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Student ID: 20411586

Dissertation Title: What changes has the development of the digital economy brought to China's employment structure?

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The University of Nottingham Ningbo China

FHSS School of Economics

ECON3067 Final Dissertation

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Word Count: 6878

This Dissertation is presented in part fulfilment of the requirement for the completion of an undergraduate degree in School of Economics, The University of Nottingham Ningbo China. This work is the sole responsibility of the candidate.

My dissertation can be made available to students in future years if selected as an example of good practice.

What changes has the development of the digital economy brought to China's employment structure?

Abstract: This paper focuses on the impact of China's digital economy development on the employment structure. Based on the panel data of 31 provinces (not include Hongkong, Macao, and Taiwan) and municipalities from 2013 to 2022, it explores regional heterogeneity of the digital economy on the distribution of human capital (the proportion of low, middle, and high-skilled employment). The research constructs a three-dimensional index system including digital infrastructure, digital industry development and digital ecological environment. The entropy weight method (EWM) and Principal component analysis (PCA) are used to comprehensively measure the development level of the digital economy. The two-way fixed effects model is adopted for benchmark regression. And the reliability of the results is ensured through Hausman test, robustness test (substitution variable method) and endogeneity test (instrumental variable method). The research finds that the digital economy has an "inverted U-shaped" impact on low-skilled employment. In the early stage, jobs are created due to the development of digital economy, and in the later stage, job substitution occurs with the popularization of automation technology. It has a "positive U-shaped" impact on high-skilled employment. In the early stage, traditional high-skilled positions were impacted, and in the later stage, with the deepening of digital technology, high-end demands such as algorithm development and big data analysis were given rise. The impact on middle-skilled employment is not significant and may be because the effect of automation substitution and the creation of new jobs cancel each other out. In terms of regional heterogeneity, the eastern coastal areas have entered the stage of enhancing high-skilled employment, while the inland areas are still dominated by the growth of low-skilled positions. The research provides a theoretical basis for the government to optimize employment policies and narrow the regional digital divide. It is suggested to strengthen digital skills training and promote regional coordinated development to facilitate inclusive growth.

Key words: human capital, employment structure, digital economy

1 Introduction

The digital economy represents a trans-formative economic activity driven by advancements in digital technologies and serves as a catalyst for economic modernization by refining resource allocation, enabling data-informed decision-making, and balancing equity with productivity. Distinct from traditional economic models, it is characterized by high automation and data-driven processes, which has a significant impact on Chinese labor-force market (Xia, 2021). This not only fosters the creation of innovative professions, but also raises competency standards for workers.

Against the background of persistent global headwinds marked by sluggish growth, rising geopolitical trade tensions, and domestic economic cooling, the digital economy, underpinned by breakthroughs in information and communication technologies (ICT) is fundamentally transforming employment structure. By accelerating structural adjustment across sectors, it disrupts conventional labor dynamics while fostering innovation-driven industrial transitions. The pervasive integration of digital tools into production networks, supply chains, and consumer ecosystems has not only deepened its societal footprint but also redefined the interplay between technology and human capital.

Therefore, an examination of the digital economy's impact on employment structure is imperative to reconcile its possible disruptive and creative forces. By devising evidence-based interventions, policymakers can harness its potential to expand job availability, elevate labor conditions, and realign occupational frameworks, ensuring inclusive growth in the digital era.

Based on the data of 31 provinces and municipalities in China (excluding Macao, Hong Kong Special Administrative Regions, and Taiwan Province), with the time span selected from 2013 to 2022, this article uses panel data to study the changes in the employment structure of the human capital brought about by the development of China's digital economy.

The research focuses on one core aspects of the employment structure: distribution of human capital. Empirical analysis shows that the digital economy has a significant driving effect on the transformation of the employment structure. In addition, in different regions (the west, the east, the central region, and the northeast), the development of the digital economy shows heterogeneity in its impact on the employment structure. Compared with existing studies, this paper achieves a dual expansion in the temporal and spatial dimensions: spatially covering the entire provincial unit and extending the time series to the relatively mature development period of the digital economy, deeply revealing the new characteristics of the evolution of the employment structure under the emerging economic form. The innovation lies in the construction of a nonlinear influence analysis framework, clarifying the differentiated role paths of the digital economy on the employment structure of human capital . This not only provides theoretical support for judging the employment trend in the digital economy era, but also offers decision-making basis with both theoretical depth and practical value for the government to formulate industrial optimization policies and improve the employment promotion mechanism.

2 Literature Review

The digital economy's transformative impact on global employment presents a complex duality of productivity enhancement and structural disruption.

2.1 Non-standardization of Employment Patterns and Reconstruction of Labor Relations

Digital technologies have catalyzed the emergence of flexible employment models, leading to the deconstruction of traditional employer-employee relationships. Ignatieva et al. (2023) highlights the surge of non-standard employment forms, such as remote work and flexible hours, which reflect a "de-socialization" of labor relations. Corporate organizational structures have shifted from vertical hierarchies to horizontal collaboration, with team-based and project-oriented work becoming central. While this transformation reduces labor costs for enterprises, it simultaneously exacerbates employment instability for workers. Wu et al. (2023) further corroborate this trend, demonstrating the rise of the gig economy and platform-based employment in China, where the proportion of flexible employment increased significantly between 2013 and 2017. However, this shift is accompanied by inadequate social security coverage and heightened occupational risks. Similarly, these findings underscore that while the digital economy enhances labor market flexibility, there is an urgent need to establish institutional frameworks compatible with these emerging labor relations.

2.2 Structural Tensions Between Job Creation and Substitution Effects

The impact of the digital economy on aggregate employment exhibits marked heterogeneity across industries and regions. Based on classical economic theory, the Petty-Clark Theorem provides a foundational framework for understanding labor migration patterns, positing that income differentials across industries drive workforce reallocation toward sectors with higher productivity and value-added returns. Contemporary empirical studies confirm this theorem's enduring relevance in the digital era, particularly through observable employment shifts from secondary to tertiary industries. Zhao and Said (2023) specifically quantify this transition, revealing significant employment contraction in manufacturing and construction sectors alongside service sector expansion, a structural realignment mirroring economic complex movement, which is also quantified by Lu and Zhou (2023) via a Spatial Durbin Model. Notably, they (Lu and Zhou, 2023) find job creation effects are stronger in small and middle-sized cities than in large cities. This ‘3-1-2’ industrial restructuring highlights the digital economy’s role in driving cross-sector labor reallocation, yet low-skilled workers face heightened vulnerability to technological displacement (Wu, 2023).

In addition, Xia and Pei (2023), using China’s pandemic period as an observational window, reveal that digital technologies generated substantial employment opportunities through new formats like e-commerce and remote work, yet simultaneously disrupted traditional manufacturing and brick-and-mortar retail sectors, resulting in structural unemployment.

2.3 Skill Demand Upgrading and Digital Divide Challenges

The digital transformation of employment structures ask for higher skill requirements on workers. Ignatieva et al. (2023) identifies advanced educational attainment and digital literacy as critical thresholds for emerging occupations, with women’s participation increasing in knowledge-intensive sectors. However, workers in traditional industries confront skill outdated risks. Rural-urban disparities in digital infrastructure exacerbate the ‘information divide’ (Xia and Pei, 2023). Lu and Zhou (2023) emphasize that innovation and entrepreneurship levels serve as key mediators in alleviating skill mismatches, necessitating enhanced industry-academia collaboration and vocational training to improve human capital adaptability. These findings highlight the urgency of reforms in skill supply systems and the establishment of lifelong learning mechanisms.

2.4 Regional Heterogeneity and Differentiated Policy Pathways

The employment effects of the digital economy demonstrate significant spatial divergence. Lu and Zhou’s (2023) empirical analysis reveals that in China’s eastern regions, characterized by high economic agglomeration, the digital economy directly stimulates service-sector employment growth. In contrast, central and western regions rely on indirect spillovers from innovation and entrepreneurship, requiring policies focused on digital infrastructure and industrial incubation. Xia and Pei (2023) advocate targeted interventions in underdeveloped areas, such as digital skills training programs ("customized training") and hourly-based social security contribution systems, while Wu (2023) proposes harmonized urban-rural household registration policies to facilitate labor mobility. These region-specific strategies provide actionable insights for addressing uneven distribution of ‘digital dividends’.

3 Methodology

Considering the established theoretical framework in the fields of digital economics and labor market studies, as well as the specific characteristics of the data --- such as its multi-year temporal span and regional coverage across Chinese 31 provinces --- this study utilizes a two-way fixed-effects panel data model. This econometric approach is chosen to systematically examine the dynamic influences exerted by the development of the digital economy on the structure of labor employment in China, accounting for both time-invariant individual heterogeneity and time-specific macroeconomic shocks. The model specification, carefully formulated to align with theoretical hypotheses and data-generating processes, is presented as follows:

$$Y_{it} = \beta_0 + \beta_1 digital_{it} + \sum_j \theta_j X_{itj} + \mu_i + \rho_t + \epsilon_{it}$$

Note: The subscript i represents different provinces or municipalities, the subscript t represents the year (2013-2022), Y_{it} represents the employment structure of the human capital (*low_skill_pct, mid_skill_pct, high_skill_pct*) in province i in the *t-th* year, $digital_{it}$ represents the development level of the digital economy in Province i in the *t-th* year, X_{itj} represents other control variables, μ_i is the individual effect, and ρ_t is the time effect, ϵ_{it} is the random error term.
(Note*: The italicized words in the brackets are the variable names.)

In panel data analysis, model specification requires rigorous verification of data-model consistency, particularly between fixed-effects and random-effects. This research uses Hausman tests for model selection. As demonstrated in Table 1, all three Hausman test statistics significantly reject the null hypothesis of exogeneity at the 1% level, quantitatively validating the superiority of fixed-effects specification for our dataset according to econometric principles.

Table1 Hausman test

	chi2 statistic	p value	result
low_skill_pct	30.64	0.001	reject
mid_skill_pct	22.23	0.0023	reject
high_skill_pct	384.68	0.0000	reject

4 Data and Variables

4.1 Variable measurement

4.1.1Explained Variables

This paper use the employment structure of the human capital as the core explained variable: it is divided into three levels based on educational attainment: the group with an educational attainment of primary school or below is defined as low human capital (*low_skill_pct*), the group with an educational attainment from junior high school to junior college is classified as intermediate human capital (*mid_skill_pct*), and the group with a bachelor's degree or above is regarded as high human capital (*high_skill_pct*).

4.1.2 Core explanatory variables

The core independent variable of this study focuses on the development level of the digital economy (*digital_e, digital_p*), and the entropy weight method (EWM) and Principal Component analysis (PCA) are adopted for comprehensive measurement.

The construction of the indicator system builds upon the methodologically rigorous research framework proposed by He et al. (2023), systematically incorporating and synthesizing three core dimensions critical to digital economy analysis: the supporting capacity of digital infrastructure, which underpins the digital economy’s foundational technological and infrastructural prerequisites; the growth capacity of the digital industry, reflecting the dynamic expansion and innovation potential of digital-related sectors; and the development environment of the digital ecosystem, encompassing institutional, regulatory, and collaborative conditions that foster digital economic activities. This hierarchical system is composed of 3 first-level indicators, 7 carefully selected second-level indicators, and 22 third-level indicators (see detailed classification in Table 2), which together form a comprehensive composite index through multi-dimensional data aggregation. This approach ensures that both quantitative metrics and qualitative environmental factors are systematically integrated to capture the complex landscape of digital economic development.

Notably, the study employs a rigorous cross-validation approach using two distinct measurement methodologies: the Entropy Weight Method (EWM) and Principal Component Analysis (PCA). By applying these complementary techniques, the research not only safeguards the objectivity and reliability of index weighting schemes but also enhances the comprehensive index’s explanatory capacity across different analytical perspectives. This dual-method validation strategy mitigates potential biases inherent in single-weighting approaches, thereby enabling a more accurate and careful measurement of the digital economy’s dynamic developmental characteristics over time and across regions.

Table 2 Digital economy measurement indicators and their weight for EWM

Primary Category	Secondary Category	Third measurement indicator	Expectation	Weight
Digital Infrastructure	Hardware Facilities	Long-Distance Optical Cable Length (km)	+	0.0499
		Internet Broadband Access Ports (10,000 units)	+	0.0484
		Mobile Phone Base Stations (10,000 units)	+	0.0484
	Software Facilities	Number of Internet Domain Names (10,000 units)	+	0.0425
		Number of IPv4 Addresses (10,000 units)	+	0.0418
		Number of Internet Websites (10,000 units)	+	0.0431
Digital Industry Development	Digital Industrialization	Software Business Revenue (100 million yuan)	+	0.0377
		Telecommunications Business Revenue (100 million yuan)	+	0.0433
	Industrial Digitalization	Number of Websites per 100 Enterprises (units)	+	0.0520
		Percentage of Enterprises with E-commerce Activities (%)	+	0.0508
		E-commerce Sales Revenue (100 million yuan)	+	0.0417
Digital Economy Environment	Application Environment	Number of Computers per 100 People (units)	+	0.0498
		Mobile Internet Users (10,000 households)	+	0.0487
		Mobile Phone Subscribers (Year-End, 10,000 households)	+	0.0489
		Digital TV Subscribers (10,000 households)	+	0.0489
		Digital Inclusive Finance Index	+	0.0508
		Digital-Real Economy Integration Index	+	0.0379
	Talent Environment	Percentage of IT-related Employment (%)	+	0.0444
		Number of bachelor's degree Graduates (persons)	+	0.0495
	Innovation Environment	Full-Time Equivalent (FTE) of R&D Personnel (person-years)	+	0.0444
		Number of R&D Institutions (units)	+	0.0357
		Region-Specific Patent Grants (units)	+	00413

4.1.3 Control Variables

To effectively control the influence of other potential factors on the employment structure of labor education level, this study introduces the following 5 types of control variables: (1) Level of industrialization (*industry*): it is calculated by industrial added value divided by GDP. (2) The intensity of government regulation (*gov_intervention*) is reflected by the proportion of fiscal expenditure to GDP, which indicates the intensity of policy intervention. (3) The level of innovation input (*rd_intensity*) is measured by the proportion of research and development expenditure to GDP, which indicates the intensity of technological innovation. (4) Information infrastructure (*digitalization*), the degree of informatization development is measured by the proportion of the total volume of postal and telecommunications services to GDP; (5) Human capital (*human_capital*) reserve is quantified by the ratio of the number of students in higher education to the permanent resident population.

4.2 Data test

Before the regression, the Pearson correlation coefficient matrix test was conducted first (shown in Table 3). The results indicated that there was a significant relationship between the core explanatory variable, the level of digital economic development, and the explained variable, the employment skills structure: the development of the digital economy can change the employment skills structure of the labor force.

However, considering that the correlation coefficient matrix only measures the relationship between two variables and has not excluded the interference of control variables and potential variables (such as time effects and individual effects), the results are for reference only. The specific relationship still needs to be determined through further regression analysis.

Table 3 Variable correlation matrix analysis

	low_skill_pct	mid_skill_pct	high_skill_pct	digital_e	digital_e2	digital_p	digital_p2	human_capital	rd_intensity	digitalization	gov_intervention	industry
low_skill_pct	1											
mid_skill_pct	-0.742***	1										
high_skill_pct	-0.495***	-0.155***	1									
digital_e	-0.366***	0.158***	0.348***	1								
digital_e2	-0.308***	0.133**	0.302***	0.958***	1							
digital_p	-0.398***	0.111*	0.474***	0.985***	0.958***	1						
digital_p2	-0.383***	0.102*	0.466***	0.976***	0.973***	0.997***	1					
human_capital	-0.433***	0.176***	0.483***	0.157***	0.094*	0.211***	0.197***	1				
rd_intensity	-0.587***	0.065	0.812***	0.625***	0.553***	0.691***	0.676***	0.501***	1			
digitalization	0.074	-0.025	-0.008	0.046	0.051	0.056	0.054	-0.002	-0.118**	1		
gov_intervention	0.745***	-0.710***	-0.163***	-0.464***	-0.356***	-0.435***	-0.406***	-0.332***	-0.445***	0.148***	1	
industry	-0.326***	0.567***	-0.292***	0.108*	0.088	0.027	0.020	-0.008	0.007	-0.229***	-0.572***	1

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

To address multicollinearity in macroeconomic data, this study employs Variance Inflation Factor (VIF) diagnostics. VIF quantifies collinearity severity by comparing regression variances under collinear versus ideal orthogonal conditions. Established thresholds indicate: VIF<10 suggests negligible collinearity; 10≤VIF<100 signals moderate collinearity; VIF≥100 denotes severe collinearity. As shown in the table 4 below, all variables exhibit VIF values below 10, confirming the absence of multicollinearity in our model specifications.

Table 4 The VIF factor for multicollinearity

Variable	VIF	1/VIF
rd_intensity	2.47	0.404239
gov_intervention	2.38	0.420112
digital_e	2.02	0.493838
industry	1.78	0.560582
human capital	1.53	0.651726
digitalization	1.13	0.887292
Mean VIF	1.89	

4.3 Data Processing

4.3.1 Entropy Weight Method (EWM)

To scientifically measure the development level of the digital economy, it is necessary to consider both the systematization of the indicator system and the objectivity of weight assignment. To this end, this paper adopts the data-driven EWM for objective weighting.

This method quantifies the dispersion degree of indicators through the principle of information entropy, effectively avoids human interference, and ensures that the weight assignment is more in line with the characteristics of data distribution. The research period is spanning from 2013 to 2022, a temporal framework meticulously chosen to align with critical milestones in China's digital economy trajectory. This time window closely corresponds to pivotal developmental phases, including the large-scale commercialization of 4G technology (which catalyzed the mobile internet boom) and the subsequent rollout of 5G infrastructure (marking the advent of high-speed, low-latency connectivity), as well as the national implementation of the Big Data Strategy in 2015. By encompassing these transformative periods, the study effectively captures the dynamic evolutionary impacts of emerging digital technologies—such as mobile payments, e-commerce proliferation, and industrial digitization—on labor market structures. This longitudinal design enables the identification of both short-term shocks and long-term trend changes driven by technological diffusion and policy interventions.

In the data processing stage, addressing the dimensional disparities among the 22 cross-level indicators listed in Table 1 necessitated a rigorous standardization protocol. The research strictly adheres to the entropy method framework proposed by He et al. (2023), which comprises three sequential analytical steps. First, the original data undergo range-standardization to eliminate unit-of-measurement discrepancies, ensuring that indicators with varying scales are converted into dimensionless metrics. This step mitigates the bias caused by dimensional heterogeneity, allowing for meaningful cross-indicator comparisons. Second, information entropy values are calculated for each indicator to objectively determine weight coefficients, a process that leverages data-driven statistical properties to reflect the relative importance of each indicator based on its information richness. Finally, through entropy-weighted aggregation, the methodology achieves two key objectives: transforming multi-dimensional data into a unified comparable space and synthesizing a comprehensive index that encapsulates the complex interplay of digital economy dimensions. This systematic approach not only maintains the technical rigor of quantitative analysis but also ensures the resultant indices are theoretically grounded and empirically robust for panel data modeling.

The specific process of the entropy weight method is as follows:

① The original data for all indicators were standardized (using normalization methods).
(Since all selected indicators are positive in direction, the construction formulas for negative indicators were omitted. This process removes dimensional discrepancies and improves data comparability.)

$$x'_{ij} = \frac{x_{ij} - min(\sum x_j)}{max(\sum x_j) - min(\sum x_j)}$$

Note: x'_{ij} represents the value of the i-th sample in the j-th dimension.

② Calculate the entropy of each dimension

$$E_j = -k\sum_{i=1}^{n} p_{ij}\, ln(p_{ij})$$

Note: $p_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}}$ ， $\mathrm{k} = \frac{1}{\ln(\mathrm{n})} > 0$ ， $E_j \geq 0$

③ Calculate the redundancy rate and weight

$$d_j = 1 - E_j$$

$$w_j = \frac{d_j}{\sum_j d_j}$$

④ Calculate the score (i.e. Comprehensive Index of Digital Economy Development)

$$s_{ij} = w_j x'_{ij}$$

Note: $s_{ij} \in [0,1]$, a bigger s_{ij} means more developed level of digital economy

Figure 1 and figure 2 illustrate the calculated results of China's digital economy composite index by EWM.

The empirical results reveal a notable upward trend in the comprehensive digital economy index, which escalated from 0.146 in 2013 to 0.273 in 2022, translating to a compound annual growth rate (CAGR) of approximately 7.22%. This sustained growth reflects the cumulative effects of technological innovation, policy-driven digital transformation, and expanding market adoption of digital services across China. While all provincial-level administrative units experienced growth in digital economy development, the overall national foundation for digitalization remains moderately low, accompanied by pronounced regional disparities that warrant detailed examination. Specifically, the Western region emerged as the fastest-growing area with a CAGR of 8.06%, driven by strategic national initiatives such as the "Belt and Road" digital infrastructure projects and local investments in cloud computing and big data hubs. The Central region followed closely with a CAGR of 8.03%, fueled by industrial digitization upgrades and the rise of e-commerce clusters in provinces like Henan and Hubei (Luo, 2017). The Eastern region, despite its leading position in digital economy maturity, recorded a relatively lower CAGR of 6.57%, likely due to its already high base effect from early digital adoption in manufacturing and services sectors. The Northeastern region trailed with the lowest CAGR of 5.95%, constrained by challenges such as traditional industrial restructuring delays and talent outflows, which hindered the pace of digital innovation.

In 2022, the national average digital economy index stood at 0.224, with significant variations across regions. The Eastern region maintained its dominant position with an index value of 0.31--- markedly 38.8% higher than the national average --- benefiting from agglomeration effects in tech hubs like the Yangtze River Delta and Pearl River Delta, where advanced digital industries (e.g., artificial intelligence, fintech) and robust venture capital ecosystems thrive. The Central region ranked second with an index of 0.219, demonstrating substantial progress in digital infrastructure expansion but still lagging the East by a 42.0% gap, primarily due to disparities in high-tech talent concentration and R&D investment intensity. The Northeastern region reported an index of 0.171, while the Western region recorded 0.158 --- both falling below the national average. These figures highlight that although the Western and Central regions have achieved higher growth rates in recent years, their lower starting bases and ongoing challenges in digital talent retention and institutional innovation mean they still face considerable hurdles. The Northeastern region's performance underscores the need for targeted policies to refresh its digital economy through state-owned enterprise digitization reforms and regional collaboration initiatives. Collectively, while the Eastern region's entrenched advantages in digital economy development are evident, the varying growth dynamics across regions emphasize the necessity of sustained investments in infrastructure, human capital, and policy coordination to foster more balanced national digital transformation.

Figure 1 Digital Economy Comprehensive Development Index of 31 Provincial-level Administrative Units (EWM)

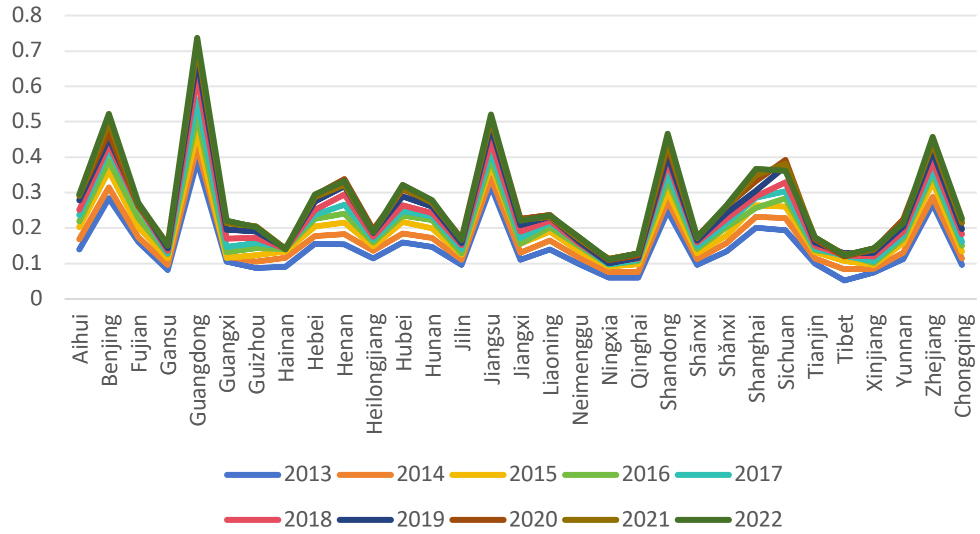
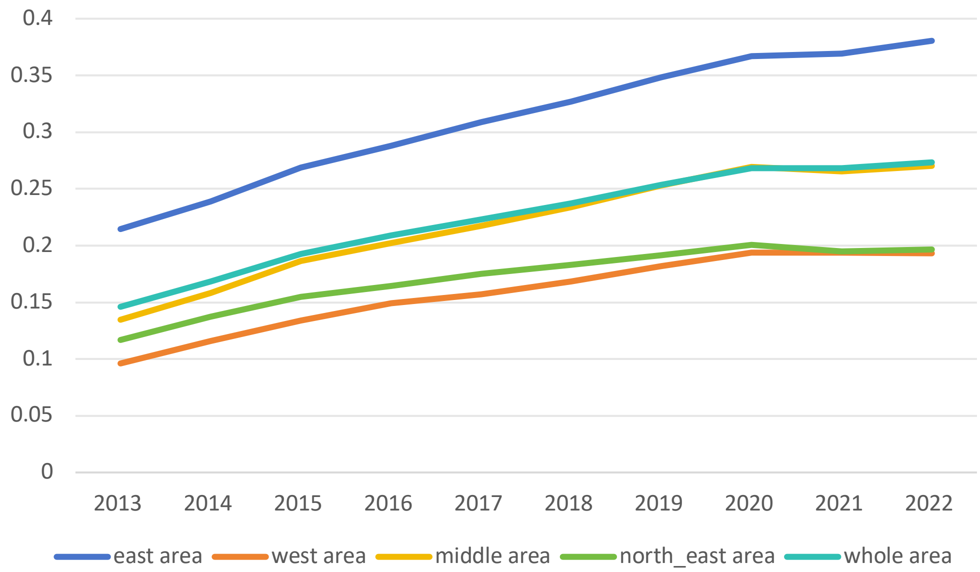


Figure 2 Regional Digital Economy Development Index (EWM)



4.3.2 Principal Component analysis (PCA)

This paper employs Principal Component Analysis (PCA) methodology proposed (Tong, 2002) to perform weighted integration of 22 observed variables. To mitigate potential biases caused by dimensional heterogeneity, all raw indicators experienced standardization preprocessing. Both Bartlett's sphericity test and the Kaiser-Meyer-Olkin (KMO) measure confirmed the data suitability for PCA implementation. The optimal number of principal components was determined by retaining the first 4 components that collectively accounted for over 80% (precise proportion 82.74%) of cumulative variance contribution.

Notably, initial composite scores exhibited negative values. To enhance metric comparability, this paper adopted the standardization approach developed by Han et al. (2014), applying linear transformation to rescale internet composite scores into the [0,1] interval, thereby constructing the Digital Economy Comprehensive Development Index. This standardized index serves as the second core explanatory variable in our analytical framework.

$$pca_i = \frac{g_i}{max(g_i) - min(g_i)} \cdot 0.4 + 0.6$$

Note: g_i is comprehensive score of province i; $max(g_i)$ and $min(g_i)$ are maximum and minimum comprehensive score respectively.

Figure 3 and figure 4 illustrate the calculated results of China's digital economy composite index by PCA.

Figure 3 Digital Economy Comprehensive Development Index of 31 Provincial-level Administrative Units (PCA)

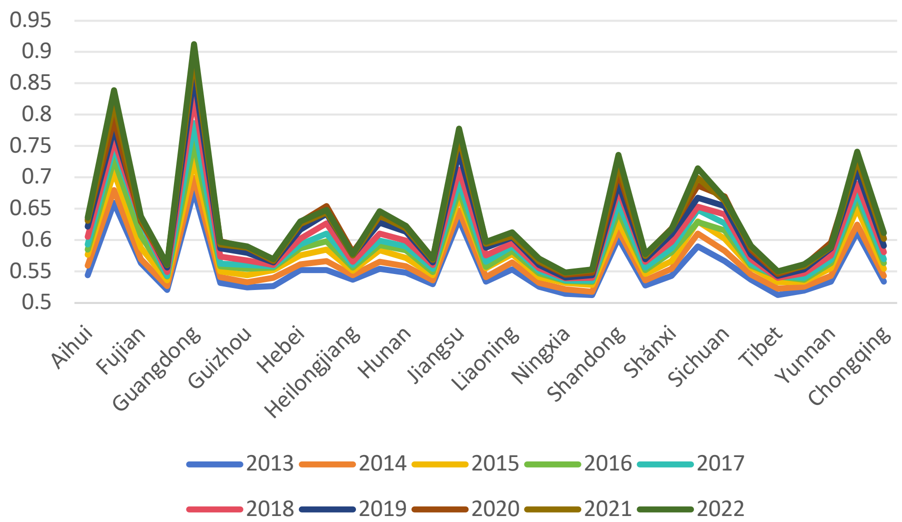
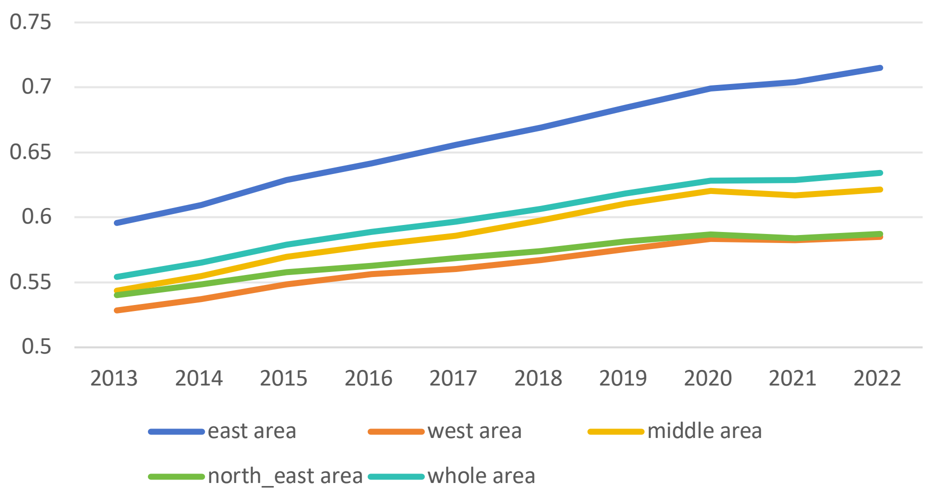


Figure 4 Regional Digital Economy Development Index (PCA)



The index of the development level of the digital economy obtained by the principal component analysis is highly consistent with the result calculated by the entropy weight method in terms of trend. Since PCA is not the core explanatory variable of the main regression, its data will not be described in detail here. However, its consistency with EWM provides a good basis for our subsequent robust test. Table 5 shows the compound annual growth rates and the average digital development indexes of four different regions.

Table 5 CAGR and average index in regions calculated by PCA.

	Eastern Area	Western Area	Middle Area	Northeastern Area	Whole Area
Index	0.660	0.562	0.590	0.569	0.600
CAGR	2.05%	1.14%	1.5%	0.93%	1.51%

5 Data Sources and Descriptive Statistics

The data employed in this study were obtained from the National Bureau of Statistics publications including China Statistical Yearbook, China Tertiary Industry Statistical Yearbook, China Education Statistical Yearbook, China Science and Technology Statistical Yearbook, and China Fixed Assets Investment Statistical Yearbook. Additional sources include provincial statistical communique on national economic and social development. Data on digital-real economy integration were sourced from Zhongli Information Network, while the digital inclusive finance index was derived from the Digital Finance Research Center of Peking University (Guo et al, 2023).

The data of variables used for empirical analysis in this paper are based on the data of 31 provinces and municipalities in China (excluding Macao, Hong Kong Special Administrative Regions and Taiwan Province), with the time span selected from 2013 to 2022. The descriptive statistics is shown in Table 6.

Table 6 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
low skill pct	310	21.09	12.05	2.1	71.232
mid skill pct	310	65.906	10.566	22.159	83.175
high skill pct	310	10.605	7.429	2.581	46.908
digital e	310	.224	.121	.052	.737
digital e2	310	.065	.08	.003	.543
digital p	310	.6	.071	.513	.913
digital p2	310	.365	.094	.263	.833
human capital	310	.022	.008	.006	.114
rd intensity	310	.018	.012	.002	.068
digitalization	310	.065	.057	.015	.29
gov intervention	310	.29	.203	.104	1.354
industry	310	.314	.085	.07	.51

6 Empirical Result

6.1 Benchmark regression analysis

The regression results in the second column of the table reveal that both the coefficients for the first order and second order terms of the core explanatory variable are statistically significant at the 5% level, indicating a nonlinear 'inverted U-shaped' relationship between digital economy development and low-skilled employment. This dynamic is characterized by an initial phase of employment promotion followed by a subsequent substitution effect: In the early stages of digital economy development, the expansion of e-commerce, logistics networks, and basic digital infrastructure creates new low-skilled positions such as warehouse workers, delivery personnel, and entry-level data clerks, which directly absorb labor from traditional sectors (e.g., manual retail and offline service industries) (Wu and Yang, 2022). However, as digital technologies like artificial intelligence (AI), robotic process automation (RPA), and smart manufacturing systems mature, these technologies increasingly replace routine and repetitive tasks historically performed by low-skilled workers. For example, automated sorting systems in logistics reduce the need for manual package handling, while AI-driven chatbots substitute basic customer service roles. This technological substitution leads to a decline in the proportion of low-skilled employment over time, consistent with the theoretical framework proposed by Wen et al. (2019), which emphasizes the dual effects of digitalization on labor markets through task reallocation. The empirical estimation results of the model are illustrated in Table 7.

The third and fourth columns of the table show that digital economy development exerts no significant impact on the proportion of medium-skilled employment. This neutral effect can be attributed to the simultaneous presence of substitution and creative effects within this skill category. On one hand, digitalization disrupts medium-skilled jobs involving standardized processes, such as routine administrative tasks, basic accounting, and production line quality control, which are increasingly automated through software systems or robotic technologies. On the other hand, new medium-skilled roles emerge to support digital infrastructure and technology adoption, including technical maintenance technicians, junior data analysts, and digital platform operators. These opposing forces—destruction of old roles and creation of new ones—offset each other, resulting in no net change in the share of medium-skilled employment within the digital economic framework. As noted by Zhao and Said (2023), this balance reflects the transitional nature of medium-skilled labor, which occupies a middle ground between the routine tasks vulnerable to automation and the complex cognitive tasks requiring high-skilled expertise.

In the fifth and sixth columns, the core explanatory variable's first-order coefficient is significantly negative at the 1% confidence level, while the second-order coefficient is significantly positive at the same level, indicating a "positive U-shaped" relationship with high-skilled employment. The underlying mechanism unfolds in two stages: During the early phase of digital technology upgrading, traditional high-skilled positions tied to pre-digital industrial structures --- such as senior engineers in legacy manufacturing sectors or traditional financial analysts --- may decline as organizations restructure to adopt digital tools, leading to a temporary reduction in high-skilled employment shares. However, as digital technologies become deeply integrated into production and service systems, the demand for advanced skills surges dramatically. New high-skilled roles emerge in specialized domains like algorithm development, big data analytics, AI system design, and digital strategy consulting, which require advanced technical and analytical capabilities. For instance, the proliferation of fintech and smart manufacturing has spurred hiring for data scientists and cybersecurity experts, driving a rebound in high-skilled employment. This long-term upward trend aligns with Jing and Su's (2019) observation that digital transformation ultimately increases demand for high-skilled labor after an initial adjustment period, as the economy shifts toward knowledge-intensive activities that rely on complex problem-solving and technological innovation.

Table 7 Benchmark regression for 3 kinds of human capital

	(1)	(2)	(3)	(4)	(5)	(6)
	low_skill_pct	lows_skill_pct	mid_skill_pct	mid_skill_pct	high_skill_pct	high_skill_pct
digital_e	11.943	47.925**	-6.607	-8.514	1.260	-35.204***
	(7.867)	(20.282)	(7.617)	(21.516)	(4.439)	(9.875)
digital_e2		-32.182**		1.706		32.613***
		(14.835)		(17.030)		(10.345)
human_capital	0.169	-0.362	-4.157	-4.129	14.627	15.166
	(9.026)	(8.457)	(14.120)	(14.229)	(14.014)	(12.421)
rd_intensity	-158.441*	-163.288**	108.516	108.773	-7.164	-2.252
	(79.402)	(75.875)	(98.387)	(98.578)	(139.690)	(130.917)
digitalization	-10.301	-10.029	9.427	9.412	-5.775**	-6.050**
	(8.179)	(7.808)	(8.707)	(8.709)	(2.658)	(2.673)
gov_intervention	10.344	10.928	-1.543	-1.574	-5.706	-6.298
	(8.534)	(7.399)	(6.561)	(6.481)	(3.428)	(3.792)
industry	6.993	11.611	-9.802	-10.047	2.088	-2.592
	(9.640)	(9.757)	(10.528)	(11.136)	(7.444)	(7.270)
_cons	17.742***	11.622*	73.819***	74.144***	7.784	13.986**
	(5.771)	(6.257)	(5.752)	(6.792)	(4.960)	(5.479)
Province-year	yes	yes	yes	yes	yes	yes
N	310	310	310	310	310	310
adj. R^2	0.300	0.319	0.721	0.720	0.775	0.789

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.2 Robustness test

To avoid the influence of proxy variable selection bias on the regression results, this paper adopts the alternative variable method for robustness tests. After replacing the digital economic development level originally calculated by the entropy weight method (EWM) with that calculated by the principal component analysis method (PCA) and conducting regression again, the replaced variables in the results (shown in Table 8) were still significantly consistent with the previous results, indicating that the results were robust.

Table 8 Substitution variable method for robustness test

	(1)	(2)	(3)	(4)	(5)	(6)
	low skill pct	lows skill pct	mid skill pct	mid skill pct	high skill pct	high skill pct
digital_p	13.279	155.941*	-15.053	-53.479	13.146	-131.572*
	(10.390)	(83.481)	(12.492)	(93.910)	(8.269)	(69.924)
digital_p2		-87.934*		23.685		89.201*
		(48.262)		(58.058)		(46.467)
human_capital	-0.875	2.740	-5.988	-6.962	18.187	14.520
	(8.963)	(9.008)	(13.343)	(12.434)	(12.951)	(11.985)
rd_intensity	-148.538*	-154.503*	127.045	128.652	-42.704	-36.653
	(81.954)	(80.314)	(90.836)	(91.927)	(132.422)	(124.730)
digitalization	-10.716	-9.711	8.816	8.545	-4.538*	-5.558**
	(8.267)	(7.886)	(8.591)	(8.478)	(2.558)	(2.530)
gov_intervention	10.522	10.762	-1.124	-1.188	-6.476*	-6.719*
	(8.841)	(8.197)	(6.614)	(6.506)	(3.455)	(3.526)
industry	5.584	9.996	-9.604	-10.792	2.825	-1.651
	(9.519)	(9.977)	(10.132)	(10.864)	(7.167)	(6.590)
_cons	12.456	-41.110	80.756***	95.184**	1.111	55.449**
	(7.884)	(32.528)	(9.387)	(36.156)	(6.156)	(25.881)
Province-year	yes	yes	yes	yes	yes	yes
N	310	310	310	310	310	310
adj. R^2	0.294	0.308	0.723	0.722	0.781	0.792

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.3 Endogeneity test

Although the benchmark regression model has controlled for some variables that affect the distribution structure of human capital, due to the data availability issue of some unobservable variables, empirical analysis may still face endogeneity bias, thereby affecting the validity of causal inference about the impact of the digital economy on the distribution of human capital. For this purpose, this paper adopts the instrumental variable method to identify and handle the endogeneity problem of the core explanatory variable.

In the process of selecting instrumental variables, this paper focuses on considering the dual exogenous characteristics of the spatial-temporal dimensions of the variables. Referring to the research design of Huang et al (2019), the terrain undulation degree was selected as the basic geographical variable, and improvements were made based on the following logic: Given that the degree of terrain undulation may cause potential interference effects by affecting the construction of digital infrastructure and the efficiency of information transmission, this paper draws on the processing methods of Ye et al (2021), takes the reciprocal of the degree of terrain undulation and multiplies it with the scale of Internet users lagging by one period to construct a combination of instrumental variables with dual characteristics of time and space. The test results in Table 9 show that the Kleibergen-Paap rk LM statistics of the regression of the three sub-samples all reject the unidentified null hypothesis at the 1% significance level, and the Cragg-Donald Wald F statistics all exceed the 10% significance threshold of 16.38. Since the number of instrumental variables is exactly equal to the number of endogenous variables, the model meets the exact identification conditions, so there is no need to conduct the over-identification test (Hansen test). The above statistics indicate that the instrumental variables have effectively passed the weak identification test and are statistically reasonable.

The two-stage least squares estimation results presented in the first column of Table 6 indicate that in the first stage of regression, the positive impact of instrumental variables on endogenous variables is significant at the 1% level; The regression results of the second stage show that the influence coefficient of the digital economy on the distribution of human capital remains highly consistent with the benchmark regression results, further verifying the robustness of the model estimation results.

Table 9 Endogeneity test by the two-stage least square method

	(1) digital_e	(2) low_skill_pct	(3) mid_skill_pct	(4) high_skill_pct
ivv	0.106***			
	(0.011)			
digital_e		20.833**	91.591***	-38.036***
		(9.657)	(18.989)	(8.805)
digital_e2		-20.162**	-113.719***	62.775***
		(8.362)	(18.226)	(9.148)
human_capital	0.007	20.213	35.221	41.188***
	(0.264)	(15.056)	(49.940)	(11.245)
rd_intensity	6.533***	-43.943	428.833***	1.346
	(0.683)	(47.455)	(136.994)	(71.960)
digitalization	0.023	-10.862***	29.142***	-1.425
	(0.030)	(2.800)	(4.007)	(1.503)
gov_intervention	0.006	10.248	-34.899***	-14.382***
	(0.058)	(7.578)	(7.435)	(3.119)
industry	-0.341***		-8.432	3.526
	(0.080)		(11.978)	(6.155)
_cons	-0.692***			
	(0.123)			
Underidentification test		(Kleibergen-Paap rk LM statistic): 63.342 Chi-sq (1) P-val = 0.0000	(Kleibergen-Paap rk LM statistic): 42.833 Chi-sq (1) P-val = 0.0000	(Kleibergen-Paap rk LM statistic): 42.833 Chi-sq (1) P-val = 0.0000
Weak identification test		(Cragg-Donald Wald F statistic): 701.773	(Cragg-Donald Wald F statistic): 344.833	(Cragg-Donald Wald F statistic): 344.833
		(Kleibergen-Paap rk Wald F statistic): 501.632	(Kleibergen-Paap rk Wald F statistic): 293.015	(Kleibergen-Paap rk Wald F statistic): 293.015
N	310	310	310	310
adj. R^2	0.728	0.053	0.183	0.624

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.4 Heterogeneity

Drawing on the literature's emphasis that regional digital economy development is strongly correlated with geographical location and economic endowments, this study classifies 31 provincial-level administrative units into inland and coastal provinces based on geographical proximity to the sea, conducting a sub-sample regression analysis to explore heterogeneous regional effects. The results, presented in Table 10, reveal distinct impacts across these two groups:

For inland provinces, the regression coefficient of the digital economy development level on low-skilled employment is positively significant at the 1% confidence level, indicating a strong positive effect. This can be attributed to their position in the early stages of digitalization, where technological applications are predominantly oriented toward labor-intensive scenarios rather than capital- or technology-intensive ones. Specifically, the rapid expansion of e-commerce platforms and on-demand service industries in inland regions has spurred demand for low-skilled jobs in logistics (e.g., warehouse sorting, delivery personnel for Alibaba's Cainiao Network), food delivery services (e.g., Meituan and Ele.me riders), and basic digital service support (e.g., data annotation clerks for AI training). These sectors rely heavily on human labor due to less advanced automation adoption compared to coastal areas, creating a short-term surge in low-skilled employment. Conversely, the coefficient for medium-skilled employment is significantly negative at the 1% level, suggesting a suppressive effect. This arises from digital technologies such as automated production lines, intelligent inventory management systems, and robotic process automation (RPA) replacing routine medium-skilled roles in traditional manufacturing and services. For example, in Hubei province's automotive industry, the introduction of robotic assembly lines in Dongfeng Motor's factories has reduced demand for medium-skilled technicians specializing in manual quality control and process supervision, illustrating how automation displaces standardized technical positions in inland industrial hubs (Zhao, 2017). The regression coefficient for high-skilled employment is statistically insignificant, reflecting a lack of robust demand for advanced roles. This gap is likely due to inland regions limited technological R&D capabilities and innovation ecosystems; without strong local tech enterprises or research institutions, the need for high-skilled jobs in AI development, big data analytics, or digital strategy remains under activated. Regarding control variables, R&D intensity exhibits a significant negative effect on low-skilled employment but a positive effect on medium-skilled labor. This dual impact suggests that increased R&D drives technological substitution: automated equipment reduces reliance on low-end manual labor, while simultaneously expanding tech-intensive industries that require skilled workers for equipment maintenance, software debugging, and process optimization, thereby creating new medium-skilled positions.

In coastal provinces, the influence coefficients for low- and medium-skilled employment are statistically insignificant, but high-skilled employment shows a significant positive effect at the 5% level. This discrepancy stems from coastal regions' more advanced digital economy maturity, where they have likely surpassed the inflection point of the nonlinear relationship observed in the full sample. Having transitioned from labor-intensive to knowledge-intensive stages, coastal areas—dominated by tech clusters in the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei region—leverage agglomeration effects to attract high-skilled talent through regional mobility. For instance, Shenzhen and Shanghai draw engineers and data scientists from inland provinces via higher salaries, better R&D resources, and access to global innovation networks, creating a self-reinforcing cycle of high-skilled employment growth. Control variable analysis reveals that government intervention significantly inhibits low-skilled employment at the 5% level in coastal areas, plausibly due to policies subsidizing enterprises to adopt automated equipment, which reduces demand for low-skilled labor. Meanwhile, government intervention exerts a strong positive effect on skilled labor at the 1% level, primarily through industrial upgrading policies such as "Created in China 2025," which prioritize advanced manufacturing, smart logistics, and digital services. These initiatives have stimulatedthe creation of high-skilled roles in precision engineering, IoT development, and fintech innovation, aligning with the coastal regions' role as hubs for technological frontier and policy-driven transformation.

Taken together, these regional disparities highlight the importance of tailoring digital policies to local development stages: inland areas require strategies to balance low-skilled job creation with gradual skill upgrading, while coastal regions need to sustain high-skilled talent attraction and foster innovation spillover to inland provinces.

Table 10 Regional Heterogenity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	inland_province			coastal_province		
	low	mid	high	low	mid	high
digital_e	43.158**	-36.492***	-5.867	0.352	14.147	6.473**
	(15.548)	(10.387)	(12.556)	(5.542)	(13.182)	(10.132)
human_capital	15.818	-15.246	12.062	-45.610*	52.298	-30.747
	(14.147)	(12.885)	(8.141)	(23.313)	(39.305)	(29.478)
rd_intensity	-412.878**	330.479**	196.178*	-100.959	-9.141	62.138
	(154.946)	(151.744)	(98.779)	(78.016)	(186.241)	(155.768)
digitalization	-2.935	5.584	-6.681*	-18.737***	14.026*	7.063
	(10.609)	(10.455)	(3.261)	(4.484)	(7.460)	(9.600)
gov_intervention	7.080	-1.082	-1.537	22.024**	-6.585	-36.610*
	(10.764)	(7.691)	(3.285)	(7.605)	(18.380)	(18.928)
industry	5.575	-11.520	10.857	-7.360	47.241	-21.422
	(12.524)	(14.626)	(9.725)	(14.342)	(46.438)	(38.774)
_cons	21.044**	72.917***	1.088	17.666**	55.609**	23.905
	(8.554)	(8.797)	(6.013)	(5.661)	(17.553)	(13.226)
province-year	yes	yes	yes	yes	yes	yes
N	210	210	210	100	100	100
adj. R^2	0.318	0.707	0.820	0.456	0.830	0.775

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7 Policy implication

The article points out that the digital economy has a positive U-shaped impact on high-skilled employment and an inverted U-shaped substitution effect on low-skilled employment. Moreover, the pulling effect of digital skills training on high-skilled employment is 2.3 times that of traditional training, and it is necessary to strengthen the institutional supply of 'industry-education integration' (Jia, 2023). Based on this, this article offers suggestions: Establish a lifelong digital learning account, led by the government and funded jointly by enterprises and individuals. Allow workers to use the account balance to purchase online digital courses, which can help to build a framework for enhancing the digital literacy of all citizens, narrow the educational gap among the employed labor force, and optimize the allocation of human resources.

The robustness test of the paper points out that the eastern coastal areas have entered the positive U-shaped upward stage of the high-skill stage, while the inland areas are still on the left side of the inverted U-shaped stage of low-skill employment. Relevant literature points out that through the spatial Durbin model, it is found that the employment effect of the digital economy in the central and western regions depends on the technology spillover in the east. It is suggested to construct 'targeted support for the digital economy' (Lu & Zhou, 2023). Based on this, it is proposed to build a 'Digital Talent Port' in the eastern region, pilot a 'Special Cooperation Zone for Digital Economy', allow overseas digital talents to work visa-free with digital technology, and establish a mechanism for the return of overseas digital talents by referring to Singapore's 'Global Alumni Network Program'. Focus on developing employment in cutting-edge fields such as blockchain and the metaverse. In the inland areas, 'Eastern Digital Enterprise Collaboration Parks' will be established in hub cities such as Zhengzhou and Chengdu. Eastern enterprises will provide technology, while the governments of the central and western regions will offer venues and labor training subsidies. These parks will develop adaptable industries such as data annotation and intelligent hardware assembly and leverage the spillover effects of the eastern digital economy to improve employees' education level in the central region.

8 Limitation and Future Research

Although this study revealed the macro employment effect of the digital economy through a panel model, due to the limitations of data availability, it failed to capture the impact of breakthroughs in generative AI technology on content creation positions after 2023. Furthermore, the study did not incorporate the moderating effect of institutional variables (such as the progress of household registration reform), which might underestimate the impact of policy synergy on the optimization of the regional employment structure. Future research can combine enterprise employment data with natural experimental methods (such as the establishment of the 'National Digital Economy Innovation and Development Pilot Zone') to further identify causal effects.

9 Conclusion

The rapid advancement of China's digital economy has brought profound transformations in the labor employment structure, characterized by distinct nonlinear dynamics, and pronounced regional disparities. Through empirical analysis, this study identifies a dualistic impact mechanism: the digital economy exhibits an inverted U-shaped relationship with low-skilled employment, whereby initial job creation in sectors such as logistics, basic data entry, and digital infrastructure construction --- driven by the expansion of e-commerce platforms and the build-out of 4G/5G networks --- is gradually replaced by automation and AI-driven technological substitution. For instance, the increase of robotic process automation (RPA) in administrative tasks and smart storage systems in logistics has reduced demand for routine manual labor, reflecting the transition from employment promotion to displacement as digital technologies mature. In contrast, high-skilled employment demonstrates a positive U-shaped trajectory: early-stage digitalization disrupts traditional high-skilled roles tied to pre-digital industrial frameworks (e.g., conventional manufacturing engineering and analog financial analysis), but as digital integration deepens --- especially in areas like cloud computing, big data analytics, and AI development --- the demand for advanced positions such as algorithm engineers, cybersecurity specialists, and digital transformation consultants surges, creating a long-term upward momentum. Medium-skilled employment remains relatively stable due to the offsetting effects of automation replacing standardized process jobs (e.g., routine quality control in production lines) and the emergence of new technical maintenance and platform operation roles that require moderate digital literacy, leading to no significant net change in their employment share.

Regionally, these effects manifest in starkly different patterns. Eastern coastal regions --- characterized by mature digital ecosystems in clusters like the Yangtze River Delta and Pearl River Delta, which benefit from cluster effects in high-tech industries, robust venture capital networks, and high talent mobility --- have already entered the upward phase of the high-skilled employment curve. Here, digital economy development is dominated by knowledge-intensive activities, such as innovation and smart manufacturing R&D, which attract and retain high-skilled workers. In contrast, inland provinces and less developed regions are largely in the early stages of digitalization, where growth primarily drives low-skilled job creation in logistics (e.g., delivery services for e-commerce platforms) and basic digital services (e.g., customer support for online platforms), while simultaneously suppressing medium-skilled employment through the automation of routine tasks in sectors like traditional retail and administrative services. This spatial divide highlights the unequal distribution of 'digital dividends', with eastern regions capitalizing on technological spillovers and innovation ecosystems, whereas inland areas face challenges such as talent outflow, inadequate digital infrastructure, and structural vulnerabilities from rapid automation without similar skill upgrading.

The findings yield critical policy implications that emphasize the need for adaptive institutional frameworks to align digital advancement with inclusive employment growth. Key strategies include: ①establishing national lifelong learning systems focused on digital literacy and skills training --- such as subsidized online courses in data analysis and AI basics --- to bridge the growing skill gap between low/medium-skilled workers and emerging digital roles; ②fostering cross-regional collaboration through initiatives like Digital Talent Exchange Hubs in eastern tech hubs, which facilitate talent mobility and knowledge transfer to inland regions via mentorship programs and joint R&D projects; ③creating Eastern-Inland Digital Industry Cooperation Parks in central and western cities, where eastern digital enterprises set up regional branches or innovation centers, channeling technology, capital, and management expertise into localized job creation --- particularly in medium-skilled technical support and digital service sectors. However, the study acknowledges limitations, including the exclusion of post-2023 generative AI impacts (e.g., large language models transforming content creation and customer service roles) and the absence of in-depth institutional variables (e.g., regional digital policy effectiveness and labor market regulations). These gaps underscore the need for future research to incorporate firm-level microdata, natural experiments in digital economy pilot zones, and longitudinal analyses of skill-biased technological change. Ultimately, proactive policy design must balance the disruptive forces of digitalization with equitable investments in human capital and regional coordination, ensuring that China's digital transformation fosters sustainable, inclusive employment structures across all geographic and skill-based segments of the labor market.

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