural embeddedness as a single variable. This approach offers a more nuanced understanding of how specific aspects of network position drive firm-level GPTs innovation.

5.2. Practical Implications

Based on a sample of 145 biopharmaceutical firms from 2010 to 2019, this study examines the relationship between supply chain network embeddedness and GPTs innovation, yielding three managerial insights:

First, focal firms should strategically increase the number of customers to enhance centrality according to their GPTs innovation needs. Customer centrality positively influences GPTs innovation, as customers help focal firms better understand market demands and guide the development of GPT-based solutions.

Second, focal firms should maintain an optimal number of suppliers. For supplier centrality, the relationship with GPTs innovation exhibits an inverted U-shape. When supplier numbers are low, adding suppliers increases centrality and leverages resource spillover effects, boosting GPTs innovation. However, when supplier numbers are high, additional suppliers may introduce a "free-rider" effect, potentially reducing the performance of GPTs innovation.

Third, focal firms should carefully assess structural hole advantages. Large firms occupying structural holes can access non-redundant knowledge across the network, facilitating cross-domain knowledge recombination and enhancing GPTs innovation. However, smaller firms with limited structural hole positions and resources may experience weakened innovation incentives if they attempt to occupy more structural holes, potentially hindering GPTs innovation performance.

5.3. Limitations and Future Research

Although this study provides insights into the relationship between supply chain network embeddedness and GPTs innovation using a sample of 145 biopharmaceutical firms from 2010 to 2019, several limitations remain:

First, the generalizability of the findings is constrained. The study focuses exclusively on the biopharmaceutical industry. Future research should expand to other sectors to validate and extend the conclusions.

Second, the measurement of the dependent variable has limitations. Current approaches to evaluating firm technological innovation performance lack consensus. Some scholars argue that patent data alone may not accurately capture innovation output, as only commercially successful patents that generate economic value constitute meaningful innovation. Therefore, future research could adopt multidimensional measures, combining patent data with economic output indicators, to more comprehensively assess innovation performance.

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