How Artificial Intelligence Shapes the Human Capital Structure: Evidence from The Supply Chain Digitalization Pilots

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Abstract. Against the backdrop of the in-depth advancement of the Digital China initiative and the accelerated restructuring of supply chain systems, digital technologies are profoundly reshaping the internal factor allocation structure of enterprises by remodeling the information flow, capital flow and collaboration modes among them. Based on the data of A-share listed companies on the Shanghai and Shenzhen Stock Exchanges from 2013 to 2022, this paper takes the pilots of supply chain innovation and application as a quasi-natural experiment and employs the difference-in-differences method to investigate the impact of supply chain digitalization on enterprises' human capital structure and its underlying mechanisms. The study finds that supply chain digitalization drives the optimization of the human capital structure. Mechanism analysis shows that supply chain digitalization enhances enterprises' capacity to absorb high-skilled labor through channels such as raising enterprises' market attention, boosting public trust in brands, alleviating financing constraints and promoting the accumulation of digital intangible assets. Heterogeneity analysis reveals that this facilitating effect is more pronounced in enterprises facing higher external environmental uncertainty, operating in more competitive industries and located in the eastern region of China. From the perspective of supply chain network collaboration and factor reallocation, this paper uncovers the micro-mechanism through which digital policies drive the upgrading of corporate human capital, and provides empirical evidence and practical insights for deepening supply chain digitalization construction and optimizing the talent structure of enterprises.

Keywords: Supply Chain Digitalization; Human Capital Level; Artificial Intelligence; Difference-in-Differences.

1. Introduction

The rapid proliferation of artificial intelligence (AI) has emerged as a pivotal force driving global productivity and organizational transformation in recent years. The advent of generative AI has significantly expanded its scope of application across enterprises and industries. According to relevant reports by the OECD, the proportion of enterprises adopting AI technologies is on the rise from 2023 to 2025, reflecting a notable increase in the adoption rate of AI at the corporate level. The International Labour Organization points out that generative AI is likely to reshape the task structure of a considerable proportion of jobs, with its impact mainly manifested in the adjustment of task content rather than the complete replacement of jobs [1]. The distributive effects brought about by AI proliferation have introduced uncertainties for workers in terms of employment quantity and quality.

The development of AI has made routine and codifiable tasks more vulnerable to technological substitution [2]. At the regional level in the United States, areas with a higher penetration of robots have witnessed a downward trend in employment and wage levels [3]. Nevertheless, AI also forms a complementary relationship with non-routine tasks, which in turn drives the differentiation of new tasks and the creation of new jobs [4]. The application of robots, while improving labor productivity and total factor productivity, has accelerated the contraction of low-skilled positions [5]. It is thus evident that the impact of AI on the labor force is not a one-way substitution effect, but a process where substitution and creation coexist. Technological progress not only changes the scale of employment, but also drives the skill-biased growth of enterprises' demand for human capital and the structural transformation of human capital.

Growth theories indicate that labor quality and human capital accumulation are crucial conditions for translating technological progress into sustained output growth. Solow emphasized that effective labor and physical capital are both core factors in the formation of output [6], and technological diffusion achieves productivity growth by enhancing labor efficiency. For developing countries, the adaptability of the human capital structure to technological change will affect the process of industrial upgrading and the quality of economic growth. The World Bank Group (2018) noted that China's economy has shifted from a factor-driven stage to an efficiency-driven stage, and against the backdrop of slowing productivity growth, the improvement of human capital quality and the optimization of skill structure are regarded as important foundations for supporting long-term growth [7]. In this context, how institutional arrangements can promote the synergy between technological progress and human capital upgrading has become a question worthy of attention.

In 2018, eight ministries including the Ministry of Commerce of China jointly issued the *Notice on Carrying out Pilots of Supply Chain Innovation and Application*, which for the first time incorporated supply chain digitalization into institutional policy experiments. The policy identified 55 pilot cities and 266 pilot enterprises, covering more than 50 sub-sectors, and supported the application of modern information technologies in supply chain management to promote the construction of a collaborative supply chain system. The pilot program required local governments to improve supporting policies and enterprises to innovate supply chain organizational models, so as to enhance industrial collaboration efficiency and resource allocation capacity. This institutional arrangement has provided a policy environment for enterprises to improve their digital capabilities and optimize human capital allocation.

Existing research on corporate digitalization and human capital structure covers multiple dimensions, including technological progress and industrial upgrading [8], the reshaping of skill demand [9], the optimization of labor structure and the improvement of employment quality [10], and the optimization of organizational structure [11][12]. However, most studies emphasize the impact of internal corporate digital transformation on human capital allocation, with few focusing on the synergistic effect of the upstream and downstream of the supply chain. The upgrading of the human capital structure depends not only on internal corporate investment, but also on the collaborative mechanisms within the supply chain network. Therefore, it remains to be further explored whether supply chain digitalization promotes the upgrading of corporate human capital structure through network collaboration mechanisms and its possible transmission paths. This study extends the research perspective from the individual enterprise level to the entire supply chain, which not only helps to deepen the understanding of human capital structure upgrading, but also provides new insights into exploring the mechanism of supply chain collaboration on the optimal allocation of labor resources in the digital environment, bearing dual theoretical and practical significance.

The marginal contributions of this paper are mainly reflected in the following three aspects. First, it breaks through the existing research paradigm that mostly focuses on the macro impact of AI on employment scale or total employment, and shifts to exploring its specific impact on the internal human capital structure of enterprises in the context of supply chain digitalization, filling the research gap in identifying the path of "structural adjustment" [10][13]. Second, it enriches the exploration of the governance factors of corporate human capital structure and expands the comprehensive factor analysis framework for corporate labor adjustment. Existing studies mostly analyze the influencing factors of human capital structure upgrading from the perspective of internal corporate characteristics such as firm size and ownership type [10], but pay little attention to the external synergistic effect of this process in the supply chain network. Extending the research perspective from individual enterprises to the entire supply chain not only enables an analysis of the mechanism through which external factors such as industry competition and environmental conditions affect human capital upgrading in the digital context, but also provides a new perspective for understanding and governing the corporate human capital structure. Third, it further deepens the boundary of policy effects in different contexts and provides certain practical guidance for human capital structure upgrading. The study not only identifies multiple transmission paths through which supply chain digitalization drives the optimization of corporate human capital structure, but also analyzes the realization conditions and constraint mechanisms of policy effects in different development contexts by combining differences in industry, regional and corporate characteristics. It provides targeted guidance for enterprises to optimize the allocation of high-skilled talents and achieve structural upgrading in a complex environment, and offers empirical evidence with practical reference value for the advancement of China's AI policies and the talent power strategy.

The rest of the paper is structured as follows. The second part is a literature review and theoretical analysis, which aims to explore the logical relationship between supply chain digitalization and human capital structure upgrading and then put forward research hypotheses. The third part is the research design, including sample selection, variable definition and model specification. The fourth part presents the empirical tests and result analysis, elaborating on the empirical results and relevant robustness tests. The fifth part is further research, mainly discussing the transmission paths and heterogeneous factors. Finally, the conclusions and implications are presented.

2. Literature Review and Theoretical Analysis

2.1. Policy Background

Since the late 1990s, Western countries have begun to apply digital technologies to promote the innovation of supply chain systems in response to the changes in the global competitive landscape, thus giving birth to the concept of "supply chain digitalization". The United States has incorporated supply chain strategy into the state-level strategic agenda since 1993 and has continuously improved supply chain efficiency through advanced technologies. Entering the 21st century, Germany launched the “Industry 4.0” strategy, emphasizing intelligent and interconnected manufacturing systems. the United Kingdom implemented the "High-Value Manufacturing" strategy to encourage enterprises to integrate digital technologies; France initiated the "New Industrial Law" to support supply chain collaboration; and Japan proposed the development of intelligent supply chain systems in its "Future Investment Strategy" to enhance industrial competitiveness.

In China, the construction of supply chain digitalization has been gradually integrated into the countrywide digital development strategic framework. As early as 2015, the State Council issued the *Guiding Opinions on the "Internet Plus" Action Plan*, which clearly proposed promoting the in-depth integration of the internet with the manufacturing and circulation industries, accelerating the construction of information infrastructure and the collaborative upgrading of industrial chains, laying an important institutional foundation for supply chain digitalization. Since then, the construction of supply chain digitalization has entered a stage of institutionalized advancement. In 2017, the General Office of the State Council issued the *Guiding Opinions on Actively Promoting Supply Chain Innovation and Application*, which clearly stated the need to build an agile, collaborative and secure intelligent supply chain. In 2018, eight ministries including the Ministry of Commerce jointly launched the "Pilots of Supply Chain Innovation and Application", taking the lead in promoting the application of digital technologies in provinces, cities and industries. In 2022, the *Specifications for the Creation of Demonstration Zones for Supply Chain Innovation and Application* was issued, providing systematic technical and institutional guidance for the construction of supply chain digitalization by enterprises and local governments. The above-mentioned policies have constructed a central-level support pathway, driving the evolution of supply chain construction from traditional collaboration to a networked and digital ecosystem, which has become a key support for strengthening the risk resistance capacity of industrial chains and enhancing the competitive advantages of enterprises.

Practical experience shows that supply chain digitalization, while promoting upstream and downstream collaboration, has strengthened enterprises' demand for high-quality labor, and the implementation of the pilot program in numerous pilot cities has achieved remarkable results. For example, the talent structure of new energy and intelligent manufacturing enterprises in the Guangdong-Hong Kong-Macao Greater Bay Area has witnessed a significant upgrading. EVE Energy Co., Ltd. has recruited more than 1,000 new employees each year from 2023 to 2025, among which more than 70% are in R&D and intelligent manufacturing-related positions, reflecting a sustained growth in its demand for highly educated and technical talents. In 2024, Nantong in Jiangsu Province introduced more than 50,000 college graduates and over 100 top-level talents, driving enterprises in the region to accelerate the absorption of technical and management talents and promoting the upgrading of corporate human capital structure.

2.2. Literature Review

2.2.1 Artificial Intelligence and the Labor Force

The impact of AI on the labor market has attracted extensive attention from academia in recent years. The adoption of AI not only concerns the total labor force, but also profoundly reshapes the structural distribution of jobs, exhibiting significant heterogeneity across different industries and types of enterprises. A core debate in existing research is whether AI promotes employment expansion and human capital upgrading, or generally squeezes employment space and exacerbates structural unemployment.

At present, some academic studies argue that the application of AI exerts a strong substitution pressure on traditional labor, thus compressing the employment scale at the macro level. Based on the theory of technological substitution, new technologies replace labor through automation, especially for codifiable and highly repetitive tasks, thereby weakening the demand for medium and low-skilled positions [13][14]. The penetration of AI has reduced the proportion of routine labor positions, leading to an imbalance in the employment structure, that is, low-skilled labor is replaced by machines, while the expansion of high-skilled positions is insufficient to fully absorb the displaced labor [15]. However, opposing views point out that AI does not simply replace labor, but creates new employment opportunities through task restructuring and productivity improvement. Technological progress usually functions by restructuring task structures rather than eliminating occupations, and new technologies create new task content while replacing some tasks [4]. Graetz and Michaels (2018) also proposed that industrial robots significantly improve labor productivity and total factor productivity, but their negative impact on the overall employment scale is limited, and their impact is more reflected in the adjustment of skill structure and changes in job types [5]. Therefore, the impact of AI is not a simple reduction in the number of jobs, but a skill-biased reshaping of the employment structure.

At the level of specific industries, the impact of AI is more reflected in the adjustment of task structures within occupations rather than the complete disappearance of occupations. In the field of financial analysis, Cao et al. (2024) found that machine learning models can significantly improve prediction accuracy when processing large-scale financial and textual information, but there are still boundaries in terms of contextual judgment and information integration capabilities possessed by human analysts. The human-machine collaboration model outperforms a single subject overall, indicating that high-skilled occupations are more likely to experience task differentiation rather than complete substitution [16]. In the field of accounting and auditing, Law and Shen (2025) pointed out that AI systems help improve the information processing efficiency and risk identification capacity of audit processes, reshaping the internal business division and organizational structure of accounting firms, but core professional judgment, liability definition and customer communication functions are still undertaken by auditors [17], which is an organizational restructuring under technological embedding rather than occupational substitution. Based on research on the capability evaluation of large language models, the impact of AI on the labor market is mainly reflected in the differences in task exposure, and the vast majority of occupations are affected at the level of partial tasks rather than overall substitution [18]. Therefore, the impact of AI on employment and human capital structure should not be understood as a one-way substitution, but a structural adjustment achieved through task restructuring and skill upgrading in the process of industrial digitalization.

2.2.2 Supply Chain Digitalization

A supply chain refers to a network system formed around meeting the needs of end users, covering the entire process from raw material procurement, production and processing, logistics and distribution to product sales. It involves not only the physical flow of products and services, but also capital flow and information flow [19]. From a traditional perspective, the core goal of the supply chain is to reduce costs and improve efficiency, and with the advancement of globalization and digitalization, its connotation has gradually expanded to systematic collaboration across organizations and regions [20]. The rise of supply chain digitalization enables enterprises to use new-generation information technologies such as the Internet of Things, big data and artificial intelligence to realize the real-time transmission and sharing of information, thus maintaining resilience and agility in a complex and volatile market environment [11].

At the macro level, existing literature mainly focuses on the impact of supply chain and its digital transformation on the optimization of economic structure and the improvement of overall performance, emphasizing its positive effects in driving the transformation of production modes, promoting the adjustment of skill demand [20], enhancing the resilience of industrial chains and the efficiency of factor allocation [20][22], advancing environmental goals such as improving energy efficiency [11], strengthening ESG performance [23], enhancing overall sustainable development performance [22], and promoting the high-quality development of regional economies [24]. In addition, relevant studies also point out that under the institutional background of different countries, supply chain digitalization strategies may reshape the division of labor pattern in the global value chain [25].

At the micro level, existing literature mostly focuses on exploring the direct impact of supply chain digitalization on enterprises' traditional economic performance, productivity and innovation activities. Studies have shown that the digital transformation of the supply chain can significantly improve corporate operational efficiency and financial performance by optimizing processes, reducing costs and enhancing resilience [26]. Han et al. (2024) and Jia et al. (2024) found that supply chain digitalization can improve the total factor productivity of enterprises [27][28]. Supply chain digitalization is also regarded as a core driving force for stimulating corporate innovation. By improving the information environment, promoting knowledge spillovers [29] and reducing collaboration costs, it effectively increases enterprises' innovation investment [30][31], innovation efficiency [32] and patent output, and to a certain extent drives the growth of demand for high-skilled labor [20][33]. The upstream and downstream spillover effects generated thereby form a multiplier effect in the entire supply chain network by influencing the production and investment decisions of partners [29][34].

To sum up, existing studies have explored the impact of AI on the labor market from the macro, micro and industrial levels, focusing on the impact of technological substitution on employment scale and structure [13][14], the structural adjustment brought about by task restructuring and productivity improvement [4][5], the heterogeneous characteristics of AI across different industries, and human-machine collaboration [16][17]. Current research on supply chain digitalization also mostly focuses on its role in promoting economic performance, industrial upgrading, corporate productivity and innovation [26][32], emphasizing its efficiency improvement in factor allocation and collaborative governance, but few combine technology adoption with the mechanism of labor structure adjustment, and there is insufficient discussion on the interaction between macro policies, industrial chain characteristics and micro corporate behaviors, as well as the reshaping of factor structures such as human capital structure. On this basis, this paper aims to explore how AI affects the corporate human capital structure under the external synergy of the upstream and downstream of the supply chain.

2.3. Theoretical Analysis

Within the framework of endogenous growth theory, human capital accumulation is regarded as an important source of driving corporate competitiveness and economic growth [35]. In a dynamically competitive environment, enterprises not only need capital and technological investment, but also rely on the continuous accumulation of knowledge, skills and creativity. However, in reality, constrained by information asymmetry and incomplete contracts, enterprises often show a preference for short-term returns in resource allocation, resulting in difficulties for high-skilled workers to accurately judge the real capabilities, organizational quality and long-term development prospects of enterprises in advance during the job-seeking process [36]. Therefore, institutional changes that can improve the external observability of enterprises, stabilize market expectations and improve the conditions for factor allocation have become an important foundation for promoting the upgrading of corporate human capital structure. By reshaping the way enterprises present information in the market, supply chain digitalization provides a key path to alleviate the above constraints.

On the one hand, digital transformation strengthens data recording, process visualization and collaborative transparency in all links of the supply chain, making enterprises' performance capacity, organizational efficiency and technical level more identifiable by external subjects [25]. Against the backdrop of information asymmetry, this external visibility formed based on the diffusion of public information constitutes an important signal for enterprises to transmit organizational quality to the labor market, helping to reduce the search costs and judgment uncertainty of high-skilled workers [37].

On the other hand, the improvement of external visibility further promotes the formation of market and public trust in brands. Existing studies have shown that the trust of market participants in enterprises' capabilities and stability is not limited to subjective cognition, but is reflected through economic behaviors such as transaction scale, cooperative relationships and operational performance [38]. By reducing transaction frictions, improving collaboration efficiency and stabilizing expectations, supply chain digitalization helps enterprises gain sustained market recognition and expand their operational scale, thus laying a foundation for forming stable employment expectations and long-term human capital allocation.

The above effects are also transmitted to the allocation of financial resources and the level of digital intangible assets. The credit decisions of financial institutions are highly dependent on information quality, and digital data and algorithm models can improve the ability to predict default risks and screening efficiency, thereby alleviating information asymmetry and improving the allocation of credit resources [39]. With the improvement of the availability and transparency of supply chain data, enterprises' financing constraints are eased, providing the necessary financial support for them to expand R&D investment, optimize job structure and introduce high-skilled workers [40]. The improvement of external visibility, the formation of trust and the improvement of financial support will jointly drive enterprises to make continuous investment in intangible assets such as digital systems, software platforms and data governance, thus increasing the accumulation of digital intangible assets.

The above paths not only reflect enterprises' long-term commitment to digital technologies, but also increase the demand for high-skilled positions such as data analysis and system integration by restructuring task structures and capability requirements [4][13]. Thus, through an integrated external information and resource allocation mechanism, supply chain digitalization drives the upgrading of the corporate human capital structure towards high skills. Based on this, this paper puts forward the following research hypothesis:

H1: Supply chain digitalization can significantly promote the upgrading of the corporate human capital structure.

3. Research Design

3.1. Sample Selection and Data Sources

Considering that the pilot policy of supply chain innovation and application was initially launched in 2018 and based on data availability, this paper takes A-share listed enterprises on the Shanghai and Shenzhen Stock Exchanges from 2013 to 2022 as the initial research sample. The data are mainly sourced from the CSMAR database, and the patent data are from the CNRDS database. In addition, the initial data are processed as follows: (1) excluding ST and *ST enterprise samples; (2) excluding financial industry enterprise samples; (3) excluding samples with missing data; (4) excluding enterprise samples whose pilot qualifications were revoked during the implementation of the pilot policy; (5) winsorizing the main continuous variables at the 1st and 99th percentiles. After sorting, this paper obtains 19,392 firm-year observations.

3.2. Model Specification

To test the impact of the development of supply chain digitalization on the upgrading of the human capital structure, this paper constructs the following benchmark regression model:

$$HC_{it} = \alpha_0 + \alpha_1(Treat_i \times Post_t) + \alpha_2 X_{it} + \lambda_i + \mu_t + \varepsilon_{it} \quad (1)$$

where HC_{it} represents the level of human capital structure upgrading of enterprise i in year t; $(Treat_i \times Post_t)$ is the core explanatory variable, representing supply chain digitalization; X_{it} is the set of control variables; λ_i and μ_t are firm and year fixed effects, respectively; and ε_{it} is the error term. This model aims to capture the causal relationship between the pilot policy and the upgrading of corporate human capital structure. In addition, this paper uses robust standard errors clustered at the firm level.

3.3. Variable Definition

The explained variable is the human capital level (HC). Referring to the practices of Barro et al. (1993) and Jin and Peng (2022) [41][42], this paper uses the proportion of employees with a bachelor's degree or above as the measurement indicator. This indicator is widely used in existing literature to measure the structural characteristics of enterprises' high-skilled labor force, that is, the higher the proportion of employees with a bachelor's degree or above, the higher the human capital level of the enterprise. In addition, this paper constructs a substitute indicator as the ratio of the proportion of employees with a bachelor's degree or above to that of employees with a college degree or below for subsequent robustness tests.

The core explanatory variable is supply chain digitalization ($Treat_i \times Post_t$), which is represented by the interaction term of the pilot dummy variable (Treat) and the time dummy variable (Post), taking the pilot policy of supply chain innovation and application enterprises as a quasi-natural experiment. Among them, Treat is a pilot dummy variable, taking the value of 1 if the enterprise is a pilot of supply chain innovation and application, and 0 otherwise; Post is a time dummy variable, taking the value of 1 for the years 2018 and later, and 0 otherwise; $Treat \times Post$ is the interaction term of the pilot dummy variable and the time dummy variable, representing supply chain digitalization.

In terms of control variables, referring to existing studies, this paper incorporates a number of micro-level corporate control variables to mitigate the omitted variable bias. The specific definitions are shown in Table 1. The model controls for both firm and year fixed effects to isolate unobservable individual heterogeneity and macro shocks.

Table 1 Definitions and Explanations of Variables

Variable Type	Variable Name	Variable Symbol	Explanation
Explained Variable	Human Capital	HC	Relative employment proportion of employees with a bachelor's degree or above
Core Explanatory Variable	Pilot Dummy Variable	Treat	1 if the enterprise is a pilot of supply chain innovation and application, 0 otherwise
	Time Dummy Variable	Post	1 for 2018 and subsequent years, 0 otherwise
Control Variable	Firm Size	Size	Ln (Total Assets)
	Asset-Liability Ratio	Lev	Total Liabilities / Total Assets
	Return on Assets	Roa	Net Profit / Total Assets
	Growth Potential	Growth	(Current Operating Income - Previous Operating Income) / Previous Operating Income
	Firm Age	Firmage	ln(Current Year - Establishment Year)
	Shareholding of the Largest Shareholder	Top1	Number of Shares Held by the Largest Shareholder / Total Shares
	Equity Balance Degree	Balance2	(Shareholding Ratio of the 2nd Largest Shareholder + Shareholding Ratio of the 3rd Largest Shareholder + Shareholding Ratio of the 4th Largest Shareholder + Shareholding Ratio of the 5th Largest Shareholder) / Shareholding Ratio of the Largest Shareholder
	Big Four Accounting Firms	Big4	1 if the company is audited by one of the international Big Four accounting firms in the current year, 0 otherwise

4. Empirical Results

4.1. Descriptive Statistics

Table 2 reports the descriptive statistical results of the main variables. The mean value of the human capital level (HC) is 29.924, with a standard deviation of 19.637, a minimum value of 0.655 and a maximum value of 100, indicating significant differences among sample enterprises in human capital investment and structural allocation, and strong heterogeneity in the human capital structure across enterprises. The proportion of enterprises included in the supply chain digitalization pilot among the core explanatory variable is relatively small in the overall sample, which is consistent with the institutional characteristics of the supply chain digitalization pilot policy with phased advancement and limited coverage. The control variables of the sample enterprises also show obvious heterogeneity in dimensions such as size, financial status and governance structure.

In summary, the mean and standard deviation distributions of each variable are reasonable, and the value ranges are in line with expectations, which can provide a solid data support for the subsequent DID identification based on the quasi-natural experiment.

Table 2 Descriptive Statistical Results

Variable	N	Mean	SD	Min	Max
HC	19392	29.924	19.637	0.655	100.000
Size	19392	22.159	1.252	19.000	26.000
Lev	19392	0.318	0.466	0	1
Roa	19392	-0.001	0.038	-1.000	0.000
Growth	19392	0.342	0.956	-1.000	12.000
Firmage	19392	2.933	0.324	2.000	4.000
Top1	19392	0.155	0.362	0	1
Balance2	19392	0.716	0.722	0.000	3.000
Big4	19392	0.056	0.231	0	1

4.2. Benchmark Regression

As shown in Table 3, in the benchmark regression, this paper adopts a progressive estimation strategy of gradually introducing fixed effects and control variables. Column (1) in the table only controls for firm fixed effects, and the estimated coefficient of *Treat×Post* is 8.186, which is significantly positive at the 1% level; when only controlling for year fixed effects, the coefficient of *Treat×Post* further increases and is significant at the 1% level; after controlling for both firm and year fixed effects, the coefficient of *Treat×Post* is 4.422, still significant at the 5% level. Furthermore, after adding some key control variables in Column (4), the estimated result of *Treat×Post* remains significantly positive; after including firm fixed effects, year fixed effects and all control variables in Column (5), the coefficient of *Treat×Post* is 4.642, significant at the 1% level.

Overall, the sign and significance of the core explanatory variable remain stable under different specifications, indicating that the supply chain digital transformation pilot can significantly improve the corporate human capital level, and the relevant conclusions have strong robustness, thus supporting Hypothesis H1.

Table 3 Regression Results of the Impact of Supply Chain Digitalization on Corporate Human Capital Level

Variable	(1)HC	(2)HC	(3)HC	(4)HC	(5)HC
Treat×Post	8.186*** (4.51)	25.685*** (9.378)	4.422** (2.52)	4.550** (2.567)	4.642*** (2.62)
Size		-2.195*** (-8.857)		-0.130 (-0.615)	-0.182 (-0.87)
Lev		-3.921*** (-7.050)		-0.981*** (-3.581)	-0.995*** (-3.61)
Roa		-13.704*** (-3.326)		-3.169 (-1.333)	-3.590 (-1.50)
Firmage		-4.575*** (-5.694)		-0.691** (-2.029)	-0.619* (-1.84)
Growth		6.024*** (21.506)			0.570*** (5.00)
Top1		1.425* (1.711)			0.712 (1.16)
Balance2		1.099** (2.515)			0.642*** (2.93)
Big4		2.053** (2.143)			-0.709 (-0.96)
Year	NO	Yes	YES	YES	YES
Company	YES	NO	YES	YES	YES
_cons	29.770*** (3407.08)	89.902*** (15.345)	29.788*** (3521.50)	35.004*** (7.394)	35.212*** (7.52)
N	19310	19，392	19310	19310	19310
Adj.R²	0.913	0.138	0.923	0.936	0.923

Note: ***, ** and * indicate that the regression coefficients are significant at the 1%, 5% and 10% confidence levels, respectively, with t-values in parentheses. The same applies to the following tables.

4.3. Robustness Tests

4.3.1 Parallel Trend Test

To test whether the difference-in-differences estimation is unbiased before the launch of the supply chain innovation and application pilot, this paper sets the following model for the parallel trend test:

$$HC_{it} = \alpha_0 + \sum_{N=2013}^{2017} \beta_k \cdot Berore_{it}^{N} + \sum_{N=2018}^{2022} \eta After_{it}^{N} + \gamma Controls_{it} + \sum Firm_i + \sum Year_t + \varepsilon_{it} \quad (2)$$

where HC_{it} represents the human capital structure level of enterprise i in year t; $Before_{it}^{N}$ takes the value of 1 if the year of enterprise i is the Nth year before the implementation of the supply chain digitalization pilot, and 0 otherwise; $After_{it}^{N}$ takes the value of 1 for the years 2018 and later, and 0 otherwise; $Controls_{it}$ represents a series of control variables; $\sum Firm_i$ and $\sum Year_t$ are firm and year fixed effects, respectively. Taking 2017, the year before the policy implementation, as the base period, the coefficient β_k reflects the dynamic difference in the corporate human capital structure level between the treatment group and the control group before the implementation of the supply chain digitalization policy.

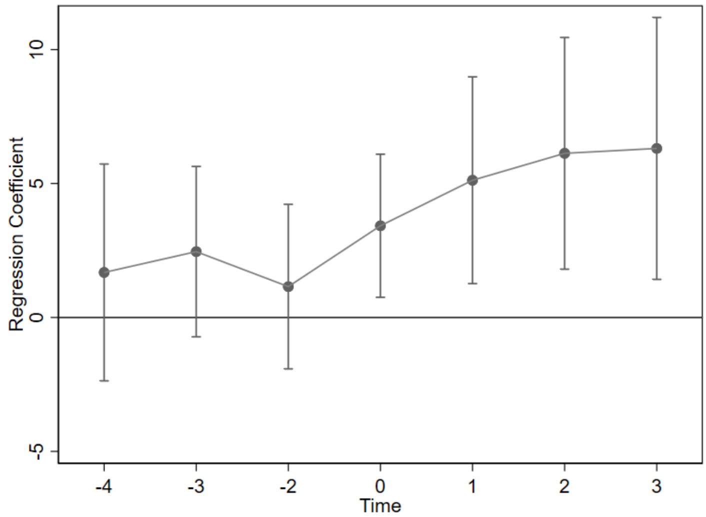

Figure 1 Parallel Trend Test

Figure 1 shows the estimated results of β_k for each year and their 95% confidence intervals. The coefficients of β_k for all years of the treatment group before the implementation of supply chain digitalization do not deviate significantly from 0, indicating that there is no significant difference in the trend of human capital upgrading between pilot enterprises and non-pilot enterprises before the policy implementation; while after the implementation of the supply chain digitalization policy in 2018, the coefficient η gradually rises and is statistically significant, that is, the pilot policy of supply chain digital transformation has a significant positive effect on the improvement of the corporate human capital structure. In summary, the parallel trend hypothesis is satisfied, and the difference-in-differences estimation results have strong identification validity.

4.3.2 Placebo Test

This paper conducts a placebo test by randomly permuting the treatment group. The specific steps are as follows: first, a new virtual treatment group is formed by randomly selecting the same number of enterprises as the treatment group in the benchmark regression, with the remaining enterprises as the new control group, and the difference-in-differences model is used for regression analysis again. Second, the above randomization process is repeated 500 times to obtain 500 estimated coefficients of the impact of the virtual supply chain digitalization policy on human capital.

As shown in the figure, the estimated coefficients of $Treat \times Post$ obtained by randomization are concentrated around 0, which is significantly different from the true value (4.642), indicating that if the policy grouping is randomly assigned, no significant treatment effect will be generated, thus further confirming the authenticity and robustness of the impact of the supply chain digitalization pilot policy on the upgrading of corporate human capital.

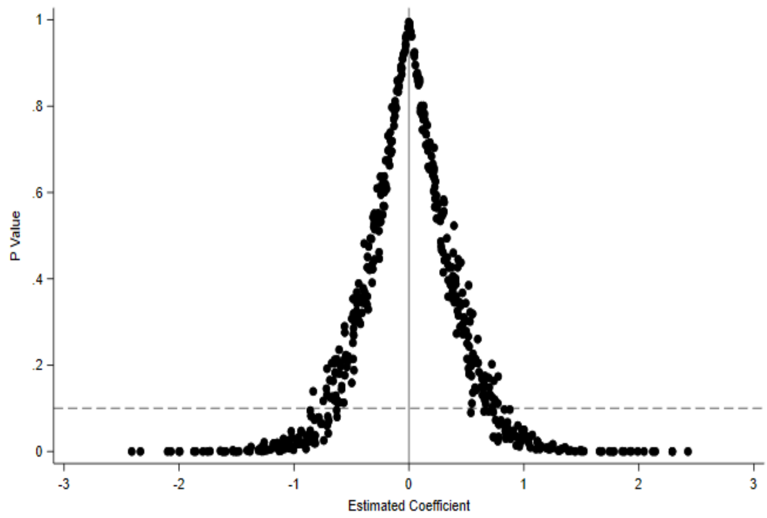

Figure 2 Results of the Placebo Test

4.3.3 Excluding the Interference of Major Concurrent Policies

To exclude the competitive explanations that may be caused by major concurrent policies, this paper focuses on four government-led strategies and pilot programs that were promoted at the same time as the supply chain digitalization pilot and may affect the corporate human capital structure: the intelligent manufacturing demonstration implemented in accordance with the *Development Plan for Intelligent Manufacturing (2016–2020)* jointly issued by the Ministry of Industry and Information Technology and the Ministry of Finance, the construction of "Made in China 2025 Pilot Cities" carried out under the *Made in China 2025* plan, the establishment of Innovative City Pilot Programs promoted in accordance with the *Guidelines for the Construction of Innovative Cities* by the Ministry of Science and Technology and the NDRC, and the "Sound Development of Smart Cities" policy implemented in accordance with the Guiding *Opinions on Promoting the Sound Development of Smart Cities* by the NDRC and other departments.

The regression results in Columns (2) to (5) of Table 4 show that after sequentially controlling for the above four policy variables, the estimated coefficients of the core variable *Treat×Post* range from 4.559 to 4.674, which have no substantial change compared with 4.642 in the benchmark regression, and all are significant at the 1% level. The results indicate that the facilitating effect of the supply chain digitalization pilot on the upgrading of the corporate human capital structure is independent of the impact of major policies such as intelligent manufacturing, Made in China 2025 pilots, innovative cities and the sound development of smart cities, and the research conclusions are robust.

Table 4 Estimation Results After Excluding Major Concurrent Interferences

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Treat×Post	4.642*** (1.775)	4.559** (1.787)	4.581*** (1.770)	4.674*** (1.776)	4.643*** (1.775)	4.523** (1.784)
Development Plan for Intelligent Manufacturing		1.099 (0.724)				1.156 (0.714)
Made in China 2025 Pilot Cities			-1.808*** (0.672)			-1.797*** (0.673)
Innovative City Pilot Programs				0.493 (0.413)		0.452 (0.414)
Sound Development of Smart Cities					-0.087 (1.637)	-0.076 (1.637)
Controls	YES	YES	YES	YES	YES	YES
Company/Year	YES	YES	YES	YES	YES	YES
N	19310	19310	19310	19310	19310	19310
R^2	0.926	0.926	0.926	0.926	0.926	0.926

4.3.4 Other Robustness Tests

As shown in Table 5, the results of the following robustness tests are reported.

(1) Replacing the explained variable. To test the impact of the measurement method of the human capital structure on the conclusions, this paper constructs a substitute indicator (HC_new) as the ratio of the proportion of employees with a bachelor's degree or above to that of employees with a college degree or below, and re-estimates the policy effect. The results show that the core interaction term *Treat×Post* is still significantly positive at the 5% significance level, and the coefficient direction is consistent with the benchmark regression, indicating that the facilitating effect of the supply chain digital transformation pilot on the upgrading of the corporate human capital structure does not depend on the specific indicator setting.

(2) Adjusting the sample interval to exclude interference factors. Considering that China's supply chain digitalization and related institutional construction have entered an accelerated stage after 2015, and the early samples may be affected by the immature digital infrastructure and policy environment, this paper excludes the observations before 2015; at the same time, taking into account the impact of the post-epidemic shocks and unconventional macro-control on corporate operation and employment decisions after 2021, the samples after 2021 are further excluded, and on this basis, the samples from both ends are excluded at the same time, and the estimation is re-conducted under different time windows. The results show that the estimated coefficients of *Treat×Post* are all significantly positive and the magnitude is stable under various sample interval settings, indicating that the benchmark conclusion is not affected by the selection of specific sample intervals.

(3) Replacing the clustered robust standard errors. Considering that corporate-level decisions may be correlated at the regional and industrial levels, this paper further uses two-way clustered robust standard errors at the province-industry level for estimation. The regression results show that the coefficient direction, significance level and model fitting degree of *Treat×Post* are consistent with the benchmark regression, indicating that after relaxing the independence assumption of the error term, the facilitating effect of the supply chain digital transformation pilot on the upgrading of the corporate human capital structure is still robust.

Table 5 Robustness Test Results

Variable	Replacing the Explained Variable	Excluding Data Before 2015	Excluding Data After 2021	Excluding Data Before 2015 and After 2021	Adjusting Clustered Robust Standard Errors
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Treat×Post	18.418** (2.11)	2.5026** (2.22)	4.0195** (2.24)	2.0187* (1.82)	4.643** (2.22)
Controls	YES	YES	YES	YES	YES
Company/Year	YES	YES	YES	YES	YES
N	19392	16687	16181	13553	19307
R^2	0.905	0.950	0.936	0.951	0.923

5. Further Analysis

5.1. Mechanism Tests

In the theoretical analysis, this paper argues that supply chain digitalization improves enterprises' attractiveness to high-skilled talents and realizes the transformation and upgrading of the human capital structure through raising enterprise reputation, boosting public trust in brands, enhancing financial support and increasing the construction of digital intangible assets. This section further identifies the above indirect transmission mechanisms, and Table 6 reports the regression results with different mechanism variables as the explained variables.

Table 6 Mechanism Tests

	(1) Enterprise Reputation	(2) Public Trust in Brands	(3) Total Credit	(4) Total Digital Intangible Assets
Treat×Post	0.239**	5.796**	17.809*	1.043*
	(2.37)	(2.00)	(1.79)	(1.79)
Controls	YES	YES	YES	YES
Company/Year	YES	YES	YES	YES
N	19310	19310	15609	19310
R^2	0.708	0.958	0.876	0.739

(1) Raising enterprise reputation. The supply chain digital transformation pilot enhances enterprises' attractiveness to high-skilled talents by improving their visibility in the market and society. Referring to the studies of Huang et al. (2022) and Wang et al. (2021) [43][44], this paper constructs an enterprise reputation indicator using web search attention and media coverage information to depict the social reputation and public attention level of enterprises. The results show that the coefficient of *Treat×Post* is significantly positive at the 5% level, indicating that enterprises participating in the supply chain digital transformation pilot have strengthened their attractiveness in the labor market through information diffusion and brand exposure mechanisms, significantly improving their social reputation and public attention, thus facilitating the agglomeration of high-skilled talents.

(2) Boosting public trust in brands. This paper uses corporate operating income as an important indicator to comprehensively reflect market recognition and operational capacity. The regression results show that *Treat×Post* is significantly positive in the regression of operating income,

indicating that the supply chain digital transformation pilot has effectively promoted the expansion of corporate operational scale. The digital pilot policy has to a certain extent enhanced the trust of market participants in the operational capacity and long-term development prospects of pilot enterprises, helping enterprises form more stable production and employment expectations and creating conditions for attracting and retaining high-skilled talents.

(3) Enhancing financial support. Referring to the practice of Ye et al. (2025) [45], this paper uses the logarithmic form of the scale of corporate bank loans to measure the availability of corporate credit. The coefficient of *Treat*×*Post* is significantly positive at the 10% level, indicating that enterprises participating in the supply chain digital transformation pilot have obtained more bank credit support. The supply chain digitalization pilot has to a certain extent played the role of government credit endorsement, reduced the uncertainty of financial institutions in evaluating corporate default risks, thus improving enterprises' ability to obtain external financing and providing the necessary financial guarantee for enterprises to expand R&D investment, optimize employment structure and introduce high-skilled talents.

(4) Increasing the construction of digital intangible assets. The supply chain digital transformation pilot strengthens the demand for high-skilled human capital by driving enterprises to increase the construction of digital intangible assets. Referring to the study of Zhang et al. (2021) [46], this paper constructs an indicator of the total digital intangible assets of enterprises based on items related to software systems, digital platforms and intelligent technologies in the detailed list of intangible assets. The results show that the coefficient of *Treat*×*Post* is significantly positive at the 10% level, indicating that the pilot policy has significantly promoted enterprises' investment in intangible assets related to digital technologies. Through increasing the accumulation of digital technologies, supply chain digital transformation has raised enterprises' demand for high-skilled positions such as R&D, data analysis and system integration, thus driving the upgrading of the corporate human capital structure towards high skills.

To sum up, the supply chain digital transformation pilot policy enhances enterprises' ability to attract and allocate high-skilled talents through multiple channels such as raising enterprise reputation, boosting market and public trust in brands, improving financial support conditions and accelerating the accumulation of digital intangible assets, thus providing support for the transformation and upgrading of the corporate human capital structure.

5.2. Heterogeneity Analysis

The impact of the supply chain digital transformation pilot policy on the upgrading of the corporate human capital structure shows significant differences under different external environments and corporate characteristics.This section further examines the heterogeneity of the policy effects across different subsamples, and Table 7 reports the corresponding regression results.

First, external environmental uncertainty. Referring to the practice of Shen (2012) [47], this paper measures environmental uncertainty by the industry-adjusted volatility of corporate sales revenue over the past five years, and conducts grouped regression accordingly. The results show that in the sample with higher environmental uncertainty, the supply chain digitalization pilot significantly promotes the upgrading of the corporate human capital structure, while this effect is not significant in the sample with lower uncertainty. The inter-group difference test shows that the policy effects of the two groups reach a marginally significant difference, that is, in the case of high uncertainty, the digital pilot can better exert the institutional compensation effect by stabilizing expectations and improving the information environment.

Second, geographical location. The policy effect is significantly positive in the eastern region, but not significant in the central and western regions. The joint Wald test shows that the facilitating effect of supply chain digitalization on the upgrading of the corporate human capital structure is more pronounced in the eastern region, and the regional development foundation and resource allocation conditions may affect the exertion of policy effects to a certain extent.

Table 7 Heterogeneous Impacts of Different Corporate Characteristics

	Environmental Uncertainty		**Environmental Uncertainty**		**Geographical Location**	
	(1) High	**(2)** Low	**(3)** Eastern	**(4)** Central & Western	**(5)** Mild	**(6)** Fierce
Treat×Post	6.6168**	2.2436	3.5998**	1.3195	1.9582	7.8358**
	(2.03)	(0.85)	(2.45)	(0.56)	(1.50)	(2.54)
Controls	YES	YES	YES	YES	YES	YES
Company/Year	YES	YES	YES	YES	YES	YES
N	6467	7036	13882	5310	8655	10,300
R^2	0.9089	0.9554	0.9391	0.9207	0.9381	0.9445
Inter-group Difference Test（F-test p value)）	0.0918		0.000		0.0646	

Third, the results of heterogeneity analysis based on the degree of industry competition. This paper uses the CR4 index to depict industry concentration, that is, the proportion of the main business income of the top four enterprises in an industry to the total main business income of the whole industry, and divides the sample according to the annual median. A larger value of this index indicates a higher industry concentration and relatively mild market competition, while a smaller value indicates more fierce competition. The regression results show that in industries with lower concentration and more fierce competition, supply chain digitalization has a significantly positive facilitating effect on the upgrading of the corporate human capital structure, while this effect is not significant in industries with higher concentration and relatively mild competition. Further inter-group difference test shows that the difference in policy effects between the two types of industries is significant at the 10% level. This indicates that competitive pressure to a certain extent strengthens the facilitating effect of supply chain digitalization on the upgrading of the corporate human capital structure.

6. Conclusions and Implications

Taking the *Notice on Carrying out Pilots of Supply Chain Innovation and Application* jointly issued by eight ministries including the Ministry of Commerce of China in 2018 as a quasi-natural experiment, this paper constructs a difference-in-differences model based on the panel data of A-share listed companies on the Shanghai and Shenzhen Stock Exchanges from 2013 to 2022 to investigate the impact of supply chain digitalization construction on the corporate human capital structure. The research results show that supply chain digitalization construction significantly drives the upgrading of the corporate human capital structure, and the conclusion remains stable under a series of robustness tests. Mechanism analysis shows that supply chain digitalization construction reshapes the talent demand structure of enterprises by raising enterprise reputation, strengthening market brand recognition, optimizing the allocation of financial resources and increasing digital intangible assets. Further analysis shows that in the context of supply chain digitalization, enterprises facing higher external environmental uncertainty, operating in more competitive industries and located in the eastern region achieve a more significant upgrading effect of the talent structure.

The research results of this paper have the following implications: (1) Give full play to the leading role of the supply chain digital transformation pilot policy and relevant departments on enterprises. First of all, government departments should accelerate the construction of a unified supply chain data standard and sharing platform, improve fiscal and tax incentive policies, guide enterprises to advance digital investment and high-skilled position allocation in a coordinated manner, and lay a solid foundation for talent upgrading. Secondly, regulatory authorities should improve the credit granting and information disclosure system based on supply chain transaction data, reduce information asymmetry, and guide more financial resources to flow into the fields of technological upgrading and human capital optimization. Finally, relevant departments should strengthen the performance supervision of policy funds, drive enterprises to incorporate digitalization into their medium and long-term strategies, improve data governance and training mechanisms, and stabilize the expected demand for high-skilled talents. (2) A "combination of measures" should be adopted to raise market attention, strengthen the foundation of brand trust, optimize the financing environment and accelerate the accumulation of digital intangible assets. Make full use of supply chain data to improve the efficiency of credit evaluation and risk identification, improve the credit support system based on transaction information and operational data, reduce the degree of information asymmetry, and provide a stable financing environment for enterprises in the stage of technological upgrading and high-skilled talent introduction. Enterprises should systematically integrate core data such as order fulfillment, capital flow and cooperation stability, transform real business behaviors into verifiable credit foundations, and enhance the ability of information docking with external capital suppliers, thus strengthening their long-term investment capacity and forming a positive cycle of mutual promotion among financing improvement, technological upgrading and human capital structure enhancement. (3) Cultivate digital strategic awareness and strengthen the construction of data networks in regions with relatively weak infrastructure. On the one hand, guide enterprises with weak competitive pressure or insufficient transformation motivation to enhance their digital strategic awareness, and stimulate their internal motivation for the allocation of high-skilled talents and the optimization of organizational structure through demonstration and benchmarking mechanisms. On the other hand, consideration should be given to the differences in regional institutional environments and factor market conditions. While consolidating the advantages of deepening innovation in digital application in the eastern region, increase investment in the construction of infrastructure such as Internet of Things equipment, wireless communication networks, cloud computing and data centers in the central and western regions and regions with relatively weak market environments, reduce the barriers to the flow of labor and data resources, thus attracting more high-skilled talents.

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