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Reexamining Digital Transformation and Intra-firm Pay Gap: Evidence from Chinese Listed Companies

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Abstract

In recent years, the question of whether digital transformation can reduce the intra-firm pay gap has sparked considerable debate. However, little attention has been given to the feedback effect that a narrower pay gap may have—an issue central to corporate sustainability. This paper examines the relationship between digital transformation and the intra-firm pay gap based on data from Chinese-listed companies from 2012 to 2023. It is found that digital transformation significantly promotes the narrowing of the intra-firm pay gap. In turn, a narrower pay gap has a nonlinear, inverted U-shaped effect on digital transformation. This suggests there is an optimal balance where both factors support corporate sustainability. Further analysis shows that this interaction is mainly achieved through human capital structure and employee effort, especially in large enterprises, non-labor-intensive industries and regions with developed digital infrastructure.

Keywords

Digital transformation; Intra-firm pay gap; Human capital structure; Employee effort

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1. Introduction

To thoroughly implement the concept of Chinese-style modernization development, China has embarked on a new journey of common prosperity[1]. However, the path toward achieving this goal involves considerable challenges. A key challenge lies in the significant imbalance in income distribution within enterprises, particularly between senior executives and ordinary employees (Gartenberg and Wulf, 2020). Statistics show that at least about one-third of a country's income inequality stems from intra-firm pay gap (Song *et al*., 2019). Some corporate executives are paid tens of times more than ordinary employees, and the phenomenon of "sky-high compensation" is common. The widening income gap not only highlights broader issues of social inequality but also creates serious challenges for enterprises' sustainable development. Enterprises with extreme compensation disparities often experience deteriorating organizational climate, declining employee loyalty, and compromised operational efficiency, which ultimately hinders their ability to maintain competitive advantages in the long run. Addressing reasonable income distribution within enterprises is therefore crucial for promoting and ensuring corporate sustainable development.

In recent years, scholars have actively explored the influencing factors of the intra-firm pay gap from many aspects, including business strategy (Kong *et al*., 2022) and tax policy (Dongxi *et al*., 2024; Lin *et al*., 2024), anti-corruption movement (Kong *et al*., 2023b), public environmental issues (Ho *et al*., 2024), political relevance (Fang *et al*., 2022) , political promotion (Kong *et al*., 2020; Kong *et al*., 2021), social trust (Yin *et al*., 2022) , pay for performance (Barth *et al*., 2012), wage agreements (Cirillo *et al*., 2019), CEO political ideology (Weng and Yang, 2024), trade impact (Friedrich, 2022), the opening of high-speed rail (Kong *et al*., 2024), innovation (Cirillo *et al*., 2017), etc.

The advent of the digital age is expected to open up new ways to adjust the intra-firm pay gap (Kong *et al*., 2023a). The popularization of digital technology can break the dominant position of capital owners in traditional economic forms and give ordinary employees more opportunities to participate in enterprise innovation and sustainable development. On the one hand, digital tools improve the transparency of information flow. This makes it easier for ordinary employees to access new knowledge and acquire valuable skills. As a result, their career competitiveness increases, supporting long-term human capital sustainability. On the other hand, digital technologies can help build flatter organizational structures. These structures weaken traditional hierarchies, allow lower-level employees to participate directly in decision-making, and expand their career advancement paths. Together, these changes enhance corporate sustainability by encouraging diverse input and fairer practices. However, digital transformation often requires significant capital investment. This tends to strengthen the dominance of capital owners, allowing them to capture greater returns. In contrast, ordinary employees may struggle to benefit equally from enterprise development. Such uneven benefit distribution may widen intra-firm pay gap, which conflict with the principles of sustainable development which call for balanced stakeholder interests. Therefore, exactly how digital transformation affects the pay gap within the enterprise is still controversial and needs to be further studied, especially in the context of sustainable business development.

As a rapidly developing country, China has shown strong growth potential in the field of digital economy by its late-comer advantage. In December 2023, China comprehensively issued the Implementation Plan of

[1] Common prosperity refers to achieving universal prosperity for all people, aiming to narrow the income and wealth gap and improve the living standards of middle- and low-income groups. It emphasizes ensuring that the fruits of economic growth reach more people through policy adjustments and social protection systems, thereby promoting social stability and sustainable development.

Digital Economy to Promote Common Prosperity, aiming to solve the problem of unfair salary distribution through digital means. If digital transformation can effectively improve the unequal distribution of income within enterprises, it will not only help break the barrier of common prosperity in China but also provide valuable lessons for other countries and make a great contribution to reducing global income inequality. While closing the intra-firm pay gap is consistent with the idea of common prosperity, must the intra-firm pay gap be as small as possible (Zahid *et al*., 2023)? When executive and employee compensation become more balanced, enterprise resources tend to favor ordinary employees. This shift can reduce the return on investment for capital owners. As a result, capital owners may have less incentive to support technological innovation and long-term investment. They may also become more risk-averse, leading to reduced funding for digital initiatives and a slowdown in transformation efforts. Therefore, it has become a complex and urgent problem to address the internal salary gap to achieve common prosperity while accelerating digital development, thereby supporting long-term corporate sustainable development and continued value creation.

Considering that this point has not been deeply explored in the existing studies, we conduct both theoretical analysis and empirical testing on the relationship between digital transformation and the intra-firm pay gap by using the panel data of China's A-share listed companies from 2012 to 2023. The results show that digital transformation significantly contributes to narrowing the intra-firm pay gap. In turn, a narrower pay gap has a nonlinear, inverted U-shaped effect on digital transformation. This relationship reveals an optimal reciprocal balance that maximizes corporate sustainability, which emerges only when pre-existing pay disparities are sufficiently large to allow for mutually reinforcing effects. The mechanism test shows that human capital structure and employee effort are two very important ways. Both the inhibition effect of digital transformation on the intra-firm pay gap and the inverted U-shaped nonlinear effect of the intra-firm pay gap on digital transformation are more obvious and stronger in large enterprises, non-labor-intensive industries and regions with developed digital infrastructure. These findings highlight the diverse paths through which firms can enhance their sustainability.

Compared with previous studies, the contributions of this paper are mainly reflected in the following aspects: First, two different perspectives on the intra-firm pay gap caused by digital transformation are compared within a unified analytical framework, effectively responding to the controversy (Li *et al*., 2023b); Secondly, it explores the influence of intra-firm pay gap on digital transformation, which is not simple or linear, and reveals the more complex driving mechanism behind intra-firm pay gap and its sustainability implications. Third, different from previous research conclusions, our study found that over-reliance on digital transformation to narrow the intra-firm pay gap of enterprises may bring counterproductive effects. It is necessary to be alert to the adverse constraints of too low intra-firm pay gap on digital transformation and provide new development ideas and suggestions for enterprises toward sustainable growth.

The structure of the remaining section of this paper is as follows: The second section is the literature review and research hypothesis; the third section is the research design; The fourth section is the empirical test; the fifth section is the conclusion and enlightenment.

2. Literature Review and Research Hypothesis

2.1. Research on the impact of digital transformation on the intra-firm pay gap

Digital transformation is an important driver of global economic development, with its impact on total factor productivity, labor market, business innovation, sustainable development, business performance, macroeconomics, income inequality, and many other aspects. For example, digital transformation can significantly improve a company's total factor productivity, but its effects vary depending on the industry context, size, and governance level of the company (Su *et al.*, 2023; Cheng *et al.*, 2023). With the development of automation and artificial intelligence, some occupations are at higher risk of substitution, especially low-skilled jobs (Dengler and Matthes, 2018; Carbonero *et al.*, 2023). At the same time, however, digital skills and Internet use significantly raise individual wages, and this effect is more pronounced in countries with higher digital capabilities (Piroșcă *et al.*, 2021). In addition, digital transformation not only improves research and development efficiency and market response speed but also promotes enterprise innovation by optimizing resource allocation and enhancing risk-bearing capacity (Farrington and Alizadeh, 2017; Zhao *et al.*, 2024). It reduces reliance on traditional internal R&D, allowing even non-R&D enterprises to innovate through digital tools. In this way, digital transformation helps narrow the innovation gap between different types of firms (Radicic and Petković, 2023; Chen and Kim, 2023). Some studies have also found that for small and medium-sized enterprises (SMEs), digitalization improves operational efficiency and value-added capabilities, but the improvement in financial performance may take a longer time to emerge (Teng *et al.*, 2022; Kádárová *et al.*, 2023). Successful digital transformation also relies on effective risk management to ensure that performance improvements are sustained (Chouaibi *et al.*, 2022).

Most relevant to the topic of this paper is the impact of digital transformation on income inequality, which demonstrates a complex dual effect. Digital transformation can potentially reduce inequality by improving corporate financing conditions that subsequently increase labor demand and wage (Li *et al.*, 2023). But more evidence suggests it predominantly exacerbates inequality through labor substitution effects, with productivity gains being disproportionately captured by capital owners rather than workers (Yang *et al.*, 2023; Chen *et al.*, 2023). The manifestation of this dual nature differs significantly across phases and regions of the digital economy's evolution. In the early stages, income inequality tends to widen due to changes in labor market structure and increased demand for highly skilled workers (Huang *et al.*, 2024; Lv *et al.*, 2025). As the digital economy matures, income inequality is expected to ease in regions dominated by high-skilled workers and in low- and middle-income countries (Wu *et al.*, 2024; Wang and Shen, 2024). In addition, the impact of digital transformation on income inequality also presents a complex duality between urban and rural areas and ethnic groups (Ma and Zhang, 2023; Deng *et al.*, 2023).

For the research on the impact of digital transformation on the intra-firm pay gap, digital transformation will trigger the adjustment of the internal power structure of enterprises. On the one hand, digital transformation can enable executives to effectively lead the strategic direction and innovative development of enterprises with the help of technological advantages, and improve the bargaining power of executives' salaries (Frydman and Papanikolaou, 2018; Kong *et al.*, 2023a). On the other hand, digital transformation can also enhance the bargaining power of ordinary employees, especially those who can quickly adapt to and master new technologies, as their skills become increasingly scarce and irreplaceable, thus gaining a greater say in salary negotiations (Li *et al.*, 2023c). While the bargaining power of both executives and ordinary employees has increased because of digital transformation, the effect has not been consistent. This difference will further affect the internal compensation distribution, which can be explained by human capital theory and market equilibrium theory.

Human capital theory points out that salary is closely related to employees' skills and knowledge reserve (Becker, 1962; Schultz, 1961). As digital transformation advances, the demand for ordinary employees with digital skills has surged. By learning and mastering new technologies, especially those enabling sustainable business operations, these employees significantly increase their value in the organization, thereby gaining greater bargaining power (Audrin *et al*., 2024). In contrast, executives' core management skills have been enhanced by digital transformation, but these improvements are mainly reflected in the understanding of new technologies and decision support, rather than fundamental skill changes (Fernandez-Vidal *et al*., 2022). While executive leadership plays a key role in sustainability strategies, it offers relatively limited gains in bargaining power compared to the employees who implement these initiatives. As a result, executive compensation tends to grow more slowly. The growing emphasis on corporate sustainability creates additional value for employees with specialized digital skills that support long-term business viability (Liu *et al*., 2025).

Market equilibrium theory points out that salary level is determined by supply and demand (Card and DiNardo, 2002). In the process of digital transformation, the demand for ordinary employees with digital skills has risen sharply, and such skills are in relatively short supply in the labor market, especially high-level digital skills (Aum and Shin, 2025). This shortage gives ordinary employees more bargaining power, forcing companies to offer better pay packages to attract and retain them, which enhances human capital retention and reduces employee turnover costs critical for corporate sustainability (Yuan *et al*., 2023). In contrast, the market demand for executives is relatively stable and the supply of management and strategic skills is abundant, and digital transformation has not significantly changed this supply-demand balance (Li *et al*., 2024). As a result, executives' bargaining power and even pay have not improved much, allowing companies to reallocate resources toward innovation and social responsibility initiatives that strengthen sustainable competitive advantage.

Based on the above analysis, under the influence of digital transformation, the improvement effect of the bargaining power of ordinary employees will surpass that of senior executives and ultimately lead to the narrowing of the intra-firm pay gap (see Fig. 1). Therefore, we propose the first hypothesis to be tested:

H1. Digital transformation helps to narrow the salary gap within enterprises.

2.2. Research on the impact of the intra-firm pay gap on digital transformation

The preceding analysis shows that digital transformation reshapes internal pay structures. However, the relationship between the two is not one-way. Pay gaps resulting from digital transformation can, in turn, affect the direction and effectiveness of future digital initiatives, forming a feedback loop. Understanding this reverse influence is essential to fully grasp the complexity of the link between digital transformation and compensation. This section, therefore, explores how existing internal pay disparities may either support or hinder further progress in digital transformation.

The intra-firm pay gap is often regarded as a part of the results of economic operations, but in fact, it can also be used as a decisive factor, which has a profound impact on economic and social development. For example, the impact of the intra-firm pay gap on enterprise performance has a dual nature. A moderate gap in the short term can motivate employees and boost market valuation and profitability (Mueller *et al*., 2017; Heyman, 2005; Lallemand *et al*., 2004; De Vito and Gomez, 2023; Connelly *et al*., 2016), but in the long run, it is easy to have adverse effects. Too large a gap will weaken team cooperation and productivity, especially the enthusiasm and productivity of ordinary employees (Dai *et al*., 2017; Yergabulova *et al*., 2024). In addition, the intra-firm pay gap may have an asymmetric effect on labor demand. As the intra-firm pay gap increases, enterprises tend to hire more low-skilled labor and reduce the demand for high-skilled and medium-skilled labor (Li *et al*., 2023a).

The influence of the intra-firm pay gap on digital transformation can be explained with the help of tournament theory and social comparison theory.

Tournament theory suggests that a moderate pay gap can motivate executives by making the prospect of promotion and higher compensation more tangible (Lazear and Rosen, 1981). Such a gap encourages senior managers to invest more actively in digital transformation and pursue innovation (Hua and Yu, 2023; Mo and Liu, 2024). With appropriate incentives, executives are more willing to take risks and explore new digital solutions (Nguyen and Zhao, 2021; Dittmann *et al*., 2017). These initiatives often improve operational efficiency and reduce environmental impact, accelerating enterprise-wide digitization. However, when the pay gap moves outside the optimal range, executives' motivation changes in ways that undermine digital transformation. If the gap is too small, the perceived benefits of successful transformation may not outweigh the personal risks, reducing executive's incentive to pursue bold changes. As a result, they may adopt risk-averse strategies and prefer incremental adjustments over comprehensive innovation. On the other hand, if the gap is too large, it may foster excessive competition rather than collaboration (Henderson and Fredrickson, 2001; Connelly *et al*., 2014). Executives may focus more on short-term personal gains than on long-term organizational goals. This misalignment can lead to fragmented strategies and a decline in the cooperation needed for effective digital transformation.

Social comparison theory holds that employees assess not only their absolute pay but also how it compares to others (Festinger, 1954). A moderate pay gap is often viewed as fair, reflecting differences in performance (Greenberg, 1990). This perception of fairness motivates employees to acquire digital skills and participate actively in transformation efforts, trusting that their contributions will be fairly recognized and rewarded (Chen *et al*., 2023). Such positive expectations foster broader support for enterprise digital initiatives (Miao *et al*., 2020). When pay gaps become too narrow, high-performing employees may feel their efforts are undervalued, leading them to reduce engagement in skill development and innovation activities (Colquitt *et al*., 2001). In contrast, when gaps are too wide, employees may perceive deep structural inequities and feel that advancement is disconnected from merit. This discourages investment in digital capabilities, as rewards seem unattainable regardless of performance. As fair perceptions erode, employees reallocate their efforts away from transformation work, weakening engagement and causing psychological strain. This disconnects between effort and perceived reward undermines the effectiveness of digital transformation (Shen and Zhang, 2018).

Based on the above analysis, the impact of the intra-firm pay gap on digital transformation is not a simple linear relationship, but a complex inverted U-shaped relationship (see Fig. 1).

Accordingly, we propose a second hypothesis to be tested:

H2. The intra-firm pay gap has an inverted U-shaped nonlinear effect on digital transformation.

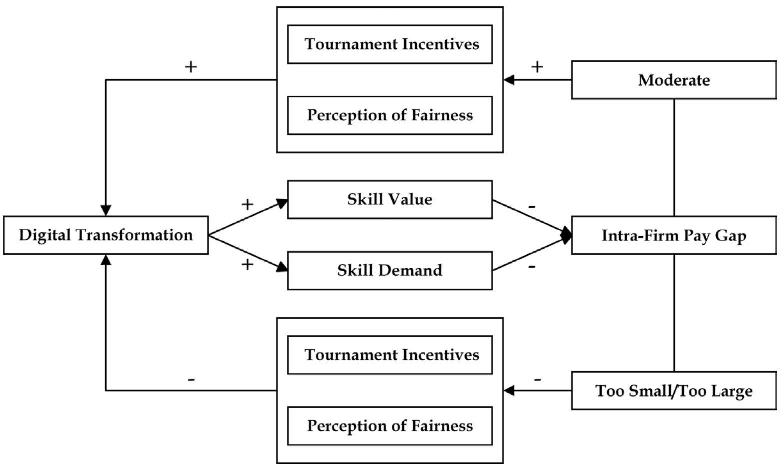

Fig. 1. Theoretical framework diagram[2]

3. Research Design

3.1. Variables

For digital transformation, this paper selects the enterprise digital transformation index of the China Economic and Financial Research Database (CSMAR) to measure the level of digital transformation (DT)[3]. The larger the index, the higher the level of digital transformation. In the past, it was common to measure digital transformation by capturing the frequency of relevant keywords in the annual reports of listed companies (Fang *et al*., 2023). Compared with this, the comprehensive evaluation index selected in this paper has two advantages. First, it not only expands the text content of word frequency analysis, covers more information about the application of digital technology by enterprises, but also includes objective indicators such as digital job creation, digital innovation papers, and digital invention patents, which can more comprehensively describe the degree of digital transformation of enterprises. Second, it is not limited to the listed company itself, but rather integrates the medium and macro-level information of the industry and region in which the enterprise is located, which can effectively reduce the bias of indicator selection and the deviation of data caused by the lack of keywords in the annual report.

For the intra-firm pay gap, we refer to the practice of Kong *et al*. (2020) and Kong *et al*. (2023b), using the ratio of the average salary of senior executives and ordinary employees to measure the intra-firm pay gap (IPG)[4]. Among them, the average executive compensation is calculated by dividing "total executive compensation" by "number of executives"[5], and the average employee compensation is calculated by dividing the "cash paid to and for employees - total executive compensation" by "total employee - number of executives".

For other control variables, this paper refers to the studies of Kong *et al*. (2021) and Kong *et al*. (2022), and the selected control variables are divided into two categories: One is the basic characteristic variables, including enterprise scale (Size), debt to assets ratio (Leverage), return on equity (ROE), operating cash flow (OCF), and enterprise age (Age). The other is the governance structure variables, including ownership concentration (EC), duality (Dual), management shareholding ratio (MH), independent director ratio (Independent), and ownership nature (SOE). See Table 1 for specific Settings.

Table 1
Main variable definitions.

Symbol	Title	Definition
DT	Digital transformation	The comprehensive evaluation index of enterprise digital transformation covers six dimensions: strategic leadership, technology-driven, organizational empowerment, environmental support, digital achievements and digital applications
IPG	intra-firm pay gap	Average executive compensation/Average employee compensation
Size	Enterprise Scale	Ln (total assets)
Leverage	Debt to assets ratio	Total liabilities/total assets

[2] The symbol "+" indicates expansion and promotion, and "-" indicates reduction and containment.
[3] The specific index system is not listed due to space limitation. If necessary, please ask the author for it.
[4] Senior executives refer to directors (excluding independent directors), supervisors (excluding independent supervisors), and managers who receive compensation.
[5] Due to the small proportion of equity compensation in China's listed companies, the calculation of average executive compensation does not consider equity payment, but controls the proportion of management shareholding in the model.

Table 1. (continued)

Symbol	Title	Definition
ROE	Return on equity	Net profit/average balance of shareholders' equity
OCF	Operational cash flow	Amount of cash flow from operating activities/total assets
Age	Enterprise age	Ln (current year-year of establishment)
EC	Ownership concentration	Share proportion of the largest shareholder
Dual	Duality	If the chairman is also the general manager, the value is 1, otherwise, the value is 0
MH	Management shareholding ratio	Management holdings as a percentage of total shares
Independent	Independent director ratio	The ratio of the number of independent directors to the size of directors
SOE	Ownership nature	If the nature of the equity is state-owned enterprise, the value is 1, otherwise the value is 0

3.2. Model

To test the interaction between digital transformation and the intra-firm pay gap, this paper sets the following measurement model:

$$IPG_{i,j,p,t}=\alpha_0+\alpha_1 DT_{i,t\text{-}1}+\alpha_n Controls_{i,t}+\mu_i+\delta_{j,t}+\tau_{p,t}+\varepsilon_{i,j,p,t} \quad (1)$$

$$DT_{i,j,p,t}=\beta_0+\beta_1 IPG_{i,t\text{-}1}+\beta_2 IPG_{i,t\text{-}1}{}^2+\beta_n Controls_{i,t}+\mu_i+\delta_{j,t}+\tau_{p,t}+\varepsilon_{i,j,p,t} \quad (2)$$

In Equations (1) and (2), the subscript i represents the enterprise, j represents the industry, p represents the province, and t represents the year. *DT* measures digital transformation and *IPG* measures the intra-firm pay gap. To alleviate the potential reverse causality problem, we adopted a one-stage lag term for explanatory variables and in both models. *Controls* reflect a set of control variables, including basic feature variables and governance structure variables. The term μ_i represents the fixed effect of the enterprise, and $\delta_{j,t}$ is the interactive fixed effect between the industry and the year, which is used to control the influence of the development trend of the industry to which the enterprise belongs. The variable $\tau_{p,t}$ is the interactive fixed effect between the province and the year, which is used to control the influence of economic development factors at the regional level of the enterprise. The term $\varepsilon_{i,j,p,t}$ is the random error term, and α_1, β_1 and β_2 are the key coefficients in this paper.

3.3. Data sources and descriptive statistics

This paper selects the data of China's A-share listed companies from 2012 to 2023 as research samples, mainly from the China Economic and Financial Research Database (CSMAR). In this paper, the data are screened and processed as follows: (1) Due to the particularity of accounting standards for enterprises, samples of financial and insurance companies are excluded. (2) To alleviate the interference of outliers and extreme values, samples of suspended, delisted and ST companies are eliminated, and 1% and 99% tail reduction are performed for all continuous variables. (3) Since we focus on the digital transformation of non-digital industries, according to the 2012 China Securities Regulatory Commission industry classification standard, we exclude computer, communications and other electronic equipment manufacturing (C39), telecommunications, radio and television and satellite transmission services (I63), Internet and related services (I64), software and information technology services (I65) and other digital industry samples.

Table 2 reports descriptive statistics for the main variables. The average DT of 33.2647 is slightly higher than the median of 30.2960, indicating that most enterprises are focused on a low level of digital transformation, but a few enterprises have reached a high level. The median IPG is 4.5296, indicating that the average salary difference between executives and ordinary employees is more than 4 times, and the pay gap within enterprises is relatively large. In addition, the standard deviation of IPG is 3.6514, indicating that there are significant differences in compensation structure among different firms.

Table 2
Descriptive statistics of variables.

Variables	N	Mean	Median	SD	Min	Max
DT	14887	33.2647	30.2960	8.4072	23.0064	64.2709
IPG	14887	5.5277	4.5296	3.6514	0.9545	26.6189
Size	14887	22.1603	22.0110	1.1985	19.8277	26.1093
Leverage	14887	0.4211	0.4123	0.1969	0.0533	0.9039
ROE	14887	0.0600	0.0673	0.1058	-1.0037	0.3067
OCF	14887	0.0470	0.0467	0.0622	-0.1569	0.2316
Age	14887	2.8214	2.8332	0.3206	1.7918	3.5553
EC	14887	35.0628	33.4000	13.9046	8.4100	74.0000
Dual	14887	0.2644	0	0.4410	0	1.0000
MH	14887	13.2943	0.4914	19.5065	0	68.9260
Indepent	14887	37.1151	33.3300	4.8986	33.3300	57.1400
SOE	14887	0.3648	0	0.4814	0	1.0000

4. Empirical Results

4.1. Benchmark results

Table 3 reports the benchmark results. Column (1) did not introduce control variables, column (2) controlled the basic characteristic variables of the enterprise level and column (3) further included the governance structure variables. It can be seen from the results in columns (1) to (3) that the estimated coefficients of L.DT are all significantly negative, which means that digital transformation has a significant negative impact on the intra-firm pay gap of enterprises. In terms of economic significance, according to the results in column (3), if other conditions remain unchanged, an increase of one unit standard deviation in L.DT will lead to an average decrease of about 15.12% (0.0183×8.2602=0.1512) in the salary gap within the enterprise. Hypothesis 1 is hence proved.

The intra-firm pay gap is not only affected by digital transformation but may in turn determine the level of digital transformation. Column (4) only introduces the first item of intra-firm pay gap, and column (5) further includes the second item of intra-firm pay gap. From the results in columns (4) and (5), when only the primary term is included, the estimated coefficient of L.IPG is not significant, but after further introducing the secondary term, the estimated coefficient of L.IPG is significantly positive, and the estimated coefficient of L.IPG^2 is significantly negative. It is calculated that there is a turning point when L.IPG=10.2292 (0.0982/2/0.0048=10.2292), which is obviously between the minimum value of L.IPG 0.9545 and the maximum value of L.IPG 26.6189. This shows that the impact of the intra-firm pay gap on digital transformation presents an inverted U-shaped relationship, rather than a simple linear effect. Hypothesis 2 is proved.

Digital transformation and narrowing the intra-firm pay gap to achieve common prosperity are consistent with China's pursuit of high-quality economic development. Although digital transformation contributes to narrowing the intra-firm pay gap, this does not necessarily imply that the two will always advance synergistically toward sustainable development; in some cases, their interaction may even produce conflicting outcomes. Driven by digital transformation, if the initial intra-firm pay gap is large, the narrowing of the intra-firm pay gap can in turn promote digital transformation, forming a complementary positive feedback loop and achieving a win-win situation. This positive cycle enables businesses to invest in innovation while maintaining social responsibility, essential for sustainable growth. On the contrary, if the initial intra-firm pay gap is small, the further narrowing of the intra-firm pay gap will form a negative feedback loop, which will adversely affect the digital transformation and run counter to the expected development goals. Organizations facing this dilemma risk compromising their technological competitiveness and environmental efficiency gains, threatening sustainable development prospects.

Table 3
Benchmark results.

Variables	(1) IPG	(2) IPG	(3) IPG	(4) DT	(5) DT
L.DT	-0.0133**(0.0064)	-0.0178**(0.0075)	-0.0183**(0.0076)		
L.IPG				0.0042(0.0221)	0.0982*(0.0524)
L.IPG^2					-0.0048**(0.0023)
Size		0.8517***(0.1310)	0.8442***(0.1308)	1.7528***(0.2040)	1.7471***(0.2041)
Leverage		-0.8949**(0.3648)	-0.8783**(0.3674)	-1.6655**(0.6593)	-1.6853**(0.6597)
ROE		1.6974***(0.2728)	1.6964***(0.2732)	-0.4347(0.4308)	-0.4408(0.4302)
OCF		0.0260(0.4787)	0.0134(0.4791)	-0.5731(0.7590)	-0.5231(0.7595)
Age		-0.4602(0.8699)	-0.5092(0.8677)	-2.4786*(1.4878)	-2.5190*(1.4880)
EC			-0.0027(0.0068)	-0.0332***(0.0125)	-0.0332***(0.0125)
Dual			-0.0173(0.1038)	0.0489(0.1759)	0.0538(0.1758)
MH			-0.0011(0.0048)	0.0086(0.0091)	0.0084(0.0091)
Independent			-0.0124(0.0092)	-0.0297**(0.0147)	-0.0297**(0.0147)
SOE			-0.3859(0.3666)	-0.6884(0.4647)	-0.6823(0.4651)
Intercept	5.9800***(0.2124)	-11.2292***(3.6559)	-10.1993***(3.6744)	5.0871(6.2004)	5.0218(6.2008)
FirmFE	Yes	Yes	Yes	Yes	Yes
Industry×year FE	Yes	Yes	Yes	Yes	Yes
Province×year FE	Yes	Yes	Yes	Yes	Yes
N	12376	12376	12376	12374	12374
Adjusted R^2	0.711	0.717	0.717	0.865	0.865

Note: L. Indicates that the variable is taken with a lag term. To mitigate the reverse causal bias of DT and IPG, L.DT, L.IPG and L.IPG^2 are introduced into the core explanatory variables. Columns (1)(3) examine the effect of DT on IPG. Columns (4)(5) investigate the effect of IPG on DT. All results controlled for firm fixed effects, interaction fixed effects between industry and year and interaction fixed effects between province and year. Cluster standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

4.2. Robustness test

4.2.1. Alternative indicators of digital transformation and intra-firm pay gap

To improve the credibility of the benchmark results, we re-measure the digital transformation and intra-firm pay gap indicators in different ways.

We analyze national digital economy policies, create a dictionary of enterprise digital terms, and use machine learning technology to conduct text analysis on the annual reports of listed companies, to measure the level of digital transformation of enterprises (DT_alternative). Specifically, first, based on the policy documents issued by the government, key digital words are selected and extracted. These words were then used to analyze the text of the annual report to record the frequency of their occurrence. Finally, the digital transformation level is obtained by calculating the keyword frequency.

Drawing on the practice of Fang *et al*. (2022), the ratio of the average salary of the top three executives to the average salary of ordinary employees is used to measure the intra-firm pay gap (IPG_alternative). Among them, the average compensation of the top three executives is calculated by dividing "total compensation of the top three executives" by 3. The average compensation of ordinary employees is calculated by dividing "changes in compensation payable to employees + cash paid to and for employees - total compensation of top three executives" by "total number of employees - 3".

The results in Table 4 show that the estimated results of digital transformation and the intra-firm pay gap are still robust and reliable after the replacement of the above variables.

Table 4
Robustness test: Surrogate indicators.

Variables	**(1)** **IPG**	**(2)** **DT_alternative**	**(3)** **IPG_alternative**	**(4)** **DT**
L.DT			-0.0233**(0.0111)	
L.DT_alternative	-0.0910**(0.0421)			
L.IPG		0.0212**(0.0101)		
L.IPG^2		-0.0010**(0.0005)		
L.IPG_alternative				0.0891**(0.0449)
L.IPG_alternative^2				-0.0037**(0.0016)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry×year FE	Yes	Yes	Yes	Yes
Province×year FE	Yes	Yes	Yes	Yes
N	11460	11462	12202	12222
Adjusted R^2	0.717	0.743	0.736	0.866

Note: Columns (1) and (2) are regression results after replacing the DT variable. Columns (3) and (4) show the regression results after replacing the IPG variable. All control variables in each column regression are included, similarly hereinafter.

4.2.2. Avoid strategic information bias

Consider that when constructing digital transformation indicators, the information disclosure of enterprises may exaggerate the digital process through strategic hype, thus reducing the accuracy of the indicators. To prevent this situation from causing bias to the benchmark regression results, we excluded the samples with unqualified information disclosure quality to conduct a robustness test. The results in Table 5 show that the estimated results are still robust after excluding the samples with unqualified information disclosure quality.

Table 5
Robustness test: Avoiding strategic information bias.

Variables	(1) IPG	(2) DT
L.DT	-0.0191**(0.0076)	
L.IPG		0.0965*(0.0535)
L.IPG^2		-0.0047**(0.0023)
Controls	Yes	Yes
Firm FE	Yes	Yes
Industry×year FE	Yes	Yes
Province×year FE	Yes	Yes
N	12124	12126
Adjusted R^2	0.721	0.865

4.2.3. Eliminate concurrent policy interference

The samples selected in this paper are at an important stage of China's economic transformation, during which many policies may have a significant impact on the salary structure and digitization process of enterprises, interfering with the research conclusions of this paper.

Through the analysis of relevant policy documents, we find that Replacement of Business Tax with Value Added Tax and Accelerated Depreciation of Fixed Assets are two tax policies that have a greater impact on the internal salary gap of enterprises[6]. The policy of Replacement of Business Tax with Value Added Tax and Accelerated Depreciation of Fixed Assets has increased enterprises' disposable funds by reducing their tax burden. However, these additional funds often benefit senior executives more, potentially widening the pay gap between executives and ordinary employees. To mitigate the interference of these policies on the benchmark results, we further control the two variables of Replacement of Business Tax with Value Added Tax (RBTVAT) and Accelerated Depreciation of Fixed Assets (ADFA) in Equation (1). Among them, the policy variable of Replacement of Business Tax with Value Added Tax (RBTVAT) is measured by the proportion of the sum of value-added tax and business tax in the operating revenue. The policy variable of Accelerated Depreciation of Fixed Assets (ADFA) is measured by constructing a dummy variable. If the enterprise's industry is listed as the pilot industry of accelerated depreciation of fixed assets after 2014, the

[6] China's policy of replacing business tax with value-added tax is an important tax reform implemented since 2012, aiming to replace business tax with value-added tax to eliminate double taxation, optimize the tax structure, and promote the integrated development of the service and manufacturing industries. The accelerated depreciation policy of fixed assets is to encourage enterprises to increase investment in fixed assets. By shortening the depreciation life of fixed assets, enterprises can recover investment costs faster, thus enhancing their capital accumulation ability and technological transformation motivation.

value is assigned to 1; otherwise, the value is assigned to 0.

In addition, Broadband China and the National Big Data Comprehensive Pilot Zone policy are also two very important factors affecting the digital transformation of enterprises[7]. To mitigate the interference of these policies on the benchmark regression results, we further controlled two variables in Equation (2): Broadband China policy (Broadband) and the National Big Data Comprehensive Pilot Zone policy (Bigdata). The Broadband China policy variable (Broadband) is measured by a dummy variable. If the city where the enterprise is located is included in the broadband China pilot city after 2014, the value will be 1; otherwise, the value will be 0. The National Big Data Comprehensive Pilot Zone policy (Bigdata) is also measured using virtual variables: if the province where the enterprise is located is included in the National Big Data Comprehensive Pilot Zone after 2016, the value is 1, otherwise, the value is 0. The results in Table 6 show that the estimated results after excluding the interference of related policies such as RBTVAT, ADFA, Broadband, and Bigdata are consistent with the benchmark results.

Table 6
Robustness test: Excluding contemporaneous policy interference.

Variables	(1) IPG	(2) DT
L.DT	-0.0180**(0.0078)	
L.IPG		0.0920*(0.0543)
L.IPG^2		-0.0051**(0.0024)
RBTVAT	-1.5870(3.5719)	5.0117(7.1194)
ADFA	0.0424(0.0513)	0.0790(0.0843)
Broadband	-0.0622(0.1341)	0.1404(0.2641)
Bigdata	-0.7634(0.8398)	2.6204*(1.5018)
Controls	Yes	Yes
Firm FE	Yes	Yes
Industry×year FE	Yes	Yes
Province×year FE	Yes	Yes
N	11644	11639
Adjusted R^2	0.723	0.866

4.2.4. Instrumental variable method

Although the adoption of the lag term of the core explanatory variable can alleviate the endogenous problem caused by reverse causality to a certain extent, if the influence of the core explanatory variable

[7] Broadband China and the National Big Data Comprehensive Pilot Zone policy are important strategic measures introduced by the Chinese government to promote the development of the digital economy. The Broadband China policy aims to promote the construction and popularization of broadband networks nationwide to meet the needs of the information society for high-speed networks and promote the deep integration of information technology and various industries. The National Big Data Comprehensive Pilot Zone policy aims to promote the opening and sharing of data resources, improve data processing and application capabilities, and promote the wide application of big data technology in various industries by creating big data industrial clusters and innovation platforms.

is persistent, the simple lag treatment cannot completely solve the reverse causality problem. Therefore, to reduce the interference of endogenous problems on the results of baseline regression, we use the instrumental variable method to re-test the regression.

In the regression model of digital transformation on the intra-firm pay gap, we construct two instrumental variables respectively: 1) An interaction term is constructed between the reciprocal of the average shortest distance from the firm's city to the cities in the "Eight Vertical and Eight Horizontal" optical cable backbone network and the number of national Internet access ports in the previous year, serving as an instrumental variable for digital transformation (DT_IV_1). Firms closer to the cities in the "Eight Vertical and Eight Horizontal" optical cable backbone network have better access to high-quality network infrastructure, providing a stronger foundation for digital transformation, which satisfies the relevance condition of the instrumental variable. Meanwhile, the average shortest distance from the firm's city to the cities in the optical cable backbone network is a historical geographic variable that is unlikely to directly affect the firm's internal pay structure, thus satisfying the exogeneity condition of the instrumental variable. Since this distance is a time-invariant cross-sectional variable, it is not suitable for use as an instrumental variable in panel data analysis. Therefore, we followed the idea of the Bartik instrumental variable method (Goldsmith-Pinkham *et al.*, 2020) and constructed a time-varying instrumental variable based on the interaction between the reciprocal of the average shortest distance and the number of national Internet access ports in the previous year. 2) The average value of the digital transformation index of other enterprises in the same industry is used as the instrumental variable of digital transformation (DT_IV_2). On the one hand, the digital transformation of enterprises is affected by the characteristics of the industry, and due to the existence of the peer effect, competition in the industry will encourage enterprises to learn from and imitate each other in terms of digital transformation. Therefore, it is expected that the digital transformation of other enterprises in the same industry is positively correlated with the digital transformation of this enterprise, satisfying the correlation condition of instrumental variables. On the other hand, the digital transformation of other enterprises in the same industry is unlikely to directly affect the internal salary structure of the enterprise, to meet the exogenous conditions of instrumental variables.

Similarly, in the regression model of the intra-firm pay gap on digital transformation, we also construct two instrumental variables that can better satisfy the correlation and exogenous conditions: 1) Share shift instrumental variable method (IPG_IV_1). First, the internal salary gap in 2011, the year before the sample, is calculated. Secondly, the Gini coefficient growth rate of per capita disposable income is calculated. Finally, the product of the two is used as an instrumental variable of the intra-firm pay gap. 2) By referring to Lewbel's (1997) idea, the cubic power of the mean difference between the intra-firm pay gap of this enterprise and that of other enterprises in the same industry is selected as the instrumental variable (IPG_IV_2).

Table 7 reports the two-stage regression results of the instrumental variable method. The first-stage regression results show that the instrumental variables passed the under identification test, weak identification test, and over identification test, indicating that the selected instrumental variables are reasonable and reliable. The second-stage regression results show that after selecting appropriate instrumental variables to mitigate endogeneity bias, the main conclusions of this paper remain robust.

Table 7
Robustness test: Instrumental variable method.

Variables	(1) First Stage L.DT	(2) Second Stage IPG	(3) First Stage L.IPG	(4) First Stage $L.IPG^2$	(5) Second Stage DT
L.DT		-0.1472***(0.0490)			
$L.DT\_IV_1$	0.0000**(0.0000)				
$L.DT\_IV_2$	0.4710***(0.0886)				
L.IPG					0.3063**(0.1362)
$L.IPG^2$					-0.0115**(0.0050)
$L.IPG\_IV_1$			10.5096***(1.4609)	121.8407***(16.3516)	
$L.IPG\_IV_1^2$			-0.1541***(0.0355)	-1.5196***(0.4002)	
$L.IPG\_IV_2$			0.0062***(0.0002)	0.1403***(0.0032)	
$L.IPG\_IV_2^2$			-0.0000***(0.0000)	-0.0000***(0.0000)	
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry×year FE	Yes	Yes	Yes	Yes	Yes
Province×year FE	Yes	Yes	Yes	Yes	Yes
N	10967	10967	9650	9650	9650
Kleibergen-Paap rk LM statistic	13.087***		142.011***		
Cragg-Donald Wald F statistic	127.920[19.93]		322.639[16.87]		
Hansen J statistic	1.180		2.300		

Note: *Kleibergen-Paap rk LM statistic* is an under recognition test statistic, *Cragg-Donald Wald F statistic* is a weak recognition test statistic, and *Hansen J statistic* is an over recognition test statistic. The numbers in [] are the critical value of the Stock-Yogo weak recognition test at the 10% significance level.

4.2.5. Model replacement

To enhance the reliability of the research results, we further use the cross-lagged model to test the interaction between the two. This method controls both autocorrelation and common time trends, allowing for a more accurate estimation of bidirectional causal effects. It enhances the credibility of causal inference and deepens the understanding of the complex interaction mechanisms between variables (Selig and Little, 2012; Yu and Fiebig, 2020; Zablah *et al*., 2016). The cross-lagged model is set up as follows.

$$IPG_{i,j,p,t}=\gamma_0+\gamma_1 IPG_{i,t-1}+\gamma_2 DT_{i,t-1}+\gamma_n Controls_{i,t}+\mu_i+\delta_{j,t}+\tau_{p,t}+\varepsilon_{i,j,p,t} \quad (3)$$

$$DT_{i,j,p,t}=\theta_0+\theta_1 DT_{i,t-1}+\theta_2 IPG_{i,t-1}+\theta_3 IPG_{i,t-1}^{\ 2}+\beta_n Controls_{i,t}+\mu_i+\delta_{j,t}+\tau_{p,t}+\varepsilon_{i,j,p,t} \quad (4)$$

Different from formula (1) and (2), formula (3) and (4) introduce an additional autoregressive effect of *IPG* and *DT*, and γ_2, θ_2 and θ_3 reflect the cross-lagged effect, which is the coefficient we focus on. The results in Table 8 show that the estimated results are still robust and reliable after model replacement.

Table 8
Robustness test: Model replacement.

Variables	(1) IPG	(2) DT
L.DT	-0.0124**(0.0048)	0.3815***(0.0128)
L.IPG	0.2992***(0.0231)	0.1182***(0.0446)
L.IPG^2		-0.0041**(0.0020)
Controls	Yes	Yes
Firm FE	Yes	Yes
Industry×year FE	Yes	Yes
Province×year FE	Yes	Yes
N	12241	11419
Adjusted R^2	0.737	0.890

4.3. Mechanism inspection

Given the results of the previous study, we will further examine the channels behind digital transformation and the intra-firm pay gap.

4.3.1. Human capital structure

Through the introduction of advanced technologies and automation tools, digital transformation promotes the upgrading of skill demands and is conducive to the optimization of human capital structure which strengthens corporate resilience in changing markets. Digital transformation has created many new jobs, increasing demand for highly skilled workers with expertise to meet evolving sustainability standards. At the same time, it improves work efficiency and reduces the need for low-skill, repetitive tasks. This forces enterprises to retrain employees and upgrade their skills, promoting labor movement toward high-value, high-tech roles that bring long-term economic and environmental benefits. The optimization of human capital structure plays a key role in narrowing the internal salary gap. Based on the above analysis, we start from the two different dimensions of functional departments and educational background, regard technical personnel and personnel with bachelor's degree or above as highly skilled employees, and construct two indicators respectively, the proportion of technical personnel (Technician) and the proportion of personnel with bachelor's degree or above (Bachelor), to describe the human capital structure.

Table 9 reports the results of the institutional examination of human capital structure. Results in columns (1) and (3) show that digital transformation significantly increases the proportion of highly skilled employees and optimizes the human capital structure. The results in columns (2) and (4) show that the optimization of human capital structure has a significant negative impact on the intra-firm pay gap. This fully confirms the influence channel of human capital structure, and digital transformation can promote the narrowing of the intra-firm pay gap through the optimization of human capital structure.

Table 9
Mechanism test: Human capital structure.

Variables	(1) Technician	(2) IPG	(3) Bachelor	(4) IPG
L.DT	0.0478**(0.0217)	-0.0177**(0.0077)	0.0825***(0.0234)	-0.0158**(0.0077)
Technician		-0.0304***(0.0054)		
Bachelor				-0.0377***(0.0054)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry×year FE	Yes	Yes	Yes	Yes
Province×year FE	Yes	Yes	Yes	Yes
N	11622	11622	12250	12250
Adjusted R^2	0.830	0.719	0.899	0.719

4.3.2. Employee effort level

When the initial intra-firm pay gap is large, narrowing the intra-firm pay gap will generate positive incentives, enhance the sense of fairness and belonging of employees, and stimulate their enthusiasm and investment in work. The resulting workforce stability becomes a crucial foundation for enterprises' sustainable competitive advantage over time. The innovation ability of enterprises and the response speed of market changes will also be improved, thus promoting the process of digital transformation. However, when the initial internal salary gap is small, further narrowing the internal salary gap will bring negative constraints, weaken the promotion motivation and high salary expectation of employees, and make employees more inclined to pursue "stability". Low input and insufficient innovation of employees will lead to the decline of the efficiency of enterprises in adopting new technologies and improving business processes and hinder the process of digital development of enterprises. The reduced capacity for technological adaptation consequently limits enterprises' ability to maintain sustainable growth in changing market environments. Based on the above analysis, we will use the grouping regression method to test whether employee effort is an effective influence channel. Due to the lack of indicators to measure the effort level of employees, we selected labor productivity to capture the changes in the effort level of employees[8].

Table 10 reports the results. The comparison of columns (1) and (2), and the comparison of columns (3) and (4) confirm our expectations, indicating that the intra-firm pay gap can have an inverted U-shaped nonlinear effect on digital transformation through employee effort.

[8] Labor productivity is measured as the ratio of operating revenue to the number of employees. According to production function theory, an increase in employee effort can directly translate into higher output efficiency. Therefore, using labor productivity as a proxy for employee effort is quite persuasive.

Table 10
Mechanism test: Employee effort level.

Variables	The initial intra-firm pay gap is large		The initial intra-firm pay gap is small	
	Labor productivity is low	Labor productivity is high	Labor productivity is low	Labor productivity is high
	(1) DT	(2) DT	(3) DT	(4) DT
L.IPG	-0.0851**(0.0407)	0.0045(0.0332)	0.0621(0.1699)	0.3014**(0.1285)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry×year FE	Yes	Yes	Yes	Yes
Province×year FE	Yes	Yes	Yes	Yes
N	2676	2843	2501	2752
Adjusted R^2	0.879	0.874	0.876	0.873

Note: The initial intra-firm pay gap and labor productivity are grouped by the median for each year.

4.4. Heterogeneity analysis

4.4.1. Enterprise scale

The uneven access to resources and technology may lead to differences in the interaction between digital transformation and the intra-firm pay gap among enterprises of different sizes. Therefore, we examined large and small companies by annual median asset size. The results in Table 11 show that, compared with small enterprises, digital transformation can significantly reduce the intra-firm pay gap of large enterprises, and the intra-firm pay gap of large enterprises has a more obvious effect on the inverse U-shaped nonlinear of digital transformation. There might be two main reasons for this. First, large enterprises, due to their abundant capital and technical resources, are at an advantage in achieving digital scale effects and promoting fairer pay distribution, while small enterprises find it difficult to promote extensive and in-depth digital development due to resource constraints and high technology access costs, so they face greater challenges in narrowing the intra-firm pay gap. Second, unlike small enterprises, large enterprises, due to their complex organizational structure and numerous layers, can more effectively release the incentives and constraints on digital transformation through salary structure adjustment.

Table 11
Heterogeneity analysis: Firm size.

Variables	Small enterprises	Large enterprises	Small enterprises	Large enterprises
	(1) IPG	(2) IPG	(3) DT	(4) DT
L.DT	-0.0009(0.0097)	-0.0401***(0.0130)		
L.IPG			0.1316 (0.0801)	0.1104*(0.0622)
$L.IPG^2$			-0.0062(0.0040)	-0.0058**(0.0026)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry×year FE	Yes	Yes	Yes	Yes
Province×year FE	Yes	Yes	Yes	Yes
N	5679	5689	5687	5676
Adjusted R^2	0.660	0.750	0.879	0.873

4.4.2. Factor intensity

Different factor-intensive industries face different technology dependence and pay elasticity, and the interaction between digital transformation and the intra-firm pay gap may also be different. Taking this in consideration, we examine labor-intensive industries and non-labor-intensive industries according to factor intensity[9]. Table 12 shows that digital transformation significantly reduces the intra-firm pay gap in non-labor-intensive industries compared to labor-intensive ones. Additionally, the intra-firm pay gap in non-labor-intensive industries has a clearer inverted U-shaped nonlinear effect on digital transformation. There might be two main reasons for this: First, in non-labor-intensive industries, digital transformation promotes the integration and application of advanced technologies, driving more and more employees with professional skills and qualities to participate, resulting in a more obvious narrowing of the intra-firm pay gap; Second, the nature of work in non-labor-intensive industries is more complex, the skills of employees are weak, and they are more sensitive to the adjustment of salary structure, which brings more obvious incentives and constraints to the digital process.

Table 12
Heterogeneity analysis: Factor intensity.

Variables	Labor-intensive industry	Non-labor intensive industries	Labor-intensive industry	Non-labor intensive industries
	(1) IPG	(2) IPG	(3) DT	(4) DT
L.DT	-0.0268(0.0165)	-0.0161**(0.0071)		
L.IPG			-0.1043(0.1032)	0.1784***(0.0616)
L.IPG^2			0.0035(0.0043)	-0.0088***(0.0027)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry×year FE	Yes	Yes	Yes	Yes
Province×year FE	Yes	Yes	Yes	Yes
N	3189	9046	3188	9051
Adjusted R^2	0.754	0.712	0.845	0.872

4.4.3. Digital infrastructure

Digital development is highly dependent on external digital infrastructure conditions, which can lead to differences in the impact that digital transformation exerts and is exerted in different regions. To differentiate the impacts, we divided the sample into two groups with developed and less developed regional digital infrastructure according to the "Broadband China" pilot cities list[10]. Table 13 shows that,

[9] Labor-intensive industries include agriculture, forestry, animal husbandry and fishery, mining, food and beverage manufacturing, textile, clothing and fur manufacturing, wood and furniture manufacturing, construction, wholesale and retail trade, transportation, warehousing and postal services, culture, sports and entertainment, and the rest are non-labor-intensive industries.

[10] "Broadband China" is a national strategy launched by the Chinese government in response to the global digital trend. The policy focuses on strengthening digital infrastructure, especially expanding and upgrading broadband network coverage and achieving universal access to high-speed Internet. The Ministry of Industry and Information Technology and the National Development and Reform Commission piloted the "Broadband China" strategy in 120 cities in three batches in 2014, 2015 and 2016. If a city where an enterprise is located is included in the pilot list, it is classified as a group with developed regional digital infrastructure.

compared to regions with underdeveloped digital infrastructure, digital transformation in regions with developed infrastructure significantly reduces the internal salary gap. Moreover, the internal salary gap in these regions has a more pronounced inverted U-shaped nonlinear effect on digital transformation. We suggest two main reasons for this. First, good digital infrastructure provides necessary technical support and access conditions, which helps to improve the depth and breadth of digital transformation and expand the impact on the internal salary gap. Second, a good digital infrastructure provides employees with more access to advanced technology, allowing for more significant pay structure adjustments.

Table 13
Heterogeneity analysis: Digital infrastructure.

Variables	Regional digital infrastructure is underdeveloped	The region has developed digital infrastructure	Regional digital infrastructure is underdeveloped	The region has developed digital infrastructure
	(1) IPG	(2) IPG	(3) DT	(4) DT
L.DT	-0.0066(0.0122)	-0.0182**(0.0079)		
L.IPG			0.0254 (0.0925)	0.1610**(0.0641)
$L.IPG^2$			-0.0016(0.0042)	-0.0065**(0.0027)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry×year FE	Yes	Yes	Yes	Yes
Province×year FE	Yes	Yes	Yes	Yes
N	4361	7869	4354	7867
Adjusted R^2	0.702	0.733	0.839	0.872

5. Conclusion and Enlightenment

Optimizing salary distribution is a shared goal for all. In China, digital transformation is a national strategy aimed at improving salary distribution, which is crucial for corporate sustainability. However, achieving this goal is more complex than anticipated. Using the data of Shanghai and Shenzhen A-share listed companies in China from 2012 to 2023 as a sample, this paper examines the relationship between digital transformation and the intra-firm pay gap. It is found that digital transformation significantly reduces the intra-firm pay gap, and the narrowing of the intra-firm pay gap has an inverted U-shaped nonlinear effect on digital transformation. This relationship reveals an optimal reciprocal balance that maximizes corporate sustainability, which emerges only when pre-existing pay disparities are sufficiently large to allow for mutually reinforcing effects. We believe that this interaction is mainly realized through two ways: human capital structure and employee effort level. These effects are more pronounced in large enterprises, non-labor-intensive industries, and regions with developed digital infrastructure, revealing diverse paths toward corporate sustainability.

This paper makes significant theoretical contributions by transcending the prevailing perspective on digital transformation and intra-firm pay gap in existing literature. While previous research primarily examined the unidirectional impact of digital transformation on intra-firm pay gap, this paper innovatively reveals a bidirectional feedback mechanism and nonlinear relationship between the two variables. The discovery of an inverted U-shaped effect of intra-firm pay gap on digital transformation enriches the application of tournament theory and social comparison theory in digital contexts. Most importantly, the identification of an "optimal reciprocal balance point" represents a breakthrough, when pre-existing pay disparities are sufficiently large, the gap-narrowing effects of digital transformation and the motivational effects of moderate intra-firm pay gap create mutually reinforcing positive cycles that maximize corporate sustainability. This insight transcends the traditional binary debate of whether intra-firm pay gap are "harmful" or "beneficial", offering more nuanced theoretical guidance for compensation management and organizational change in the digital era.

These findings have important policy implications. For enterprises with large pay gaps, they should establish mentorship programs where senior employees guide colleagues in digital transformation. These enterprises should also create skill-based career progression pathways that directly link compensation advancement to digital competency development, with tiered tax incentives supporting comprehensive employee development. For enterprises with small pay gaps, they should create cross-functional teams that bring together employees with different digital skills to collaborate on transformation projects and share performance bonuses equally. By linking collective digital achievements to uniform team rewards, enterprises can accelerate digital transformation through knowledge sharing while preserving their equitable compensation.

There are still some limitations in this study. The data sample of this study only covers A-share listed companies in China, excluding SMEs and non-listed firms. This sample selection limits the generalizability of the research findings. SMEs and non-listed firms differ fundamentally from large listed companies in terms of resource endowment, corporate governance structure, and the standardization of compensation systems. These differences may lead to completely different mechanisms and magnitudes of the bidirectional relationship between digital transformation and intra-firm pay gap. Therefore, the application of the findings of this study should be done with caution, and future research should expand the sample scope to enhance the robustness of the conclusions.

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Conflicts of Interest

The authors declare no conflict of interest.

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