

# New Quality Productive Forces Empowering Innovation in China's Pharmaceutical Manufacturing Industry: Pathways toward High-Quality Development

Han Li<sup>1</sup>, Ziyue Jin<sup>2</sup>, Ronghe Liu<sup>3</sup>, Yueting Dong<sup>4</sup>, Dicheng Wang<sup>5\*</sup>

1.School of Business, Gachon University, Seongnam 13120, Republic of Korea

2.School of Graduate, Shenyang Ligong University, Shenyang 110159, China

3.School of Business, Dalian University of Finance and Economics, Dalian 116622, China

4.Tiexi District Center for Disease Control and Prevention, Shenyang 110021, China

5.School of Economics, Gachon University, Seongnam 13120, Republic of Korea

\*Corresponding author: Dicheng Wang, [powwwer@163.com](mailto:powwwer@163.com)

**Copyright:** 2026 Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY-NC 4.0), permitting distribution and reproduction in any medium, provided the original author and source are credited, and explicitly prohibiting its use for commercial purposes.

**Abstract:** This study examines the impact of new-quality productive forces (NQPF) on the innovation performance of China's pharmaceutical manufacturing enterprises and explores its internal mechanisms. Using panel data of A-share listed pharmaceutical firms from 2015 to 2023, a fixed-effects model is constructed, with instrumental variable (IV) and system GMM estimations applied to address endogeneity. The empirical results show that NQPF significantly enhance firms' innovation performance, and the findings remain robust under multiple model specifications. Mechanism analysis further reveals that NQPF promote innovation both directly and indirectly by improving technological stability and technological diversification. These results indicate that NQPF strengthen the depth of technological accumulation while expanding the breadth of innovation exploration. From a policy perspective, fostering NQPF should be prioritized to upgrade China's pharmaceutical industry. Governments should enhance innovation policy frameworks and digital infrastructure, while firms should advance intelligent transformation and data-driven innovation management to achieve high-quality and sustainable development.

**Keywords:** New-Quality Productive Forces; Pharmaceutical Manufacturing; Innovation Performance; Technological Stability; Technological Diversification

**Published:** Feb 24, 2026

**DOI:** <https://doi.org/10.62177/apemr.v3i1.1046>

## 1.Introduction

The pharmaceutical manufacturing industry serves as a strategic pillar for ensuring national health and promoting socioeconomic well-being. Against the backdrop of accelerated population aging, rising health consciousness, and intensified global innovation competition, innovation has emerged as the essential driver for enterprises to overcome development bottlenecks and enhance their core competitiveness. However, Chinese pharmaceutical manufacturers are generally confronted with several structural and technological constraints, including prolonged R&D cycles for original drugs, high research costs, and heavy reliance on imported core technologies<sup>[1]</sup>. Under the traditional productivity paradigm, the

efficiency of factor allocation and the pace of technological iteration are insufficient to sustain high-quality, innovation-driven growth <sup>[2,3]</sup>. Consequently, a new productivity paradigm centered on scientific and technological innovation has become imperative.

The concept of new-quality productive forces (NQPF) embodies this emerging paradigm. By integrating cutting-edge technologies such as digital transformation, bioengineering, and green manufacturing with production factors, NQPF restructure industrial production processes and achieve leaps in productivity and innovation efficiency <sup>[4,5]</sup>. This transformation emphasizes the synergistic integration of technology and resources, providing pharmaceutical firms with novel pathways to address innovation bottlenecks. For instance, digital green transformation frameworks have demonstrated positive spillover effects on innovation efficiency and environmental sustainability across China's manufacturing sectors <sup>[6,7]</sup>. Moreover, intelligent manufacturing initiatives have proven to significantly enhance resource utilization and green innovation performance in pharmaceutical enterprises <sup>[8]</sup>.

Compared with traditional productivity, NQPF highlight the leading role of technological innovation, the creativity of factor recombination, and the systematic nature of industrial collaboration <sup>[9]</sup>. These characteristics enable continuous empowerment of pharmaceutical manufacturing innovation through intelligent R&D upgrades, lean production reforms, and ecosystem-based collaborative innovation <sup>[10]</sup>. Building on this perspective, this study investigates how NQPF influence the innovation performance of pharmaceutical manufacturing enterprises. It systematically examines the underlying mechanisms through which technology integration and production restructuring shape innovation outcomes. The research not only enriches theoretical discussions on NQPF and industrial innovation but also provides practical guidance for enhancing innovation capacity and achieving high-quality growth in the pharmaceutical manufacturing industry.

## 2.Literature Review and Theoretical Hypotheses

### 2.1 Innovation in the Pharmaceutical Manufacturing Industry

The pharmaceutical manufacturing industry is characterized as both knowledge-intensive and technology-intensive, serving as a core driver of industrial upgrading and public health improvement <sup>[11]</sup>. Innovation in this sector represents a crucial mechanism for sustaining competitiveness, enhancing productivity, and supporting the broader transition toward high-quality economic development <sup>[2]</sup>. The complexity of pharmaceutical production—encompassing drug discovery, clinical development, and large-scale manufacturing—requires continuous technological advancement and organizational learning to maintain efficiency and innovation performance <sup>[3]</sup>.

Enterprise innovation in pharmaceutical manufacturing is influenced by both internal and external factors. Internally, R&D investment, technological absorptive capacity, and human capital accumulation are key determinants of innovation output <sup>[4,11]</sup>. Externally, institutional frameworks, regulatory environments, and policy incentives play critical roles in shaping innovation efficiency and market orientation <sup>[7,12]</sup>. The interaction between these internal and external forces determines firms' ability to transform scientific knowledge into commercially viable pharmaceutical products <sup>[9,11]</sup>.

With the rapid development of intelligent manufacturing and digital technologies, pharmaceutical innovation has entered a stage characterized by the deep integration of information technology, biotechnology, and green production <sup>[5,6]</sup>. Digitalization and artificial intelligence improve research accuracy, shorten R&D cycles, and enhance the reliability of experimental results. Meanwhile, smart manufacturing technologies increase production flexibility and precision, enabling real-time process optimization and improving the scalability of innovative drug manufacturing <sup>[8,11]</sup>. The adoption of green and sustainable production systems further strengthens environmental performance, contributing to both cost reduction and social responsibility <sup>[6,13]</sup>.

In parallel with technological advancement, innovation models in the pharmaceutical industry have evolved from closed to open and collaborative frameworks <sup>[4,12]</sup>. Firms are increasingly engaging in knowledge sharing, cross-industry partnerships, and joint R&D initiatives to overcome resource constraints and accelerate innovation diffusion <sup>[9,12]</sup>. The integration of upstream and downstream enterprises in innovation networks promotes efficient information exchange and resource complementarity, leading to higher innovation productivity across the value chain <sup>[9,12]</sup>.

Overall, pharmaceutical manufacturing innovation reflects a multidimensional process driven by the convergence of

technology, knowledge, and institutional dynamics <sup>[2,4,7]</sup>. The continuous advancement of digital and intelligent systems redefines the boundaries of pharmaceutical R&D and production, fostering a transition toward more flexible, sustainable, and collaborative innovation ecosystems <sup>[11-13]</sup>. This evolution provides a solid foundation for subsequent discussions on how NQPF reshape the innovation dynamics and efficiency of the pharmaceutical manufacturing sector.

## 2.2 New-Quality Productive Forces

NQPF represent an advanced form of productivity driven by technological innovation, knowledge integration, and systemic coordination across industries <sup>[14]</sup>. They emphasize the transformation of traditional production systems from factor-based expansion to innovation-led efficiency, marking a shift from quantity accumulation toward qualitative upgrading <sup>[9]</sup>. This concept highlights the centrality of science and technology as the core driver of economic growth and industrial competitiveness in the new era of digital and intelligent economies <sup>[15,16]</sup>.

In essence, NQPF reshape the relationship between technology, labor, and capital through the deep integration of digitalization, intelligence, and sustainability-oriented production. The integration of emerging technologies such as artificial intelligence, big data, and cloud computing enhances the precision and flexibility of manufacturing systems, allowing for dynamic adjustment of production processes and accelerating innovation diffusion <sup>[17]</sup>. At the same time, bioengineering and green manufacturing promote resource efficiency and environmental sustainability, thereby contributing to both economic and ecological performance <sup>[18]</sup>.

From a structural perspective, NQPF reconstruct the configuration of production factors by embedding information technology into the entire value chain, including R&D, production, and market operations. This integration not only improves resource allocation efficiency but also facilitates the emergence of new business models and industrial ecosystems <sup>[14]</sup>. As digital infrastructure becomes more pervasive, data and algorithms increasingly function as key production factors alongside labor and capital, reshaping the productivity foundation of modern enterprises <sup>[17]</sup>.

Moreover, the transformation toward NQPF enhances industrial resilience and innovation capacity. Intelligent decision-making systems, digital collaboration platforms, and sustainable production processes enable enterprises to adapt quickly to external shocks and technological uncertainties <sup>[16]</sup>. This adaptive capability supports continuous innovation and value creation, allowing firms to maintain long-term competitiveness in rapidly evolving markets.

In the context of the pharmaceutical manufacturing industry, the adoption of NQPF provides a strategic pathway for achieving high-quality development. The integration of digital R&D systems, automated production, and environmentally friendly processes reduces development costs, shortens innovation cycles, and enhances product quality <sup>[15]</sup>. Through these mechanisms, NQPF not only optimize internal production efficiency but also foster external industrial linkages and collaborative innovation networks, laying the foundation for sustainable growth and technological independence.

## 2.3 Theoretical Hypotheses

Building upon the above discussion, this study proposes that NQPF enhance enterprise innovation by optimizing factor allocation and improving technological efficiency through digitalization, intelligentization, and green transformation.

H1: The development of new-quality productive forces significantly promotes the innovation performance of pharmaceutical manufacturing enterprises.

Furthermore, NQPF may influence innovation indirectly via two mediating mechanisms: technological stability and technological diversification.

Technological stability refers to the firm's ability to maintain consistency in technological trajectories during R&D activities. Given the high uncertainty and path dependency of pharmaceutical R&D, intelligent information management under NQPF can strengthen technological accumulation and reduce resource redundancy.

H2: New-quality productive forces enhance innovation performance by improving firms' technological stability.

In addition, technological diversification broadens the boundaries of innovation. By providing digital platforms that facilitate cross-disciplinary knowledge integration, NQPF promote the expansion of firms' innovation flexibility and scope.

H3: New-quality productive forces enhance innovation performance by promoting technological diversification.

### 3. Research Design

#### 3.1 Variable Selection

##### 3.1.1 Dependent Variable

The enterprise innovation level is measured by the total number of invention patents applied for by each firm in a given year, including both independent and joint patent applications. The sum of these two types of applications provides a comprehensive representation of a firm's overall innovation capacity. Independent patent applications reflect a firm's internal innovation capability, while joint applications capture its ability to engage in external collaborative innovation. By combining these two indicators, the natural logarithm of the total number of patent applications is used to more comprehensively evaluate firms' innovation performance.

##### 3.1.2 Core Independent Variable

NQPF represent an advanced form of productivity characterized by innovation orientation, technological sophistication, and efficiency enhancement. This construct emphasizes a break from traditional development paths, focusing on high technology, high efficiency, and high quality as its core attributes. Drawing on the frameworks proposed by Song et al. [19] and Lu et al. [20], this study constructs an evaluation index system for NQPF based on two dimensions: labor input and upgrading of production tools. These dimensions collectively capture the extent to which pharmaceutical manufacturing enterprises achieve innovation-driven growth and factor restructuring, thereby reflecting their overall development level under the paradigm of NQPF.

##### 3.1.3 Control Variables

To mitigate the potential impact of firm-specific heterogeneity, several control variables are incorporated into the regression model, including firm size (Size), asset-liability ratio (Lev), profitability (Roa), cash flow ratio (Cashflow), current ratio (Liquid), and listing age (ListAge). Firm size is measured as the natural logarithm of total assets, while the asset-liability ratio is calculated as the proportion of total liabilities to total assets. Profitability is represented by the ratio of net profit to average total assets. The cash flow ratio reflects the proportion of net operating cash flow to total liabilities, and the current ratio is defined as the ratio of current assets to current liabilities. Listing age is measured as the difference between the sample year and the firm's initial listing year. Collectively, these control variables capture essential firm characteristics that may influence innovation behavior and productivity dynamics, thereby enhancing the robustness and reliability of the empirical results.

#### 3.2 Model Specification

To examine the impact of NQPF on enterprise innovation, this study constructs a fixed-effects model. The model is specified as follows:

$$Innovation_{it} = \beta_0 + \beta_1 Nqpf_{it} + \beta_2 Control_{it} + Firm_i + Year_t + \varepsilon_{it} \quad (1)$$

where subscripts  $i$  and  $t$  represent the firm and year, respectively.  $Innovation_{it}$  denotes the level of enterprise innovation, and  $Nqpf_{it}$  represents the NQPF.  $Control_{it}$  is a vector of control variables.  $Firm_i$  and  $Year_t$  denote firm-fixed and year-fixed effects, respectively, to control for unobserved heterogeneity across firms and temporal variations. The error term  $\varepsilon_{it}$  captures random disturbances. To ensure robustness, industry-year clustered standard errors are applied.

#### 3.3 Data Sources

The sample of this study consists of A-share listed pharmaceutical manufacturing firms in China over the period 2015–2023. Patent data were obtained from the IncoPat global patent database, while financial data were collected from the CSMAR database. To ensure data reliability, financial firms, ST, and ST companies were excluded, and continuous variables were winsorized at the 1% and 99% levels to mitigate the influence of outliers. After data cleaning and screening, the final sample includes 241 firms and 1,443 firm-year observations, forming a balanced panel dataset. Descriptive statistics for all variables are presented in Table 1.

Table 1. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Innov	1463	1.371	1.097	0	4.762

Variable	Obs	Mean	Std. Dev.	Min	Max
NQPF	1463	0.0090	0.0110	0	0.0950
Size	1463	22.06	0.937	19.45	25.45
Lev	1463	0.300	0.165	0.0140	1.645
ROA	1463	0.0620	0.0920	-0.662	0.969
Cashflow	1463	0.0700	0.0800	-0.647	0.726
Liquid	1463	3.486	3.345	0.0840	40.17
ListAge	1463	2.102	0.787	0.693	3.434

## 4. Empirical Analysis

### 4.1 Baseline Regression Results

Table 2 reports the results of the baseline regressions. Column (1) presents the estimation results without any control variables. The coefficient of NQPF is significantly positive, indicating that an improvement in NQPF effectively promotes enterprise innovation. In column (2), after incorporating firm-level control variables, the coefficient of NQPF remains significantly positive at the 1% level. Column (3) introduces year-fixed effects to account for macroeconomic influences, and the results remain consistent. Furthermore, column (4) adds firm-fixed effects to control for unobservable firm-specific characteristics, and the coefficient of NQPF continues to be significantly positive, confirming the robustness of its positive effect on innovation.

From an economic perspective, a 1% increase in the level of NQPF is associated with an approximate 7.2% improvement in firms' innovation performance. This result provides strong empirical evidence that NQPF significantly enhance innovation in the pharmaceutical manufacturing industry by facilitating factor restructuring and knowledge integration, thereby promoting industrial upgrading and technological progress.

Table 2. Benchmark regression results.

	(1)	(2)	(3)	(4)
	Innov	Innov	Innov	Innov
NQPF	16.1134*** (1.8781)	17.9677*** (1.4953)	18.6297*** (1.7607)	7.2046** (2.6180)
Control FE	NO	YES	YES	YES
Firm FE	NO	NO	YES	YES
Year FE	NO	NO	NO	YES
N	1463	1463	1463	1445
(within)	0.0269	0.1338	0.1415	0.6126

Note: \*\*\*, \*\*, and \* indicate 10%, 5%, and 1% significance levels, respectively. Robust standard errors in parenthesis.

### 4.2 Endogeneity Treatment

#### 4.2.1 Omitted Variable Bias Test

Enterprise innovation is influenced by multiple factors, and if relevant variables are omitted from the model, potential endogeneity bias may arise. This study examines the extent of omitted variable bias by calculating the ratio of coefficient differences between models with and without observable controls. This ratio serves as an indicator of the magnitude of unobservable bias relative to observable factors.

As reported in Table 3, when no control variables are included, the ratio is less than 1, indicating the presence of bias due to omitted variables. After incorporating control variables and fixed effects, the ratio increases to a range between 7.49 and 10.3, suggesting that the estimation results would only be significantly biased if the influence of unobservable factors were

more than seven times stronger than that of observable variables. Therefore, the potential impact of omitted variable bias is minimal, confirming the robustness and reliability of the baseline regression results.

Table 3. Omitted Variable Bias Test.

Specification	Restricted Regression Coefficient	Full Sample Coefficient	Ratio of Differences
Without control variables and without fixed effects	16.113449	7.2045756	0.80869659
Without control variables but with firm and year fixed effects	6.5043977	7.2045756	10.289636
With control variables and firm fixed effects only	6.2432845	7.2045756	7.4946872

#### 4.2.2 Instrumental Variable Approach

To address potential reverse causality concerns, this study employs the IV method for robustness testing. The provincial average of NQPF among other listed firms in the same province is selected as the instrumental variable. This variable is highly correlated with a firm's own level of NQPF but is exogenous to its individual innovation output.

The 2SLS estimation results are reported in columns (1) and (2) of Table 4. The first-stage regression shows a significantly positive association between the instrumental variable and the firm's level of NQPF, confirming instrument relevance. In the second stage, the coefficient of NQPF remains significantly positive, indicating that the positive effect of NQPF on enterprise innovation persists even after accounting for potential endogeneity. These findings suggest that the baseline conclusions are robust and not driven by reverse causality.

#### 4.2.3 GMM Estimation

To further verify robustness and account for potential dynamic characteristics in innovation behavior, this study applies a system GMM estimator. The one-period lag of the innovation variable is included as an endogenous regressor to capture innovation persistence and mitigate simultaneity bias.

As reported in column (3) of Table 4, the coefficient of NQPF remains significantly positive at the 1% level, while the lagged innovation variable also exhibits a significant positive effect. This indicates that enterprise innovation demonstrates strong persistence over time and that the promoting effect of NQPF remains robust within a dynamic estimation framework.

Table 4. IV and GMM test.

	(1) IV NQPF	(2) IV Innov	(3) GMM Innov
NQPF		27.9699*** (6.2609)	9.4076*** (3.0052)
IV	0.5961*** (0.0375)		
L_Innov			0.4992*** (0.0426)
Control FE	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	1464	1463	1219
(within)	0.1638	0.1234	-

Note: \*\*\*, \*\*, and \* indicate 10%, 5%, and 1% significance levels, respectively. Robust standard errors in parenthesis.

#### 4.3 Robustness Tests

To further validate the reliability of the baseline regression results, a series of robustness tests were conducted from three perspectives: (1) substitution of the dependent variable, (2) adjustment of the sample period, and (3) introduction of lagged variables. As shown in Table 5, the estimation results across all alternative models remain consistent with the

baseline findings, indicating that NQPF significantly promote the innovation performance of pharmaceutical manufacturing enterprises.

#### 4.3.1 Alternative Dependent Variable

To mitigate potential measurement bias arising from the choice of innovation indicators, the number of invention patents granted is used as an alternative measure of enterprise innovation performance. To address the presence of zero values, the logarithm of the number of invention patents granted plus one is employed. The regression results reported in column (1) of Table 5 show that the coefficient of NQPF remains significantly positive at the 5% level, suggesting that higher levels of NQPF continue to enhance firms' innovation output. This finding confirms that the baseline conclusion is not driven by the choice of innovation indicators, thereby reinforcing the robustness of the results.

#### 4.3.2 Alternative Sample Period

Considering that the outbreak of the COVID-19 pandemic at the end of 2019 may have caused structural disruptions to R&D activities and innovation investment in the pharmaceutical manufacturing industry, the sample year 2020 was excluded to eliminate the potential influence of the pandemic. As shown in column (2) of Table 5, after removing the pandemic period, the coefficient of NQPF remains significantly positive at the 1% level, indicating that the positive effect of NQPF on innovation is not limited to a specific period. This suggests that the promoting role of NQPF is robust across different economic phases, further supporting the generalizability and reliability of the results.

#### 4.3.3 Lagged Patent Variables

Innovation activities in the pharmaceutical manufacturing industry exhibit a strong time-lag effect, as firms often complete technological development and accumulation prior to patent applications or approvals. To account for this temporal delay, the dependent variable is lagged by one period, and regressions are re-estimated using the lagged innovation level. The results, presented in column (3) of Table 5, show that the estimated coefficient of NQPF remains significantly positive, with no notable change in the level of significance. This indicates that even when considering the time gap between technological accumulation and innovation output, the core conclusion remains robust, underscoring the stability of the positive effect of NQPF on enterprise innovation.

Table 5. Robustness tests.

	(1)	(2)	(3)
	Indep	Innov	lag_Innov
NQPF	8.3266** (3.4390)	7.2172** (2.8281)	8.2535*** (2.0236)
Control FE	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
N	878	1285	1443
(within)	0.6939	0.5979	0.6219

Note: \*\*\*, \*\*, and \* indicate 10%, 5%, and 1% significance levels, respectively. Robust standard errors in parenthesis.

#### 4.4 Mechanism Analysis

The baseline regression results demonstrate that NQPF significantly enhance the innovation performance of pharmaceutical manufacturing enterprises. However, this positive effect is not achieved through a direct linear relationship but rather through the restructuring of firms' technological foundations and knowledge accumulation mechanisms. To further uncover the underlying transmission pathways, the mechanism analysis is conducted from two dimensions: technological stability and technological diversification. These two dimensions represent firms' distinctive capabilities in the depth of technological accumulation and the breadth of knowledge exploration, while also reflecting the intrinsic features of technological integration and innovation-driven development embedded in NQPF. The mediating effect is tested using the following model specifications:

$$M_{it} = \beta_0 + \beta_1 Nqpf_{it} + \beta_2 Control_{it} + Firm_i + Year_t + \varepsilon_{it} \quad (2)$$

$$Innovation_{it} = \beta_0 + \beta_1 Nqpf_{it} + \beta_2 M_{it} + \beta_3 Control_{it} + Firm_i + Year_t + \varepsilon_{it} \quad (3)$$

where subscripts  $i$  and  $t$  represent the firm and year, respectively.  $M_{it}$  denotes the mediating variable, while other variables are defined consistently with Equation (1).

#### 4.4.1 Technological Stability

Technological stability reflects a firm's ability to maintain continuity in technological trajectories and sustain long-term knowledge accumulation. In the pharmaceutical manufacturing industry, R&D processes are typically characterized by long cycles and high risks, requiring persistent technical expertise and information management. Under the framework of NQPF, digitalization and intelligent manufacturing enhance the efficiency of technological accumulation and improve the reliability of knowledge retention.

To measure this construct, a technological stability index (Stabi) is developed based on technological concentration, core patent maintenance rate, and patent commercialization rate. As shown in columns (1) and (2) of Table 6, the results indicate that higher levels of NQPF significantly improve firms' technological stability. When this mediating variable is incorporated into the innovation model, the direct effect of NQPF on innovation decreases but remains statistically significant, suggesting a partial mediating effect. This finding implies that NQPF enhance innovation partly by strengthening firms' technological persistence and reinforcing path dependence. By improving knowledge continuity and reducing technological fragmentation, NQPF establish a solid foundation for sustainable and cumulative innovation.

#### 4.4.2. Technological Diversification

Technological diversification captures a firm's capacity for cross-domain collaboration and knowledge integration. It reflects the ability to expand the scope of technological exploration and engage in multi-disciplinary innovation activities. In this study, the degree of technological diversification (Div) is measured based on the distribution of patent International Patent Classification (IPC) subclasses, which quantifies the variety of technological fields covered by a firm's patents.

Regression results presented in columns (3) and (4) of Table 6 show that the coefficient of NQPF is significantly positive, indicating that NQPF effectively promote technological diversification. Further regression including Div as a mediating variable reveals that the direct effect of NQPF on innovation weakens but remains significant, confirming another partial mediation mechanism. This suggests that NQPF stimulate innovation by promoting cross-domain knowledge sharing and intelligent collaboration. Through digital data platforms and automated coordination systems, firms can reduce the costs of interdisciplinary innovation, achieve parallel exploration across multiple technological trajectories, and integrate resources from diverse fields. Consequently, NQPF expand the technological boundaries of firms and foster a dynamic and inclusive innovation ecosystem.

Table 6. Benchmark regression results.

	(1) Stabi	(2) Innov	(3) Div	(4) Innov
NQPF	21.1294*** (4.8471)	5.2976* (2.5685)	10.4951*** (3.0701)	4.2682* (2.2504)
Control FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	1446	1445	1446	1445
(within)	0.4047	0.6422	0.4252	0.6658

Note: \*\*\*, \*\*, and \* indicate 10%, 5%, and 1% significance levels, respectively. Robust standard errors in parenthesis.

## 5. Conclusions and Implications

This study systematically examines the impact of NQPF on the innovation performance of pharmaceutical manufacturing

enterprises and explores the underlying mechanisms through which such effects occur. The empirical findings demonstrate that NQPF significantly enhance firms' innovation performance, and this conclusion remains robust across multiple tests addressing endogeneity and robustness concerns.

Further analysis reveals that the effect of NQPF on innovation operates through both direct and indirect pathways. Specifically, NQPF not only directly improve firms' innovation output but also indirectly promote sustained innovation performance by enhancing technological stability and technological diversification. These findings suggest that NQPF serve as a dual driver of innovation—deepening technological accumulation and broadening the scope of knowledge exploration—thereby acting as a critical engine for achieving high-quality innovation and sustainable growth in the pharmaceutical manufacturing sector.

From a policy perspective, developing NQPF should be regarded as a key lever for the structural transformation and upgrading of the pharmaceutical industry. Government authorities should foster an enabling institutional environment by improving the innovation policy framework, increasing investment in digital infrastructure, and optimizing the allocation of scientific and technological resources. These efforts will support the growth and diffusion of NQPF across industries.

At the enterprise level, pharmaceutical manufacturers should actively advance intelligent and digital transformation of production systems, promote data-driven innovation models, and strengthen long-term management of core technological R&D. These initiatives will enhance firms' innovation capacity and improve their ability to respond to technological changes. At the industrial level, fostering cross-disciplinary knowledge collaboration and open innovation networks is essential. Encouraging technological integration and collaborative innovation can accelerate the formation of an innovation ecosystem characterized by synergy, inclusiveness, and sustainable competitiveness.

Future research could extend this study by exploring the heterogeneous effects of NQPF across different types of pharmaceutical enterprises, such as those varying in ownership structure, firm size, or regional innovation environments. Moreover, examining the long-term influence of NQPF on innovation efficiency and industrial competitiveness would provide deeper theoretical and practical insights for promoting sustainable innovation within China's pharmaceutical manufacturing industry.

## Funding

No

## Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

## Reference

- [1] Wang, S., & Chen, Y. (2021). How technological innovation affect China's pharmaceutical smart manufacturing industrial upgrading. *Journal of Healthcare Engineering*, 2021(1), 3342153. <https://doi.org/10.1155/2021/3342153>
- [2] Lai, H., Shi, H., & Zhou, Y. (2020). Regional technology gap and innovation efficiency trap in Chinese pharmaceutical manufacturing industry. *PloS one*, 15(5), e0233093. <https://doi.org/10.1371/journal.pone.0233093>
- [3] Guan, X., Chen, L., Xia, Q., & Qin, Z. (2022). Innovation efficiency of Chinese pharmaceutical manufacturing industry from the perspective of innovation ecosystem. *Sustainability*, 14(20), 12993. <https://doi.org/10.3390/su142012993>
- [4] Tang, J. (2024). New Quality Productivity and China's Strategic Shift Towards Sustainable and Innovation-Driven Economic Development. *Journal of Interdisciplinary Insights*, 2(3), 36-45. <https://doi.org/10.5281/zenodo.13845756>
- [5] Zhu, W., Ouyang, P., & Kong, M. (2024). Research on the evolution mechanism of intelligent manufacturing transformation of Chinese pharmaceutical manufacturing enterprises based on system dynamics. *Heliyon*, 10(13). <https://doi.org/10.1016/j.heliyon.2024.e33959>
- [6] Yin, S., Zhang, N., Ullah, K., & Gao, S. (2022). Enhancing digital innovation for the sustainable transformation of manufacturing industry: a pressure-state-response system framework to perceptions of digital green innovation and its performance for green and intelligent manufacturing. *Systems*, 10(3), 72. <https://doi.org/10.3390/systems10030072>
- [7] Zhang, G., Gao, Y., & Li, G. (2023). Research on digital transformation and green technology innovation—evidence

- from China's listed manufacturing enterprises. *Sustainability*, 15(8), 6425. <https://doi.org/10.3390/su15086425>
- [8] Xu, M., Liu, X., & Li, O. (2024). Can intelligent manufacturing drive green development in China's pharmaceutical industry?--Evidence from listed enterprises. *Energy*, 308, 132953. <https://doi.org/10.1016/j.energy.2024.132953>
- [9] Li, Z., Guo, L., & Ping, Y. (2024). Revolutionizing pharmaceutical innovation: Unveiling the impact of endogenous knowledge spillover in China. *PloS one*, 19(9), e0307171. <https://doi.org/10.1371/journal.pone.0307171>
- [10] Yin, S., Wang, Y., & Xu, J. (2022). Developing a conceptual partner matching framework for digital green innovation of agricultural high-end equipment manufacturing system toward agriculture 5.0: A Novel Niche Field Model Combined With Fuzzy VIKOR. *Frontiers in Psychology*, 13, 924109. <https://doi.org/10.3389/fpsyg.2022.924109>
- [11] Miozza, M., Brunetta, F., & Appio, F. P. (2024). Digital transformation of the Pharmaceutical Industry: A future research agenda for management studies. *Technological Forecasting and Social Change*, 207, 123580. <https://doi.org/10.1016/j.techfore.2024.123580>
- [12] Obradović, T., Vlačić, B., & Dabić, M. (2021). Open innovation in the manufacturing industry: A review and research agenda. *Technovation*, 102, 102221. <https://doi.org/10.1016/j.technovation.2021.102221>
- [13] Fitzgerald, L., Niarchou, E., Jones, I., & Naughton, B. (2026). Emerging Digital Innovations in Pharmaceutical Manufacturing Quality: A Systematised Review. *Journal of Pharmaceutical Innovation*, 21(1), 46. <https://doi.org/10.1007/s12247-025-10272-5>
- [14] Zhang, B., Dong, W., & Yao, J. (2025). The Digital Transformation of the Manufacturing Industry, the Double-Factor Allocation Efficiency of the Manufacturing Industry, and Carbon Emissions: Evidence from China. *Sustainability*, 17(14), 6564. <https://doi.org/10.3390/su17146564>
- [15] Ghobakhloo, M., Mahdiraji, H. A., Iranmanesh, M., & Jafari-Sadeghi, V. (2024). From Industry 4.0 digital manufacturing to Industry 5.0 digital society: A roadmap toward human-centric, sustainable, and resilient production. *Information Systems Frontiers*, 1-33. <https://doi.org/10.1007/s10796-024-10476-z>
- [16] Rejeb, A., Rejeb, K., Süle, E., Hassoun, A., & Keogh, J. G. (2025). Knowledge flows in industry 4.0 research: a longitudinal and dynamic analysis. *Journal of Data, Information and Management*, 1-23. <https://doi.org/10.1007/s42488-025-00146-3>
- [17] Vărzaru, A. A., & Bocean, C. G. (2024). Digital transformation and innovation: The influence of digital technologies on turnover from innovation activities and types of innovation. *Systems*, 12(9), 359. <https://doi.org/10.3390/systems12090359>
- [18] Harikannan, N., & Vinodh, S. (2025). State of art review on sustainable manufacturing and Industry 4.0. *Business Strategy and the Environment*, 34(1), 872-913. <https://doi.org/10.1002/bse.4013>
- [19] Song, J.; Zhang, J.; & Pan, Y. (2024). The impact of ESG development on enterprises' new quality productive forces: Empirical evidence from China's A-share listed companies. *Contemporary Economic Management*, 46(6), 1–11. <https://doi.org/10.13253/j.cnki.ddjjgl.2024.06.001>
- [20] Lu, J.; Guo, Z.; & Wang, Y. (2024). The Development Level, Regional Differences, and Improvement Paths of New Quality Productive Forces. *Journal of Chongqing University (Social Sciences Edition)*, 30(3), 1–17. <https://doi.org/10.11835/j.issn.1008-5831.jg.2024.03.002I>