Can Generative Artificial Intelligence Facilitate Cross-Border Innovation for Traditional Firms--Empirical Analysis Based on Digital Innovation Data of Chinese A-share Listed Companies

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Abstract: As a strategic technology leading the new round of scientific and technological revolution and industrial change, whether Generative Artificial Intelligence(AIGC) can drive traditional enterprises to break through organizational boundaries and realize cross-border innovation is a core issue of concern for both academics and practitioners. This paper takes Chinese A-share listed companies in Shanghai and Shenzhen from 2011 to 2022 as research samples, constructs firm-level generative artificial intelligence development indicators, empirically examines them using a multidimensional fixed-effect model, and ensures the reliability of the conclusions after a series of robustness tests. The study finds that: firstly, AIGC significantly promotes cross-border innovation; secondly, the driving effect of technology on convergence innovation is stronger than that of pure digital innovation, but there exists the "innovation quantity-quality paradox"; thirdly, the mechanism analysis confirms that the "upgrading of human capital structure" and "upgrading of R&D structure" are more important than the "innovation quantity-quality paradox". Third, the mechanism analysis confirms that "human capital structure upgrading" and "R&D resource adsorption" are the two key paths; finally, the heterogeneity analysis shows that the technology effect is more significant in state-owned enterprises, high-tech enterprises and non-regulated industries. This study provides new empirical evidence for understanding the macroeconomic consequences of AIGC, and has important implications for policymaking in digital transformation.

1. Introduction

As a strategic technology leading the new round of scientific and technological revolution and industrial change, AIGC is driving AI to realize the paradigm shift from perception and understanding to content creation. Unlike traditional analytical AI that focuses on classification and prediction, AIGC offers new possibilities for reshaping the enterprise innovation process with its powerful content generation and cross-disciplinary knowledge reorganization capabilities.[1][2] However, in contrast to this technological potential, the economic consequences of this technology have been recognized in existing studies mostly from the perspective of "efficiency gains".[3]The research gap is particularly evident in the fact that the literature on digital transformation generally treats digital technology as a homogenous whole, which is not enough to reveal its strategic value as an "innovation ontology" in driving enterprises to break through organizational inertia and capability boundaries. This research gap is particularly reflected in the following aspects: first, when exploring digital transformation, the existing literature generally treats digital technology as a homogenized whole[4]Secondly, the micro-studies focusing on AI are mostly concerned with its application in areas such as process automation.[1]Lack of a clearer understanding of how AIGC affects the fundamental innovation activities of firms -- especially cross-border innovation.[5] Finally, there is still a lack of mechanistic knowledge about the channels and boundary conditions of AIGC technology development. In order to fill the above research gaps, this paper takes Chinese A-share listed companies in Shanghai and Shenzhen from 2011 to 2022 as the research samples,

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constructs enterprise-level AIGC technology development indicators, and empirically examines the causal effect of AIGC on cross-border innovation of traditional enterprises by adopting a multidimensional fixed-effects model and a systematic robustness test. The theoretical analysis of this paper is based on knowledge reorganization theory[6]and further from "Upgrading the Human Capital Structure".[7]and "R&D Resource Adsorption"[8]The dual path reveals its mechanism of action, and at the same time deeply explores the heterogeneity of the effect in the dimensions of property rights, technological attributes and industry regulation. The theoretical value of this study is to promote the academic discussion of AIGC to shift from "efficiency narrative" to "innovation narrative", and to deepen the understanding of the heterogeneity of digital technology empowerment by linking its technological characteristics with the theoretical core of cross-border innovation. At the practical level, the findings of the study provide important decision-making references for enterprises to avoid the innovation trap of "focusing on quantity rather than quality" and realize valuable cross-border transformation, as well as empirical bases for government departments to formulate differentiated technology promotion policies.

The subsequent structure of this paper is organized as follows: Part II reviews the relevant literature and formulates the research hypotheses; Part III describes the research design in detail; Part IV presents the empirical results and analyses; Part V summarizes the research findings and elaborates the policy implications.

2. Literature Review and Theoretical Assumptions

2.1 Literature Review

Existing research has laid an important foundation for understanding the economic impact of corporate innovation and artificial intelligence, but there are also obvious research limitations. In the field of corporate innovation, scholars have mainly explored innovation drivers from internal and external perspectives of organizations. Internal factors emphasize the knowledge base[7]In addition to the role of redundant resources and dynamic capabilities, external factors focus on the impact of institutional environment and market competition. With the development of digital economy, research has begun to focus on the macro impact of digital transformation on enterprise innovation.[4][5]However, most of these studies treat digital technologies as a homogenized whole and fail to distinguish in detail the differences in the enabling mechanisms of different types of digital technologies. However, most of these studies treat digital technologies as a homogenized whole and fail to distinguish carefully the differences in the enabling mechanisms of different types of digital technologies.

At the same time, research on the economic consequences of AI is limited in perspective. Existing literature focuses either on macro-level productivity and employment effects[1]or focusing on the efficiency gains of process automation at the micro level, the unique value of AIGC - i.e., AI technologies capable of generating new, original content - as a creative technology to drive breakthrough innovation has generally been overlooked. AIGC is a unique technology that is capable of generating new, original content. This limitation has led to the failure of existing research to effectively reveal how AIGC, through its "creative and convergent" technological qualities, facilitates enterprises to realize cross-border innovation - that is, the strategic behavior of enterprises to transcend the existing technological track and knowledge base, and enter into new technological or market domains through the integration of internal and external heterogeneous knowledge.[6]In general, existing research has two important limitations. Generally speaking, there are two important limitations in the existing research: firstly, it fails to distinguish the difference in technical characteristics between AIGC and traditional AI, ignoring the unique value of the former in knowledge creation; secondly, it lacks a rigorous identification of the causal relationship between AIGC and cross-boundary innovations, and especially lacks an in-depth analysis of the mechanism of its role.

2.2 Theoretical Analysis and Research Hypotheses

Based on the theory of knowledge reorganization, enterprise innovation is essentially a process of creative reorganization of existing knowledge elements.[8]AIGC significantly facilitates cross-border innovation in enterprises through a dual mechanism. AIGC significantly promotes cross-border innovation through a dual mechanism: first, as a "knowledge synthesizer", it can quickly absorb, understand and reorganize knowledge from different fields; second, as a "low-cost trial-and-error platform", it can generate a large number of alternatives through simulation, significantly reducing the uncertainty and sunk costs of innovation exploration, thus easing the "fear of failure" faced by enterprises in cross-border exploration. Fear[9]Accordingly, the main effect hypothesis H1 is proposed. Accordingly, this paper proposes the main effect hypothesis H1: the level of generative artificial intelligence has a significant positive impact on corporate cross-border innovation.

Further, the promotion of cross-border innovation by AIGC is expected to be realized through two key paths. First, the application of AIGC will lead to the demand for high-quality and complex technical talents in enterprises, which is consistent with the theory of skill bias in technological progress.[10]In this way, it promotes the upgrading of the human capital structure of enterprises and lays the talent foundation for complex innovation activities. Accordingly, H2 is proposed: generative artificial intelligence promotes cross-border innovation by upgrading the human capital structure of enterprises.

In addition, the innovation potential demonstrated by AIGC can send positive signals to the marketplace and enhance a firm's ability to attract R&D resources because it constitutes an important R&D project in its own right. This resource clustering effect is similar to the ability of successful innovation activities to attract external investment.[11] Accordingly, it is proposed that H3: generative artificial intelligence promotes cross-border innovation by enhancing the adsorption capacity of enterprises' R&D resources.

3. Literature Review and Theoretical Assumptions

3.1 Sample Selection and Data Sources

This study takes Chinese A-share listed companies in Shanghai and Shenzhen from 2011 to 2022 as the initial research sample and screens them according to the following criteria: first, financial and insurance listed companies are excluded; second, companies with special trading status such as ST and *ST are excluded; then, observations with missing key variables are excluded; finally, all continuous variables at 5% and 95% quartiles are deflated to mitigate the effect of extreme values. Finally, all continuous variables at 5% and 95% quartiles are deflated to mitigate the effect of extreme values. The corporate financial data are from CSMAR database, the patent data are from CNRDS China Research Data Service Platform, and the data related to generative artificial intelligence are constructed by text analyzing method. After the above processing, 31,743 firm-year observations are obtained, which constitute the unbalanced panel data.

3.2 Definition of Variables

Drawing on existing research, this paper measures corporate cross-border innovation across three dimensions:(1) DigitalPat: The natural logarithm of one plus the number of digital technology-related patents applied for by the enterprise in a given year,(2) FusionPat: The number of patents applied for by the enterprise in a given year that integrate digital technology with traditional business,(3) DigitalQual: The average number of citations received by the enterprise's digital patents.

3.3 Modelling

In order to test the impact of generative artificial intelligence on firms' cross-border innovation, this paper constructs the following benchmark regression model:

$$DigitalInnovation_{it}=\alpha+\beta AIGC_{it}+\gamma Controls_{it}+\mu_i+\lambda_t+\delta_i+\varepsilon_{it} \tag{1}$$

where $DigitalInnovation_{it}$ represents the level of cross-border innovation of firm $i$in year t, measured by the number of digital patents, the number of convergence patents, and the quality of digital innovation, respectively; $AIGC_{it}$ denotes the development level of AIGC for the firm;$Controls_{it}$is the vector of control variables;μ_i, $\lambda_t$and$\delta_i$represent firm, year, and industry fixed effects, respectively; and ε_{it} is the random error term.

3.4 Descriptive Statistics

Table 1 reports the descriptive statistics of the main variables. Table 1 shows that the mean value of the number of digital patents (DigitalPat) is 0.6228, the standard deviation is 1.0940, and the median is 0, indicating that there is a large variation in the digital innovation activities of the sample firms, and most of the firms have not yet carried out substantial digital innovation. The mean value of generative artificial intelligence level is 0.1082, and the median is 0, indicating that the application of generative artificial intelligence technology by enterprises is at a lower level, and the distribution is right-skewed; in terms of control variables, the distribution of state-owned enterprises (SOE), enterprise size, financial characteristics (Lev, ROA, CashFlow) and other variables is within a reasonable range, and the distribution is closer to that of existing studies. The distribution of variables such as SOE (Size), financial characteristics (Lev, ROA, CashFlow) are all within a reasonable range, which is close to the existing studies.

Table 1 Descriptive statistics.

variant	observed value	average value	(statistics) standard deviation	minimum value	upper quartile	maximum values
explanatory variable						
Number of digital patents	35,000	0.6228	1.094	0	0	8.7368
explanatory variable						
Generative Artificial Intelligence Levels	68,500	0.1082	0.3878	0	0	5.1591
control variable						
Nature of ownership (SOE)	55,500	0.3473	0.4761	0	0	1
Enterprise Size	55,500	22.0962	1.1787	20.3272	21.9224	24.6076
Gearing ratio (Lev)	55,500	0.418	0.1982	0.1008	0.4127	0.7717
Return on total assets (ROA)	55,500	0.0362	0.0475	-0.0767	0.036	0.1236
Cash flow from operating activities (CashFlow)	55,500	0.0466	0.0605	-0.071	0.0458	0.1634
Fixed assets ratio (Fixed)	55,500	0.2071	0.1492	0.0125	0.1776	0.5345
Growth in operating income (Growth)	51,300	0.1212	0.2589	-0.3131	0.0908	0.7428
Size of the Board	55,500	2.1207	0.1681	1.7918	2.1972	2.3979
Proportion of Independent Directors (Indep)	55,500	0.3726	0.0443	0.3333	0.3636	0.4545
Dual	54,200	0.298	0.4574	0	0	1
Shareholding Concentration (Top1)	55,500	0.338	0.1401	0.1288	0.3174	0.6149

This research design lays a solid foundation for subsequent empirical tests through rigorous variable measurement, perfect modeling and systematic statistical description.

4. Analysis of Empirical Results

4.1 Benchmark Regression Analysis

In order to test the impact of AIGC on cross-border innovation of traditional firms, this paper adopts a stepwise regression approach to systematically examine the relationship between the two, from a simple model to a complete model that includes multidimensional fixed effects. Table 2 reports the benchmark regression results.

Table 2 Benchmark regression results of AIGC on firms' cross-border innovation.

VARIABLES	(1)Number of digital patents	(2)Number of digital patents	(3)Number of digital patents	(4)Number of digital patents	(5)Number of digital patents
Generative Artificial Intelligence Levels	0.640*** (0.020)	0.592*** (0.020)	0.083*** (0.014)	0.084*** (0.014)	0.071*** (0.015)
Constant	0.589*** (0.006)	0.595*** (0.006)	0.669*** (0.004)	0.675*** (0.004)	-1.904*** (0.322)
controlled variable	NO	NO	NO	NO	YES
Fixed effects					
Year	NO	YES	YES	YES	YES
ID	NO	NO	YES	YES	YES
Industry	NO	NO	NO	YES	YES
Observations	30,793	30,793	30,667	29,939	27,363
R-squared	0.063	0.079	0.798	0.801	0.809

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$; robust standard errors in parentheses, same as below.

As shown in columns (1) to (5) of Table 2, with the gradual addition of fixed effects and control variables, the estimated coefficient of AIGC remains positive and significant, supporting hypothesis H1. Specifically, in column (2) controlling for year effects only, the coefficient of AIGC is 0.592; after further controlling for individual fixed effects (column (3)), the coefficient drops to 0.083, indicating that ignoring individual heterogeneity will lead to severely overestimated results; in the full model (column (5)) controlling for year, individual and industry fixed effects simultaneously and adding all the control variables, the coefficient drops to 0.083. The coefficient of AIGC is 0.592; after further controlling for individual fixed effects (column (3)), the coefficient drops to 0.083, indicating that ignoring individual heterogeneity will lead to a serious bias in the estimation results; in the complete model (column (5)), which simultaneously controls for year, individual and industry fixed effects and adds all control variables, the coefficient of AIGC is 0.071, and it is significant at the level of 1%, which indicates that for every one unit of the level of AIGC, the number of digital patents of the enterprise will be increased by about 0.071 units on average. In terms of model fit, from column (1) to column (5), R^2 gradually increases from 0.063 to 0.809, indicating that the complete model can explain 80.9% of the variation in the number of digital patents, and the model setting is reasonable. In summary, the benchmark regression results robustly support the facilitating effect of AIGC on cross-border innovation of traditional enterprises, which lays a solid foundation for the subsequent in-depth analysis.

4.2 Analysis of Multidimensional Innovation Effects

After confirming the contribution of AIGC to overall digital innovation, The paper further examines its differential impact on different types of innovation. Table 3 reports the results of the dimensionalized regressions of AIGC on the three types of digital innovation, with all models controlling for year, firm and industry fixed effects and the full set of control variables.

Table 3 Impact of AIGC on different types of digital innovation.

	(1)	(2)	(3)
VARIABLES	Number of Fusion Patents	Number of digital-only patents	Quality of digital innovation
Generative Artificial Intelligence Levels	0.101*** (0.014)	0.031*** (0.011)	-0.046*** (0.005)
Constant	-1.368***	-1.522***	0.251**
	(0.292)	(0.238)	(0.127)
Observations	27,363	27,363	27,363
R-squared	0.763	0.786	0.350
fixed effect	Year - Individual - Industry	Year - Individual - Industry	Year - Individual - Industry

Table 3 shows that the innovation effect of generative artificial intelligence presents significant structural differentiation characteristics: first, its promotion effect on the number of fusion patents is the strongest (coefficient = 0.101), which can effectively integrate digital technology and traditional business knowledge, and give rise to cross-border fusion innovation results; second, the effect on the number of pure digital patents is significantly positive but the coefficient is small (0.031), indicating that its core advantage This shows that its core advantage lies in the promotion of cross-fertilization of technology tracks rather than deep breakthroughs in a single technology field; particularly important is that AIGC has a significant negative impact on the quality of digital innovation (coefficient=-0.046), revealing the "innovation quantity-quality paradox", which may be due to the combined effect of the dilution effect of innovation, the dispersion effect of resources and the path-dependence effect. This may be due to the combined effect of the innovation dilution effect, resource dispersion effect and path dependence effect, which suggests that enterprises need to be vigilant against the tendency of "emphasizing quantity over quality" in the application of technology.

4.3 Robustness Tests

To ensure the robustness of the findings, this paper conducts systematic tests in the following three dimensions: first, adjusting the clustering level of the standard errors, clustering the robust standard errors to the firm level to control the autocorrelation at the individual level; second, replacing the measures of the core explanatory variables, using four alternative indicators, namely, RUmig, RInvjg, RInvig, and RDesjg, respectively, to re-metric the AIGC level; finally, the sample period was adjusted to limit the sample to 2011-2022 to exclude the potential interference of recent technological mutations. The results of each test are summarized in Table 4.

Table 4 Comprehensive results of robustness test

	return to baseline	Firm-level clustering	RUmig indicators	RInvjg indicator	RInvig Indicators	RDesjg indicator	Sample 2011-2022
Generative Artificial Intelligence Levels	0.071*** (0.015)	0.071*** (0.021)	0.010*** (0.004)	0.005*** (0.002)	0.002* (0.001)	0.016*** (0.006)	0.055** (0.021)
observed value	27,363	27,363	24,270	24,270	24,270	24,270	20,757
R^2	0.809	0.809	0.816	0.815	0.815	0.815	0.815

Table 4 shows that despite different standardized error clustering assumptions, variable measures and sample periods, the promotional effect of AIGC on corporate cross-border innovation maintains statistical significance, and the direction of the coefficients is consistent with the baseline regression, indicating that the conclusions of this study are highly robust.

4.4 Endogenous Treatment

Although the baseline regression has controlled for multidimensional fixed effects and correlated variables, endogeneity bias between AIGC and firms' cross-border innovations may still be caused by problems such as reverse causation, omitted variables, or measurement errors. To mitigate this problem, this paper employs an instrumental variables approach to estimation, which has been widely used in addressing the endogeneity of the economic impact of technological innovation.

Instrumental variables are constructed with reference to the industry cohort effect idea[13],The mean IV of the level of AIGC development of other firms within the same industry in the same year is used as an instrumental variable for the level of AIGC in this firm. The design follows the Angrist and Pischke (2009)[15]The proposed principles of instrumental variable selection are: on the one hand, they satisfy the relevance condition, i.e., there is a significant correlation between the technological decisions of firms in the same industry due to similar technological environments and institutional pressures; on the other hand, they satisfy the exclusivity constraint, i.e., the technological choices of other firms are mainly indirectly applied to their own firms by influencing the overall technological climate of the industry and do not directly determine the innovation output of their own firms. Table 5 reports the estimation results of the two-stage least squares method.

Table 5 Instrumental variable method regression results.

variant	Phase I Generative Artificial Intelligence Levels	Phase II Number of digital patents
Generative Artificial Intelligence	0.981***	0.296***
Levels	(-0.028)	(-0,042)
control variable	YES	YES
fixed effect	YES	YES
observed value	43,256	27,358
Stage I F-statistics	1226.45	
Kleibergen-Paap LM statistic	985.32***	

The regression results show that the coefficient of instrumental variables is 0.981 and significant at 1% level, indicating that instrumental variables are highly correlated with endogenous variables. The F-statistic of the first stage is 1226.45, which far exceeds the critical value of the weak instrumental variable test and rejects the original hypothesis of the weak instrumental variable.The Kleibergen-Paap LM statistic is significant at 1% level, which further confirms the correlation of the instrumental variable. In the second stage estimation, the coefficient of AIGC is 0.296, which is significant at 1% level.The findings on AIGC for innovation are consistent, confirming the causal contribution of technology to innovation.

4.5 Mechanism Analysis

To reveal the intrinsic channels through which AIGC affects cross-border innovation, this paper focuses on the two mechanism paths of "human capital structure upgrading" and "R&D resource adsorption" based on the causal inference framework of Jiang Ting (2022).[14]The framework emphasizes the strict identification of the treatment effects of mechanism variables, and we construct the following first-stage regression model of mediating effects:

$$Mediator_{it}=\gamma_0+\gamma_1 AIGC_{it}+\gamma_2 X_{it}+\mu_i+\lambda_t+\delta_i+\varepsilon_{it} \tag{2}$$

Among them, $Mediator_{it}$ denotes the two mechanism variables, technician ratio and R&D staff share, respectively.

Table 6 Results of Mechanism Analysis.

	(1)	(2)
VARIABLES	Percentage of technical staff	Percentage of R&D staff
Generative Artificial Intelligence	0.011***	0.449***
Levels	(0.003)	(0.164)
Constant	0.194***	25.167***
	(0.059)	(5.891)
Observations	33,118	8,612
R-squared	0.746	0.903
fixed effect	Year - Individual - Industry	Year - Individual - Industry

4.5.1 Mechanisms for Upgrading the Human Capital Structure

Column (1) of Table 6 reports the results of the impact of AIGC on the proportion of technicians. The estimation shows that the coefficient of AIGC is 0.011 and significant at the 1% level, indicating that the application of AIGC technology significantly increases the share of highly qualified technicians in firms. This finding is consistent with the theory of skill-biased technological progress (Bresnahan et al., 2002).[10]This suggests that AIGC promotes the optimization and upgrading of the human capital structure by inducing enterprises to demand for complex technical talents.

4.5.2 Mechanisms for Adsorption of R&D Resources

Column (2) of Table 6 presents the results of the impact of AIGC on the R&D staff share. The coefficient of AIGC is 0.449 and significant at 1% level, indicating that AIGC technology significantly enhances firms' ability to pool R&D resources. This finding is in line with Hsu et al.(2014)[11]The findings on innovation signaling to attract resource investment echo the findings that the innovation potential demonstrated by AIGC can send positive signals to the market, thus enhancing firms' R&D resource adsorption capacity.

The results of the comprehensive mechanism analysis show that generative artificial intelligence acts on cross-border innovation of enterprises through the dual paths of "human capital structure upgrading" and "R&D resource adsorption", revealing the complex internal logic of technology influencing the innovation behavior of enterprises.

4.6 Heterogeneity Analysis

The previous analysis suggests that AIGC has a significant facilitating effect on cross-border innovation of enterprises, however, this effect may vary systematically depending on the characteristics of enterprises and the external environment. In order to examine the boundary conditions of the impact of AIGC in depth, this paper analyzes the heterogeneity from the three dimensions of property rights, technology attributes and industry characteristics. Table 7 reports the grouped regression results.

Table 7 Results of heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	nationalized business	non-state enterprise	High-tech enterprises	Low-tech enterprises	Regulated industries	Non-regulated industries
Generative Artificial Intelligence Levels	0.126***	0.064***	0.080***	0.041	-0.007	0.091***
	(0.039)	(0.016)	(0.017)	(0.032)	(0.037)	(0.016)
Constant	0.879	-3.616***	-2.634***	0.656	2.174***	-3.065***
	(0.699)	(0.368)	(0.391)	(0.572)	(0.819)	(0.352)
Observations	7,450	19,863	20,006	7,287	4,789	22,481
R-squared	0.822	0.814	0.818	0.704	0.749	0.824
fixed effect	Year - Individual - Industry	Year - Individual - Industry	Year - Individual - Industry	Year - Individual - Industry	Year - Individual - Industry	Year - Individual - Industry

4.6.1 Heterogeneity in the Nature of Property Rights

The results in columns (1)-(2) of Table 7 show that the promotional effect of AIGC in SOEs (coefficient = 0.126) is significantly stronger than that in non-SOEs (coefficient = 0.064). This suggests that although the overall innovation efficiency of SOEs is relatively insufficient, the rich data and R&D resources accumulated by SOEs, activated by AIGC, produce stronger marginal innovation enhancement.

4.6.2 Heterogeneity of Technical Attributes

Columns (3)-(4) of Table 7 show that AIGC has a significant effect on high-tech firms (coefficient = 0.080), while its effect on low-tech firms is not significant (coefficient = 0.041). This difference is mainly due to the complementarity of the knowledge base and the level of technology absorption capacity - the deep digital technology accumulation of high-tech enterprises matches well with the knowledge reorganization characteristics of AIGC, and its strong absorption capacity can better transform the technological potential into innovation results.[12].

4.6.3 Heterogeneity of Industry Characteristics

The results in columns (5)-(6) of Table 7 show that the promotional effect of AIGC is significant in non-regulated industries (coefficient = 0.091), while it is not significant in regulated industries. Institutional theory suggests that institutional constraints such as strict access restrictions and price controls may weaken enterprises' incentives to innovate, distort resource allocation, and limit the application scenarios of the technology, thus inhibiting the innovation effect of AIGC.

5. Research Findings and Policy Implications

5.1 Main Findings

Based on the empirical analysis of Chinese A-share listed companies in Shanghai and Shenzhen from 2011 to 2022, this paper systematically examines the impact of AIGC on cross-border innovation of traditional firms and its internal mechanism, and mainly draws the following conclusions: firstly, the results of the baseline regression show that AIGC significantly promotes the cross-border innovation activities of traditional firms. This conclusion is still robust after the instrumental variable method to deal with the endogeneity problem, and the estimated coefficient of the instrumental variable is significantly larger than that of the baseline regression results, which indicates that ignoring the endogeneity problem will seriously underestimate the real scale of the impact of the technology. Second, the innovation effect of AIGC shows significant structural differentiation. The dimensional test finds that the promotion effect of technology on the number of fusion patents is significantly stronger than the number of pure digital patents, which confirms its unique value as a "technology fusion device". However, AIGC has a significant negative impact on the quality of digital innovation, revealing the existence of the "innovation quantity-quality paradox", which may be due to the combined effects of innovation dilution, resource dispersion and path dependence. Thirdly, the mechanism analysis confirms the joint effect of the dual paths of "human capital structure upgrading" and "R&D resource adsorption". AIGC optimizes the human capital structure of enterprises by upgrading the proportion of technicians and provides resource guarantee for enterprise innovation by enhancing the adsorption capacity of R&D resources, and the two paths together constitute the transmission mechanism of technology-influenced innovation. Finally, the heterogeneity analysis reveals the context-dependent nature of technology effects. The promotion effect of generative artificial intelligence in state-owned enterprises is significantly stronger than that in non-state-owned enterprises, reflecting the marginal improvement value of technology for organizations facing "innovation dilemma"; the promotion effect in high-tech enterprises is significantly better than that in low-tech enterprises, reflecting the importance of technological match; the effect in non-regulated industries in non-regulated industries is significantly better than that in regulated industries, highlighting the moderating role of institutional environment on the effect of technological empowerment.

5.2 Theoretical Contributions and Practical Implications

The theoretical contributions of this study are mainly reflected in three aspects: first, it breaks through the existing literature's single focus on the effect of technological efficiency enhancement, and provides a new theoretical perspective for understanding the microeconomic consequences of AIGC; second, it deepens the understanding of the mechanism of heterogeneity of digital technology empowerment, and enriches the theoretical research on digital technology and enterprise innovation by identifying the essential differences between AIGC and traditional analytical AI in the empowerment mechanism; third, it expands the theoretical framework of technological innovation boundary conditions, especially finding that AIGC can generate more innovation in state-owned enterprises with poor innovation performance in the normal situation. Third, it expands the theoretical framework of technological innovation boundary conditions, especially finds that

AIGC can produce stronger marginal promotion effects in state-owned enterprises with poor innovation performance under normal circumstances, revealing the unique value of general-purpose technology in "activating" organizational redundant resources and solving the "innovation dilemma".

Based on the conclusions of the study, this paper puts forward the following policy insights: for government departments, they should formulate differentiated technology promotion strategies, focusing on supporting high-tech enterprises in the application of deep integration of technology and strengthening the digital infrastructure of low-tech enterprises, while optimizing the innovation policy environment of the regulated industries and establishing a technology promotion system that matches the characteristics of the industry. It is necessary to build a quality-oriented incentive mechanism for innovation, improve the innovation evaluation system, strengthen the quality-oriented appraisal mechanism while encouraging innovation output, and guide enterprises to focus on the substantive value and technological content of innovation. It should also strengthen the synergistic input of human capital and innovation resources, synchronize the promotion of technology application, talent training and resource support policies, and maximize the synergistic effect of technological innovation. In terms of enterprise practice, we should formulate technology application strategies that match with organizational characteristics. State-owned enterprises should give full play to their resource advantages and scale effects, and carry out cutting-edge technology exploration and major innovation research; non-state-owned enterprises should focus on application innovations in niche fields, and give full play to their comparative advantages of mechanism flexibility and market sensitivity. It is necessary to pay attention to the synergistic promotion of technological innovation and organizational change, and at the same time of introducing generative artificial intelligence technology, promote the adjustment of organizational structure and optimization of the talent system, and establish a management mode and incentive mechanism that matches the characteristics of the technology. It should also establish the strategic orientation of integration and innovation, focus on exploring the innovation potential of AIGC in the areas of business integration and technology intersection, and build a digital innovation ecosystem around its core business, so as to realize the strategic shift from "technology application" to "innovation leadership".

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