

Enterprise Digital Transformation and High-Quality Employment—Empirical Evidence from Employment Scale and Employment Structure

Jinghao Liao

*Southwestern University of Finance and Economics, Chengdu, China
3022540241@qq.com*

Abstract. As digital technologies accelerate their integration into enterprise production and operations, how to balance digital transformation with employment expansion and structural improvement has become an important issue. This paper uses data from China's A-share listed companies from 2007 to 2024, employing a firm-year two-way fixed effects model, to examine the employment effects of enterprise digital transformation from the perspectives of employment scale and employment structure. We find that the degree of enterprise digital transformation is significantly associated with employment expansion and an increase in the number of highly educated and highly skilled employees; in the baseline regression, the proportions of both types of employees increase significantly, but the structural proportion results are relatively sensitive to measurement and identification methods. Heterogeneity analysis shows that inter-group differences by ownership type and industry attributes are generally insignificant, while regional differences are more pronounced. Mechanism tests indicate that digital transformation is significantly associated with firm size expansion and increased R&D investment. This paper provides micro-level evidence for the coordinated promotion of digital transformation and high-quality employment.

Keywords: Enterprise digital transformation, Employment scale, Employment structure, High-quality employment, R&D investment

1. Introduction

As digital technologies integrate into enterprise production, traditional production methods and job divisions are undergoing profound changes. Enterprise digital transformation may substitute routine tasks while increasing labor demand through efficiency gains and new task creation. Therefore, identifying its impact on employment scale and structure is important.

Enterprise digital transformation involves the deep integration of digital technologies with enterprise strategy, processes, and organizational management [1]. Studies using annual report keyword indices find that digital transformation promotes specialization, improves productivity, and drives human capital adjustments [2, 3].

Existing research has also explained employment effects through business expansion and innovation. Digital technologies reduce coordination costs, expand enterprise boundaries, and

enhance R&D activities. Therefore, firm size expansion and R&D investment may constitute two important channels. Although the literature has formed a basic framework, employment scale and structure are often discussed separately, and effects across different digital technologies need further examination.

This paper uses China's A-share listed companies from 2007 to 2024, employing a firm-year two-way fixed effects model to examine employment effects from the perspectives of overall employment, employee types, and proportions, with robustness checks, IV analysis, heterogeneity analysis, and mechanism tests. Digital transformation is significantly associated with employment expansion and increases in highly educated and skilled employees; structural proportion results are relatively sensitive to variable definitions.

2. Literature review

Regarding employment scale, existing research offers two explanations: technology substitution and employment creation. Digital technologies can substitute routine tasks, but productivity gains and market expansion also create labor demand [4]. Firm-level evidence shows digital investment drives employment growth through business expansion and innovation [5], with domestic research generally finding a stabilizing or expanding effect [6].

On employment structure, digital development relies more on specialized knowledge, potentially increasing demand for highly educated and skilled workers [7]. Digital transformation can drive human capital upgrading [8], though it may also improve mid- to low-skilled productivity [9]. Structural improvement may thus manifest as faster growth in skilled labor.

3. Theoretical analysis and research hypotheses

3.1. The impact of enterprise digital transformation on employment scale and structure

Digital transformation can substitute routine tasks through automation while reducing coordination costs and driving business expansion and new task formation [10]. When market expansion exceeds local substitution effects, overall labor demand will increase.

Digital technologies are more complementary with specialized knowledge and complex problem-solving, increasing demand for highly educated and highly skilled labor [11]. Digital tools may also enhance mid- to low-skilled productivity [12], so structural optimization may manifest as faster growth in skilled labor rather than absolute decline in low-skilled employment. Based on the above analysis, we propose:

H1: Enterprise digital transformation can expand firm employment scale.

H2: Enterprise digital transformation can increase the number and proportion of highly educated and highly skilled employees, promoting the optimization of firm employment structure.

3.2. The channel roles of firm size expansion and R&D investment

Digital transformation can reduce coordination costs and promote market expansion [13], leading to firm asset size expansion that provides resources for more production activities and job creation. Therefore, firm size expansion may constitute an important channel.

Digital technologies can improve information search and knowledge combination efficiency, reducing R&D costs and enhancing firms' ability to sustain R&D activities [14]. As R&D intensity

increases, demand for R&D personnel and technical staff rises, supporting the growth of highly educated and highly skilled employees. Based on this, we propose:

H3a: Firm size expansion is an important channel through which digital transformation expands employment.

H3b: R&D investment intensification is an important channel through which digital transformation increases demand for highly educated and highly skilled labor.

4. Research design

4.1. Data sources and sample selection

This paper uses China's A-share listed companies from 2007 to 2024. Data on digital transformation and financials are from the CSMAR database, while employee data are from the Wind database. We exclude ST, *ST, PT, and financial firms, delete observations with missing variables, and winsorize continuous variables at the 1% and 99% levels. The final baseline sample includes 5,255 listed companies and 52,017 firm-year observations.

4.2. Variable definitions

4.2.1. Dependent variables

We construct eight dependent variables from three dimensions: employment scale, educational structure, and occupational skill structure [15]. Employment scale is measured by total and regular employee numbers (natural logarithms). For educational structure, employees with associate degree or above are highly educated; for occupational structure, technical and managerial personnel are highly skilled. Employee counts are processed as $\ln(1 + \text{count})$, and proportions are calculated as respective counts divided by total employee count.

4.2.2. Core independent variable

The core independent variable is enterprise digital transformation, measured by identifying digital keywords from five dimensions: artificial intelligence, blockchain, cloud computing, big data [16], and digital technology applications. Firm-level annual word counts are processed as $\ln(1 + \text{word count})$. The baseline model uses the one-period-lagged indicator to reflect the time lag between digital investment and hiring decisions.

4.2.3. Control variables

Referencing relevant research, we control for firm age, asset-liability ratio, operating cash flow, return on net assets, Tobin's Q, revenue growth rate, proportion of independent directors, shareholding ratio of the largest shareholder, duality of chairman and general manager, and ownership type.

4.3. Model specification

To examine the relationship between enterprise digital transformation and employment scale/structure, we construct the following two-way fixed effects model:

$$Employ(i, t) = \alpha_0 + \alpha_1 Digital(i, t - 1) + X'(i, t)\beta + \mu_i + \lambda_t + \varepsilon(i, t) \quad (1)$$

5. Empirical results and analysis

5.1. Baseline regression

Table 1 reports the baseline regression results. The estimated coefficient of digital transformation on total employees is 0.0677, significant at the 1% level; the effect on regular employees is also significantly positive, indicating that rising enterprise digitalization is stably associated with employment expansion, supporting Hypothesis H1. Further examination of employee structure reveals that digital transformation has a significantly positive effect on the number of highly educated, lowly educated, highly skilled, and low-skilled employees, indicating that digital transformation does not manifest as widespread substitution of low-educated or low-skilled employees. Meanwhile, the proportions of highly educated and highly skilled employees increase significantly, indicating relatively faster growth in skilled labor; the baseline results support Hypothesis H2.

Table 1. Enterprise digital transformation and employment — baseline regression

Variable	Total Employees	Regular Employees	Highly Educated	Lowly Educated	Highly Skilled	Low-Skilled	Highly Educated %	Highly Skilled %
Digital Trans. (lagged)	0.0677*** (0.0077)	0.0681*** (0.0078)	0.0819*** (0.0079)	0.0267** (0.0111)	0.0810*** (0.0073)	0.0570*** (0.0094)	0.0072*** (0.0020)	0.0050*** (0.0015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	45,662	45,315	43,903	35,497	44,051	44,051	43,903	44,051

5.2. Robustness checks

5.2.1. Sample and model specification adjustments

Table 2 conducts checks through unified estimation samples, industry-specific trends, exclusion of the IT sector and special years, and replacement of the digital transformation indicator. Under different specifications, the effects on employment scale and employee numbers are broadly consistent with the baseline and generally remain significant, indicating the employment expansion conclusion is robust. The proportion of highly educated employees is also stable, but the proportion of highly skilled employees becomes insignificant after replacing the indicator.

Table 2. Robustness checks — sample and model specification

Test Method	Total Employees	Regular Employees	Highly Educated	Lowly Educated	Highly Skilled	Low-Skilled	Highly Educated %	Highly Skilled %
Common sample	0.0606*** (0.0084)	0.0612*** (0.0085)	0.0755*** (0.0082)	0.0301*** (0.0111)	0.0758*** (0.0081)	0.0504*** (0.0102)	0.0067*** (0.0018)	0.0051*** (0.0016)
Obs.	33,337	33,337	33,337	33,337	33,337	33,337	33,337	33,337
Industry lineartrends	0.0602*** (0.0075)	0.0604*** (0.0076)	0.0747*** (0.0074)	0.0277*** (0.0105)	0.0702*** (0.0069)	0.0524*** (0.0089)	0.0074*** (0.0019)	0.0035** (0.0014)
Obs.	45,662	45,315	43,903	35,497	44,051	44,051	43,903	44,051

Table 2. (continued)

Exclude ITsector	0.0630*** (0.0079)	0.0632*** (0.0080)	0.0763*** (0.0082)	0.0287*** (0.0110)	0.0761*** (0.0074)	0.0514*** (0.0092)	0.0066*** (0.0021)	0.0050*** (0.0014)
Obs.	42,458	42,121	40,722	33,501	40,933	40,933	40,722	40,933
Exclude2020-2022	0.0701*** (0.0084)	0.0703*** (0.0086)	0.0855*** (0.0085)	0.0264** (0.0121)	0.0816*** (0.0079)	0.0594*** (0.0102)	0.0078*** (0.0022)	0.0047*** (0.0016)
Obs.	34,451	34,139	32,774	26,907	33,010	33,010	32,774	33,010
Replace digitalindicator	0.0550*** (0.0119)	0.0538*** (0.0121)	0.0656*** (0.0121)	0.0372** (0.0154)	0.0598*** (0.0113)	0.0528*** (0.0139)	0.0062** (0.0031)	0.0006 (0.0022)
Obs.	45,662	45,315	43,903	35,497	44,051	44,051	43,903	44,051

5.2.2. Employment variable measurement

Table 3 further adjusts employment variable measurement. After adopting a stricter occupational classification, digital transformation remains significantly associated with increased highly skilled employee numbers, but its effect on the proportion becomes insignificant; after deleting observations with conflicting educational information, the number and proportion of highly educated employees remain significantly positive. These results indicate the conclusion that digital transformation drives skilled labor growth is robust.

Table 3. Robustness — employment variable measurement

Variable	Highly SkilledCount (Strict)	Highly Skilled% (Strict)	Highly EducatedCount (Excl. Conflict)	Highly Educated% (Excl. Conflict)
Digital Trans. (lagged)	0.0706*** (0.0172)	-0.0006 (0.0045)	0.0812*** (0.0079)	0.0069*** (0.0020)
Controls	Yes	Yes	Yes	Yes
Firm & Year FE	Yes	Yes	Yes	Yes
Obs.	8,759	8,759	43,784	43,784

5.2.3. Extended analysis of different digital technologies

Table 4 examines the employment effects of different digital technologies. AI, cloud computing, big data, and digital technology applications generally expand employment and increase most employee types; blockchain-related indicators show negative effects on some outcomes. The results suggest different digital technologies vary in maturity and application scenarios, and the composite indicator reflects average effects.

Table 4: Employment Effects of Different Digital Technologies

Table 4. Employment effects of different digital technologies

Variable	Total Employees	Regular Employees	Highly Educated	Lowly Educated	Highly Skilled	Low- Skilled	Highly Educated %	Highly Skilled %
AI	0.0506*** (0.0099)	0.0507*** (0.0101)	0.0346*** (0.0101)	0.0351** (0.0148)	0.0516*** (0.0099)	0.0350*** (0.0117)	-0.0056** (0.0025)	0.0037** (0.0019)
Blockchain	-0.0381** (0.0194)	-0.0386* (0.0197)	-0.0505** (0.0198)	-0.0998*** (0.0318)	-0.0384** (0.0184)	-0.0283 (0.0243)	-0.0069 (0.0048)	-0.0023 (0.0038)
Cloud Computing	0.0387*** (0.0107)	0.0397*** (0.0109)	0.0445*** (0.0116)	0.0364** (0.0147)	0.0525*** (0.0110)	0.0265** (0.0126)	0.0033 (0.0028)	0.0050** (0.0022)

Table 4. (continued)

Big Data	0.0417*** (0.0096)	0.0425*** (0.0097)	0.0455*** (0.0104)	-0.0106 (0.0147)	0.0532*** (0.0097)	0.0354*** (0.0113)	0.0048* (0.0026)	0.0046** (0.0020)
Digital Tech. Applications	0.0314*** (0.0082)	0.0311*** (0.0084)	0.0485*** (0.0080)	0.0189 (0.0125)	0.0322*** (0.0074)	0.0327*** (0.0098)	0.0058*** (0.0021)	-0.0002 (0.0015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	45,662	45,315	43,903	35,497	44,051	44,051	43,903	44,051

5.3. Instrumental variable estimation

We use the interaction term between the 'Broadband China' pilot policy and a virtual variable for core digital economy industries as the instrumental variable [17]. In the first stage, the coefficient is 0.6096, significant at the 1% level, indicating the policy shock significantly explains changes in enterprise digital transformation.

Table 5 reports the IV estimation results. In the second stage, digital transformation remains significantly positively associated with total and regular employees and maintains positive effects on most employee counts, further supporting the conclusion that digital transformation promotes employment expansion. By contrast, results for the proportions of highly educated and highly skilled employees are not entirely consistent with the baseline, suggesting the evidence for structural improvement is relatively limited.

Table 5. Instrumental variable reduced form and 2SLS estimation

Estimation Method	Total Employees	Regular Employees	Highly Educated	Lowly Educated	Highly Skilled	Low-Skilled	Highly Educated %	Highly Skilled %
Reduced Form:IV	0.1875*** (0.0655)	0.1885*** (0.0661)	0.0896 (0.0599)	0.1748** (0.0804)	0.1798*** (0.0652)	0.1903*** (0.0718)	-0.0325*** (0.0096)	-0.0002 (0.0065)
2SLS: DigitalTrans.	0.3076*** (0.1046)	0.3092*** (0.1052)	0.1469 (0.0954)	0.2868** (0.1330)	0.2950*** (0.1007)	0.3121*** (0.1153)	-0.0533*** (0.0174)	-0.0003 (0.0107)
Controls &Low-orderTerms	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	31,875	31,875	31,875	31,875	31,875	31,875	31,875	31,875

6. Heterogeneity analysis

6.1. Ownership type

Table 6 reports results for firms with different ownership types. Digital transformation significantly expands employment in both state-owned and non-state-owned enterprises. The proportions of highly educated and highly skilled employees are significantly positive only in non-state-owned enterprises [18]. However, inter-group differences in the fully interactive model do not reach statistical significance, so ownership type does not constitute a stable moderating effect.

Table 6. Ownership type

Group	Total Employees	Regular Employees	Highly Educated	Lowly Educated	Highly Skilled	Low-Skilled	Highly Educated %	Highly Skilled %
Non-state-owned	0.0591*** (0.0092)	0.0590*** (0.0093)	0.0803*** (0.0102)	0.0212* (0.0127)	0.0731*** (0.0089)	0.0488*** (0.0105)	0.0091*** (0.0026)	0.0048*** (0.0017)
Obs.	29,393	29,237	28,654	22,516	28,683	28,683	28,654	28,683
State-owned	0.0686*** (0.0134)	0.0692*** (0.0137)	0.0723*** (0.0120)	0.0268 (0.0202)	0.0767*** (0.0121)	0.0628*** (0.0177)	0.0037 (0.0033)	0.0037 (0.0028)
Obs.	16,269	16,078	15,249	12,981	15,368	15,368	15,249	15,368
Inter-groupDiff. P-val.	0.5645	0.5426	0.6129	0.8186	0.8105	0.4987	0.1947	0.7370

6.2. Core digital economy industries

Table 7 shows that regardless of whether firms belong to core digital economy industries, digital transformation significantly expands employment and increases most employee types. Inter-group difference tests are generally insignificant, and structural proportion differences are also not prominent. Industry attributes have not yet constituted a stable source of heterogeneity.

Table 7. Core digital economy industries

Group	Total Employees	Regular Employees	Highly Educated	Lowly Educated	Highly Skilled	Low-Skilled	Highly Educated %	Highly Skilled %
Non-coredigital industry	0.0566*** (0.0084)	0.0570*** (0.0085)	0.0714*** (0.0087)	0.0197* (0.0116)	0.0679*** (0.0080)	0.0470*** (0.0098)	0.0076*** (0.0023)	0.0043*** (0.0014)
Obs.	37,909	37,606	36,291	30,236	36,448	36,448	36,291	36,448
Core digitalindustry	0.0846*** (0.0168)	0.0842*** (0.0170)	0.0967*** (0.0171)	0.0623** (0.0258)	0.0840*** (0.0166)	0.0884*** (0.0207)	0.0040 (0.0034)	0.0002 (0.0033)
Obs.	7,753	7,709	7,612	5,261	7,603	7,603	7,612	7,603
Inter-groupDiff. P-val.	0.1295	0.1474	0.1824	0.1253	0.3749	0.0661	0.3822	0.2491

6.3. Region

Table 8 reports regional results. Digital transformation significantly expands employment in both provincial capitals/municipalities and other cities, indicating a certain universality. Inter-group difference tests show stronger expansion effects for regular and lowly educated employees in provincial capitals, while the increase in highly educated proportion is more pronounced in other cities. Regional differences are mainly reflected in some employment quantity and educational structure indicators [19].

Table 8. Region

Group	Total Employees	Regular Employees	Highly Educated	Lowly Educated	Highly Skilled	Low-Skilled	Highly Educated %	Highly Skilled %
Other cities	0.0540*** (0.0101)	0.0527*** (0.0102)	0.0802*** (0.0112)	0.0069 (0.0142)	0.0763*** (0.0099)	0.0409*** (0.0116)	0.0108*** (0.0029)	0.0069*** (0.0019)
Obs.	24,126	23,952	23,214	19,468	23,506	23,506	23,214	23,506

Table 8. (continued)

Provincialcapital/ municipality	0.0834*** (0.0116)	0.0852*** (0.0119)	0.0836*** (0.0111)	0.0522*** (0.0173)	0.0858*** (0.0106)	0.0763*** (0.0149)	0.0025 (0.0027)	0.0024 (0.0023)
Obs.	21,536	21,363	20,689	16,029	20,545	20,545	20,689	20,545
Inter-groupDiff. P- val.	0.0565	0.0386	0.8299	0.0426	0.5126	0.0614	0.0382	0.1261

7. Mechanism tests

To examine the two channels of firm size expansion and R&D investment, we adopt a unified two-step approach. The first step tests the relationship between digital transformation and employment from the baseline regression; the second step uses firm size and R&D investment as dependent variables to examine whether digital transformation significantly changes these channel variables. Both mechanisms use the same controls, fixed effects, and clustering:

$$M(i, t) = \beta_0 + \beta_1 Digital(i, t - 1) + X'(i, t)\gamma + \mu_i + \lambda_t + \varepsilon(i, t) \quad (2)$$

7.1. Firm size expansion channel

Column (1) of Table 9 shows that digital transformation is significantly positively associated with contemporaneous asset size, indicating that higher digitalization accompanies asset expansion, supporting the firm size expansion channel.

7.2. R&D investment channel

Columns (2)–(3) of Table 9 show that digital transformation is significantly positively associated with both R&D expenditure and R&D intensity. Increased R&D investment may further elevate demand for highly educated and skilled employees, supporting the R&D investment channel.

Both channel results are consistent with the theoretical analysis, supporting Hypotheses H3a and H3b.

Table 9. Firm size expansion and R&D investment channels

	(1)	(2)	(3)
	SizeExpansion	R&DExpenditure	R&DIntensity
Digital Trans.(lagged)	0.0832***(0.0067)	0.0820***(0.0103)	0.1109***(0.0402)
Controls	Yes	Yes	Yes
Firm & Year FE	Yes	Yes	Yes
Sample	45,690	38,796	38,797
Adj. R ²	0.5658	0.3991	0.0004

8. Conclusions

This paper uses China's A-share listed companies from 2007 to 2024 to examine the impact of digital transformation on employment scale and structure. Digital transformation is significantly associated with employment expansion and increases in different employee types, without widespread substitution of low-educated or low-skilled workers. Heterogeneity analysis shows regional differences are more pronounced, while ownership and industry differences are generally

insignificant. Mechanism tests support the firm size expansion and R&D investment channels. Then, we have some suggestions. First, promote coordinated digital transformation and employment policies, guiding firms to translate efficiency gains into job creation. Second, improve digital skills training and job transition support. Third, strengthen support for R&D innovation and talent allocation.

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