

The Impact of Artificial Intelligence on Corporate Digital Technology Innovation: A Perspective Based on Workforce Skill Structure

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Abstract. Digital economy is the core driving force for cultivating new quality productivity. According to the policy of Statistical Classification of Digital Economy and Its Core Industries (2021), artificial intelligence plays a significant role in promoting enterprise digital technology innovation, but the transformation process of intelligent technology to innovation achievements still needs to be clarified, and the transmission mechanism of labor skill structure as an intermediary mechanism between the two is not clear. Existing research suffers from unclear mechanisms and insufficient empirical evidence. Therefore, this study adopts the chain analysis framework of technology-skill-innovation, adopts the data of A-share listed companies in Shanghai and Shenzhen Stock exchanges from 2010 to 2022, and adopts the mediating effect model to deeply study its effect and influence mechanism. The study finds that artificial intelligence can promote the digital technology innovation of enterprises, and the skill structure of labor force plays a partial mediating role in it. The results of heterogeneity analysis show that this promotion effect is more pronounced for large SOEs and firms in the central region. This study decomposes the skill mediation indicators and combines the multidimensional data with the theoretical framework to provide firm-level empirical evidence on the transmission mechanism of AI-driven firm innovation and provide ideas for relevant policy formulation.

Keywords: artificial intelligence, digital technology innovation, workforce skill structure, substitution effect, complementarity effect

1. Introduction

The digital economy is the core driving force for building a new development model and fostering new quality of productive forces. Artificial intelligence (AI) is a strategic technology and a key production factor, occupying a core position in national strategies. Research has confirmed the enabling role of artificial intelligence in enterprise digital innovation [1,2], but the process by which intelligent technologies are transformed into innovative achievements remains unclear [3]. Existing research on the impact of AI on production efficiency and the skill structure of the labor force [4] remains a core issue in the context of the intensive implementation of digital economy policies. However, how AI influences digital innovation through the intermediary mechanism of skill

structure remains a key concern. Most current studies focus on the impact of AI on skill structure [5-7], but they have not explored its mediating role in innovation; A few other studies have linked skills to innovation [8], but few have regarded AI as a core variable in the system framework, and there is also a lack of empirical evidence at the company level.

Based on this, this study uses the data of A-share listed companies on the Shanghai and Shenzhen stock exchanges from 2010 to 2022 to construct A technology-skills-innovation chain analysis framework. With the "Statistical Classification of Digital Economy and Its Core Industries" in 2021 as the policy background and employs mediation analysis, the aim is to explore the specific paths by which artificial intelligence influences the digital innovation of enterprises. There are two core reasons for choosing this perspective: First, "Classification" provides an exogenous policy benchmark. It reduces the subjectivity of measurement and helps define digital technology innovation. Second, the skill structure of the labor force is a key carrier of human-machine collaboration. Linking artificial intelligence technology with innovation output and focusing on this connection helps to reveal the dissemination mechanism of artificial intelligence. At the same time, at the micro level, it is conducive to exploring the impact of artificial intelligence on both digital innovation and the labor force structure.

The innovation points of this article include two aspects: First, it reveals the heterogeneous skill mediation mechanism, which fills the gap in the existing research on communication channels. The existing research widely discusses the impact of artificial intelligence on enterprise innovation. This paper adopts decomposed skill indicators and, by subdividing the mediation indicators (high-skilled and low-skilled labor force), more accurately characterizes the influence path of skill structure on AI-innovation. This approach better reflects the real predicaments of enterprises, such as high-skill shortages and low-skill redundancies. Second, it integrates multi-dimensional data and theories, enhancing practical relevance. It combines the theory of skill-biased technological change [9] and the theory of human capital [10], fusing multi-source data on patents and employee structure. This study refines the theoretical framework of artificial intelligence - skills - innovation, providing inspiration for the government to formulate specific policies and achieving a closed loop from theory to practice.

2. Literature review and research hypotheses

Based on the skills-biased technological progress theory proposed by Acemoglu, artificial intelligence amplifies the innovation-driven effect through the complementarity with high-skill factors [11], reconstructs the knowledge production mode, enables the innovation link of the value chain, provides systematic impetus for the upgrading of the independent innovation system. It also drives the transformation of innovation models toward human-machine collaboration by promoting knowledge diversity and organizational practice breakthroughs [12]. Existing empirical studies have demonstrated the positive impact of artificial intelligence on digital technology innovation from multiple dimensions. At the micro level, AI can promote enterprise innovation, which is achieved by improving the skill structure of the workforce and increasing R&D expenditure [13,14], and the degree of its application has a nonlinear impact on the innovation results of different enterprises [15]. At the micro level, the driving effect of AI development policy is significant, which promotes radical innovation and high-quality development of enterprises [16], improves the technical complexity and market value of digital patents [17], and promotes progressive and radical digital innovation [12]. To sum up, artificial intelligence promotes enterprise digital technology innovation in a variety of ways. These include data support, process improvement, and pattern innovation.

Based on this, the following research hypotheses are proposed:

H1: Artificial intelligence technology has greatly promoted the improvement of enterprise digital technology innovation level.

Based on the theory of task characteristics, AI affects the skill structure through a dual mechanism of "substitution-complement" [18], that is, replacing regular low-skill positions and supplementing non-routine high-skill positions, which encourages companies to upgrade their skill configuration. This optimized high-skill composition is essential to help absorb and adapt new technologies, further enhancing the role of AI in driving digital innovation. Empirical studies confirm this dual approach. In terms of substitution, artificial intelligence and robot use have significantly reduced the demand for low-skilled labor [19,20]. In terms of complementarity, AI increases the demand for highly skilled personnel. For example, R&D and compound talents can optimize the structure of human capital [21,22]. This upgraded skill structure promotes enterprise digital technology innovation through various ways, such as knowledge spillover from skill agglomeration [23], innovation brought by diversity [21], and improvement of dynamic adjustment ability [24]. AI reshapes the skill structure of enterprises, replacing low-skilled labor and supplementing high-skilled labor, thus driving digital technology innovation of enterprises.

Based on this, the following research hypotheses are proposed:

H2: The skill composition of the workforce is a mediating factor in the link between AI and corporate digital innovation. AI facilitates the upskilling of the workforce, which it does by replacing routine low-skilled tasks and supporting non-routine high-skilled roles, thus in turn increasing the degree of digital technology innovation in the enterprise.

3. Methodology

3.1. Data sources

This paper takes A-share listed companies in Shanghai and Shenzhen as the research objects, covering the time sample range from 2010 to 2022. The patent data used in this paper are mainly from the IRPDB intellectual property database, the labor-related data are from the RESSET database, and the data of listed companies are from the annual reports, China Securities Information Network and Cathay Pacific CSMAR database.

The sample data underwent the following processing: ① Financial sector firms were excluded; ② Samples of firms designated as ST or *ST during the year were excluded; ③ Samples with severe data missingness were excluded; ④ To reduce the impact of outliers, all micro-level continuous variables underwent trimming at the 1% and 99% levels.

3.2. Variable selection and explanation

(1) Core Explanatory Variable: Artificial Intelligence Technology (AI). Its measurement method draws on the method proposed by Yao Jiaquan et al. [4] and is refined at the same time to match the specific focus of this study on digital technology innovation. To accurately capture AI related only to digital innovation, the scope of patent keywords was narrowed: only those patents whose title or abstract contained terms such as "AI", "deep learning" or "machine learning" that were also related to digital technologies (e.g., digital algorithms, intelligent data processing) were included. This filtering step intentionally excludes AI patents that are not related to digital innovation, such as traditional manufacturing patents used for control purposes. Finally, the natural logarithm of the number of patent applications is taken as the measurement index, so as to reduce the potential distortion caused by zero value.

(2) **Dependent Variable: Digital Technology Innovation (Digtech).** To measure this variable, the present research utilizes the annual count of invention patent applications in digital technology. Following the guidelines provided in the "Statistical Classification of the Digital Economy and Its Core Industries (2021)" and the "Correspondence Table between International Patent Classification and National Economic Industry Classification (2018)," relevant patent classifications within the digital technology field are first determined. The annual total of corresponding invention patent applications is then summed, and the indicator is calculated as the natural logarithm of this total after adding one.

(3) **Mediating Variable:** Following research by Autor [18], Yao Jiaquan et al. [4], Routine low-skill labor (Routine) and non-routine high-skill labor (Non-routine) are two key categories. The former is derived from the workforce percentage in production, operations, marketing, and finance roles, while the latter corresponds to the percentage employed in technical and R&D positions.

(4) **Controlling Variables.** Following common research practice, this study incorporates a set of firm-level control variables that may substantially affect corporate innovation. These controls are: Size (natural logarithm of total assets), Age (years since establishment), Lev (total liabilities/total assets), Roa (net profit/total assets), Dual (whether the chairman also serves as general manager), HHI (Herfindahl Index based on sales share, reflecting industry competition), BoardSize (number of directors), Rdintensity (R&D expenditure/operating revenue), IAR (current assets/total assets), and Growth (annual revenue growth rate). See Table 1 for details.

Table 1. Descriptive statistics

Variable Name	Variable Symbol	Observed Value	Mean	Standard Deviation	Minimum	Maximum
Artificial Intelligence Technology	AI	20,343	0.649	6.469	0	479
Digital Technology Innovation	Digtech	20,343	10.12	94.68	0	4,500
Current Ratio	IAR	20,343	4.403	4.758	0	83.56
Enterprise Growth	Growth	20,343	19.77	118.2	-98.18	5,884
Age	age	20,343	9.909	6.906	1	33
Board Size	BoardSize	20,343	8.417	1.651	4	18
Dual Role	Dual	20,343	0.319	0.466	0	1
Debt-to-Asset Ratio	Lev	20,343	40.33	19.56	2.026	351.3
Profitability	Roa	20,343	3.469	8.255	-212.0	75.86
Intensity Rdintensity	Rdintensity	20,343	5.642	6.408	0.0300	217.5
Herfindahl Index	HHI	20,343	0.171	0.135	0.0391	0.885
Firm Size	Size	20,343	12.98	1.243	10.74	16.89
Routine Low-Skilled Labor	Routine	20,343	0.611	0.213	0.0346	0.917
Non-Routine High-Skilled Labor	Non_routine	20,343	0.236	0.182	0.0121	0.839

3.3. Metric model

Using panel data from A-share listings on the Shanghai and Shenzhen stock markets, this paper examines the effect of artificial intelligence on digital innovation within companies. The core regression model is set as:

$$Digtech_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \sum \alpha_m Control_{i,t} + \lambda_i + \mu_t + \eta + \varepsilon_{i,t} \quad (1)$$

Here, *i* and *t* refer to province and year. The variable AI stands for the Artificial Intelligence Technology Index, Digtech indicates the Digital Technology Innovation Index, and Control_{*i,t*}

represents a vector of control variables. The terms $\lambda_i, \mu_t,$ and η capture province, year, and industry fixed effects, respectively, while $\epsilon_{i,t}$ denoting the random disturbance term.

4. Empirical analysis

4.1. Benchmark regression

The regression results of Equation (1) are summarized in Table 2. The results in Column (1) show that the coefficient of artificial intelligence is significantly positive at the level of 1%, which supports the positive role of artificial intelligence in promoting enterprise digital technology innovation; After considering year, province and industry fixed effects in Column (2), the positive significance of AI still exists; Column (3) introduces the enterprise-level control variables for analysis, and the results show that the coefficient of AI is significantly 1.000. In economic terms, this means that a 1% increase in AI capability corresponds to a 1% increase in digital innovation. This effect exceeds the productivity effect found by Yao et al. [4], which may be due to a closer alignment between AI and digital innovation.

Table 2. Baseline regression results

VARIABLES	(1)	(2)	(3)
	Digtech	Digtech	Digtech
AI	1.365*** (0.058)	1.154*** (0.051)	1.000*** (0.047)
Observations	20,343	20,337	20,337
R-squared	0.256	0.391	0.438
Controls	NO	NO	YES
Year FE	NO	YES	YES
Pro FE	NO	YES	YES
Ind FE	NO	YES	YES

Note: ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively. The figures in parentheses represent the industry-level cluster standard errors.

4.2. Robustness testing

To ensure the reliability and accuracy of the research results, we conducted robustness tests from the following five aspects respectively.

(1) Replace the core variable. Since the differences in the measurement methods of the explanatory variables might affect the estimation results, the explanatory variables were substituted. Consistent with Yao weighted [4], the indicator of artificial intelligence is re-estimated by adding 1 to the natural logarithm of the number of AI-related keywords extracted from the annual report (denoted as AI_text). The results of the robustness test are shown in the first column of Table 3, which confirm that the coefficient of AI_text is still positive and significant, supporting the initial conclusion.

(2) Consider the lag effect. Considering that there may be a time series correlation in the implementation of the impact of artificial intelligence, and it may take at least one year for the influence of AI to manifest, the AI is regressed one period later. Column (2) confirms a sustained positive significance coefficient.

(3) Adjust the fixed effect. To address the potential model specification bias, this study adjusted the clustering to that at the city and company levels. The AI coefficient remained significantly positive, indicating robust results.

(4) Adjust the sample range. In order to control the negative impacts of exogenous shocks (such as COVID-19 and policy changes), the observational results after 2020 were excluded. Column (4) of Table 3 continues to show a significant positive AI coefficient.

(5) Delete extreme samples. In this paper, 3% of the observed values at both ends of all continuous variables were truncated. The robustness test in the fifth column of Table 3 further verifies that the AI maintains a statistically significant positive coefficient, whose magnitude differs slightly from the benchmark regression estimate.

Table 3. Robustness testing

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Replace independent variable	Lag Effect	City-level clustering	Enterprise-level clustering	Reducing the sample interval	Remove outliers
AI	0.171*** (0.021)	0.950*** (0.051)	1.010*** (0.036)	1.010*** (0.031)	1.045*** (0.058)	0.931*** (0.066)
Observations	18,316	17,875	21,412	21,462	13,376	21,462
R-squared	0.356	0.439	0.444	0.444	0.463	0.405
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Pro FE	YES	YES	YES	YES	YES	YES
Ind FE	YES	YES	YES	YES	YES	YES

Note: Same as Table 1

4.3. Heterogeneity analysis

4.3.1. Property rights heterogeneity

In order to investigate the heterogeneous impact of property rights, we divide enterprises into SOEs and non-SOEs according to ownership. The regression results in Table 4 show that the AI coefficients for both groups are significantly positive, but the coefficients for SOEs are larger. After adding the interaction term and controlling for fixed effects, the interaction effect remains significant, confirming that SOEs play a stronger role in promoting innovation. This may be attributed to the superior resource endowments of SOEs, lower financing costs, greater financial support, and closer ties to the national digital strategy. These advantages enable SOEs to better absorb high fixed costs, attract high-end AI talent, and more effectively transform AI into tangible digital innovation results.

Table 4. Heterogeneity regression results

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	State-owned enterprises	Non-state-owned enterprises	Large enterprises	Small and medium-sized enterprises	Eastern regions	Central regions	Western regions
AI	1.143*** (39.72)	0.879*** (30.90)	1.073*** (41.33)	0.814*** (23.42)	0.960*** (40.13)	1.132*** (20.18)	1.045*** (17.20)
Observations	5,505	13,356	9,430	9,432	13,578	2,736	2,032
R-squared	0.549	0.396	0.495	0.364	0.436	0.474	0.487

Table 4. (continued)

Controls	YES						
Year FE	YES						
Pro FE	YES						
Ind FE	YES						

Note: Same as Table 1

4.3.2. Scale heterogeneity

The effect of firm size heterogeneity is examined, that is, the sample is divided into large firms and small and medium-sized firms (SMEs) according to whether the total assets of the firm are higher than the median of the industry. Columns (3) and (4) of Table 4 show that the AI coefficients of the two groups are significantly positive, among which the AI coefficient of large-scale enterprises is larger, indicating that AI has a stronger role in promoting innovation in large-scale enterprises, which may be because they have more resources, a stronger ability to resist risks, and easy-to-form economies of scale, which helps to attract composite talents and integrate technology and human capital. In contrast, SMEs are limited in terms of data, capital, and infrastructure, and AI can only be applied to more narrow scenarios, and the innovation results achieved are not comprehensive, leading to its relatively small effect.

4.3.3. Regional heterogeneity

To explore the impact of the regions where enterprises are located on the mechanism, the study classified the samples into the eastern, central and western regions according to the classification of the National Bureau of Statistics. Columns (5)-(7) of Table 4 show that the positive impact of AI in all regions is significant at the level of 1%, and the order of effect size is central>western> eastern. With advanced digital infrastructure, the eastern region has limited room for AI-driven incremental benefits and faces constraints such as competition for resources and long innovation cycles. Benefiting from policy incentives and cost advantages, the central region has strong compatibility between AI and traditional industries, and the marginal effect is the most obvious. The western region was initially underdeveloped but then used policy support to bridge the infrastructure gap; however, talent and infrastructure constraints made its overall influence lower than that of the central region.

5. Mechanism research

The hypothesis section above points out that both conventional low-skilled and non-conventional high-skilled labor act as mediating variables through which AI technology affects digital technological innovation. AI technology reduces labor demand for conventional occupations, demonstrating substitution effects on routine positions [6]; simultaneously, AI adoption stimulates demand for roles requiring advanced cognitive and social interaction skills, suggesting complementarity between AI and non-routine task labor [25]. Accordingly, it is posited that AI fosters digital technological innovation by diminishing conventional low-skilled labor's demand and elevating the request for non-routine high-skilled labor. Building on the mediation models developed by Yao Jiaquan et al. [4] and Shi Bingzhan et al. [26], an indicator reflecting corporate labor skill structure is constructed to examine this mechanism. Our model is formulated as follows:

$$Digtech_{i,t} = \alpha_0 + \alpha_1 AI_{i,t} + \sum \alpha_m Control_{i,t} + \lambda_i + \mu_t + \eta + \varepsilon_{i,t} \quad (2)$$

$$Labor_{i,t} = \delta_0 + \delta_1 AI_{i,t} + \sum \delta_m Control_{i,t} + \lambda_i + \mu_t + \eta + \varepsilon_{i,t} \quad (3)$$

$$Digtech_{i,t} = \theta_0 + \theta_1 AI_{i,t} + \theta_2 Labor_{i,t} + \sum \theta_m Control_{i,t} + \lambda_i + \mu_t + \eta + \varepsilon_{i,t} \quad (4)$$

The variable Labor captures a firm's workforce skill composition, distinguishing between routine low-skilled (Routine) and non-routine high-skilled (Non-routine) categories, following Autor et al. [18] and Yao Jiaquan et al. [4]. Routine labor is measured as the share of personnel in production, operations, marketing, and finance, while non-routine labor is the share of technical and R&D staff. Other terms remain consistent with previous sections. AI denotes the artificial intelligence indicator, Digtech represents the enterprise digital technology innovation indicator, and Control_{i,t} constitutes a vector of control variables. λ_i, μ_t, and η account for province, year, and industry fixed effects, respectively, while ε_{i,t} represents the error term.

Model (2) is consistent with Model and represents the principal regression of artificial intelligence and enterprise digital technology innovation. The AI coefficient α₁ captures AI's total effect on corporate digital innovation, while δ₁ in Model (3) reflects AI's impact on two distinct labor skill categories (Labor). Based on the theoretical hypotheses presented earlier, when the dependent variable is conventional low-skilled labor, the estimated AI coefficient δ₁ is significantly negative; when the dependent variable is unconventional high-skilled labor, the estimated AI coefficient δ₁ is highly positive. Model (4) adds the firm-level labor indicator Labor on the basis of Model (3), where the AI coefficient θ₁ indicates the direct effect of artificial intelligence on a enterprise's digital technology innovation, while the Labor coefficient θ₂ shows the independent contribution of labor skill structure after accounting for AI.

The stepwise regression of the mediating effect's result is reported in Tables 5 and 6. The first column of Table 5 signifies that holding other levels constant and controlling for fixed effects of year, province, and industry, a 1% increase in AI level correlates with a 1% increase in digital innovation level. The second column indicates that AI significantly reduces firms' demand for routine low-skilled labor, with δ₁ being significantly negative, suggesting AI replaces routine manual labor positions. Column (3) includes both AI and Routine as explanatory variables. The significantly positive θ₁ confirms AI's independent positive influence on innovation, while the significantly negative θ₂, alongside a decline in AI's coefficient from 1 to 0.991, indicates that routine low-skilled labor partially mediates the relationship. AI promotes digital technological innovation by substituting the workforce engaged in routine repetitive tasks within enterprises.

Table 5. Mediating effect test (conventional low-skilled labor substitution effect)

VARIABLES	(1)	(2)	(3)
	Digtech	Routine	Digtech
AI	1.000*** (0.047)	-0.032*** (0.009)	0.991*** (0.048)
Routine			-0.299*** (0.068)
Observations	20,337	20,337	20,337
R-squared	0.438	0.461	0.439
Controls	YES	YES	YES
Year FE	Yes	Yes	Yes

Table 5. (continued)

Pro FE	Yes	Yes	Yes
Ind FE	YES	YES	YES

Note: Same as Table 1

Column (1) of Table 6 is still the benchmark regression result of AI on innovation, and the coefficient of AI is the same as that in Table 5. The AI coefficient in Column (2) is significantly positive, which means that artificial intelligence has increased the demand for unconventional highly skilled labor. In Column (3), the coefficients of AI and Non_routine are both significantly positive, and the coefficient of AI drops from 1 to 0.982, which indicates that the indicator of non-routine highly skilled labor plays a partial mediating role in the impact of artificial intelligence on enterprise digital technology innovation. AI drives innovation in digital technology, and it does so by complementing abstract task labor positions in businesses.

Table 6. Mediated effect test (unconventional high-skilled labor complementarity effect)

VARIABLES	(1)	(2)	(3)
	Digtech	Non_routine	Digtech
AI	1.000*** (0.047)	0.030*** (0.008)	0.982*** (0.049)
Non_routine			0.616*** (0.154)
Observations	20,337	20,337	20,337
R-squared	0.438	0.522	0.442
Controls	YES	YES	YES
Year FE	YES	YES	YES
Pro FE	YES	YES	YES
Ind FE	YES	YES	YES

Note: Same as Table 1

6. Research conclusions and policy recommendation

This research explores and analyzes the effect of artificial intelligence (AI) on digital innovation within corporations, utilizing panel data from A-share listed companies (2010–2022). The key results reveal that: (1) AI has a quite positive promoting effect on digital technology innovation, and every 1% increase in the level of AI technology will increase the results of digital technology innovation by about 1%. (2) The core channel of AI optimization lies in adjusting the skill structure of employees. The replacement of routine, low-skilled jobs by AI also raises the demand for non-routine, high-skilled positions. (3) The results of heterogeneity analysis show that the promotion effect of AI is more obvious in SOEs, large enterprises and enterprises in central region of China.

In light of these conclusions, the study offers several policy implications: First, public authorities should support AI-driven innovation. They can use tax incentives and investment in digital infrastructure to accelerate core technology breakthroughs. Second, companies should adapt their workforces to AI technology. They need to match the skills of the workforce with the development of artificial intelligence, strengthen the introduction of talent in cutting-edge fields, and provide retraining and social protection for manual workers who lose their jobs. Third, implement regional

coordination policies. The government should encourage large SOEs to lead industrial development, provide financial support for SMEs, optimize resources in the east, increase investment in the west, strengthen the advantages of the central region, and narrow the regional development gap.

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