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FACTORS INFLUENCING THE SPATIAL LABOR EMPLOYMENT STRUCTURE IN THE DIGITAL ECONOMY: BASED ON A SPATIAL PANEL MODEL

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Abstract: In the context of the rapid development of the digital economy, global labor markets and employment structures are undergoing profound transformations. This study focuses on the interactive relationship between the digital economy and labor employment structures, exploring the impact of digital economy development on the labor employment structure across different regions in China. By employing global principal component analysis (GPCA) and the global entropy method, this study quantifies the level of digital economy development in various regions. Panel models and spatial panel models are utilized to analyze the changing characteristics of labor employment structures during the digital transformation process across regions. The quantification of digital economy levels across provinces reveals that the eastern regions exhibit the highest levels of digital economy development, followed by the central and western regions. To account for spatial differences, this study innovatively applies spatial panel models and uses the Akaike Information Criterion (AIC) to compare models, ultimately selecting the spatial Durbin model and spatial lag model for regression analysis. The findings indicate that the digital economy exerts differential impacts on labor employment. On the one hand, the digital economy creates opportunities for skill training for workers with low to medium educational attainment, with the level of digital economy development having a significant positive effect on the employment scale of these workers. This suggests that economic expansion and agglomeration effects in high-density regions remain key drivers for absorbing low-skilled labor. On the other hand, higher levels of digital economy development, economic growth, and population agglomeration effects promote the concentration of highly educated workers, though the effect is less pronounced compared to that for workers with lower educational attainment. Based on these findings, this study proposes several policy recommendations. First, it is necessary to strengthen inter-regional coordination of digital infrastructure and facilitate the gradient transfer of industries to leverage population agglomeration effects and expand employment channels for low- to medium-skilled workers. Second, policies should be refined to attract and nurture high-skilled talent by promoting industry-academia-research integration and optimizing urban ecosystems to enhance the absorption capacity for high-end factors. Additionally, attention should be paid to the structural impacts of educational investment, foreign trade policies, and urbanization processes on employment structures, using spatial governance tools to mitigate negative spillovers in regional labor markets. Future research could incorporate micro-level indicators, such as technology penetration rates and enterprise digital maturity, to further explore the heterogeneity of underlying mechanisms.
Keywords: Digital economy development level; Labor employment structure; Global principal component analysis; Global entropy method; Spatial panel model

1 INTRODUCTION

1.1 Rationale and Significance of the Study

1.1.1 Purpose of the study

With the rapid development of new-generation information technologies such as artificial intelligence, cloud computing, and blockchain, the global digital economy has entered a new phase of deep integration and innovative breakthroughs. According to the latest "Global Digital Economy White Paper (2024)" released by the China Academy of Information and Communications Technology, China's digital economy scale exceeded 60 trillion yuan in 2023, accounting for more than 41% of GDP, becoming a core engine driving high-quality economic development. At the same time, the widespread penetration of digital technologies is profoundly reshaping the structure and form of the labor market: on one hand, new employment forms such as platform economy and gig economy continue to emerge; on the other hand, traditional positions face substitution pressures from automation and intelligence, leading to significant differentiation in skill structures and regional employment patterns.

In this context, exploring the spatial heterogeneity impacts of the digital economy on labor employment structures not only helps understand the interaction mechanisms between technological changes and the labor market but also provides empirical evidence for formulating regional coordinated development strategies and talent policies. This study, based on provincial panel data from China spanning 2013–2022, constructs a multidimensional digital economy evaluation system and employs spatial panel models to systematically analyze the impacts of digital economy

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development on employment for workers with different educational levels, as well as its spatial spillover effects. The aim is to provide theoretical support and policy insights for promoting inclusive digital economy development.

1.1.2 Theoretical significance

Investigating the impact of the digital economy on the employment structures of workers with different educational levels holds multifaceted theoretical importance. First, this research contributes to a deeper understanding of the dynamic evolution mechanisms of labor markets. In the context of the rapidly advancing wave of digitalization, educational attainment serves as a critical variable, significantly influencing workers' access to employment opportunities and their adaptability to market changes. Through this study, we can precisely discern the pivotal role of education in the digital economy era, thereby gaining a clearer understanding of the complex dynamics of labor markets.

Second, this study provides an in-depth analysis of the root causes and underlying mechanisms of employment inequality among groups with different educational levels during the digital economy's development. This not only offers robust empirical evidence for related economic theories, enabling a more thorough understanding of the complex interplay between education and employment, but also enriches and refines the theoretical framework of economics.

Furthermore, the research findings provide strong theoretical support for optimizing educational policies and reforming labor markets. When policymakers address the challenges posed by the digital economy, they can rely on these scientifically grounded theoretical insights to make rational and informed decisions. This facilitates the coordinated development of education and labor markets, ensuring better alignment with the demands of the digital economy era.

1.1.3 Practical significance

The findings of this study hold significant scientific value for guiding governments and relevant institutions in formulating employment promotion policies, particularly in addressing employment inequalities arising from the development of the digital economy. Based on this research, policies can be more precisely targeted toward workers with lower educational attainment, promoting skill training programs and creating suitable job opportunities to optimize their employment structure.

The study's conclusions also provide strong momentum for the deep reform of educational systems. By highlighting the critical role of vocational education and skill training in the digital economy era, the education system can be adjusted to meet the diverse demands of digital economic development. This will enable more workers to acquire essential skills, significantly enhancing their employability and market competitiveness, and achieving an effective alignment between labor quality and market demands.

At the enterprise level, the study's findings offer valuable references for recruitment and human resource management. Enterprises can optimize talent selection processes and develop tailored training strategies for employees with different educational backgrounds based on these insights. This not only improves the overall efficiency of human resource allocation but also enhances employee satisfaction, fostering a more harmonious and efficient workplace and achieving mutual benefits for enterprises and employees.

From a broader societal perspective, the research findings help identify and address social stratification and employment inequality issues that may be exacerbated during the digital economy's development. By encouraging society to adopt effective measures, this study promotes equal participation in economic activities among workers with diverse educational backgrounds, laying a solid foundation for building a harmonious and stable social environment.

Moreover, actively disseminating the research findings can significantly enhance public understanding of the intrinsic relationship between the digital economy and educational attainment, further raising societal awareness of the importance of education. This will foster a positive social atmosphere that values and supports educational investment, providing continuous talent and intellectual support for the sustained development of the economy and society.

2 LITERATURE REVIEW

2.1 Conceptual Definitions of the Digital Economy

The concept of the digital economy has evolved considerably in both domestic and international scholarship. Early work emphasized information and communication technologies (ICT) as the core drivers of digital transformation. Wu and Wang (2021), for example, moved beyond a narrow ICT focus to define the digital economy as a systemic process whereby digital technologies penetrate and reshape traditional industries[1]. Later, Chen (2022) emphasized data as a fundamental factor of production, framing the digital economy as economic activity driven by digital information and platform-enabled innovation[2]. Similarly, Jia (2023) highlighted the formation of digital ecosystems in which data elements interact with traditional factors of production. Parallel to these perspectives, international organizations such as the OECD have advanced operational definitions grounded in statistical frameworks[3]. Ahmad and Riarsky (2018), for instance, described the digital economy in terms of "digital delivery," while Ahmad et al. (2017) proposed a satellite account framework that distinguishes digital-specific, integrated, and enabling activities[4]. Together, these studies reflect a trajectory from technology-centered views toward ecosystemic and measurable frameworks that facilitate both theoretical refinement and cross-country comparability[4-5].

2.2 Measurement and Evaluation Methods

A second body of literature focuses on the measurement of digital economy development levels. In China, Li and Liu (2021) constructed a three-dimensional evaluation framework encompassing digital industries, application scenarios, and infrastructure, applying the entropy weight method for dynamic weighting[6]. Ma and Zhu (2022) extended this to four dimensions by incorporating industry integration and sustainability indicators, thereby enriching the assessment of structural and long-term effects[7]. Internationally, organizations such as the OECD have promoted standardization through indices such as the Digital Economy Index (DEI), which covers six dimensions including infrastructure and skill reserves and has been applied in more than 100 countries. Academic studies have also introduced frontier technologies for monitoring, such as blockchain-based statistical models for digital services trade and real-time measurement of platform activity using web crawlers. Compared with domestic work that emphasizes multi-dimensional adaptability, international studies highlight comparability and technological innovation. These two strands of research are complementary, offering opportunities to integrate methodological rigor with innovative monitoring tools.

2.3 Impacts on the Labor Market

The employment effects of the digital economy constitute another major research theme. Domestic studies generally adopt a systemic approach, emphasizing employment scale, structure, and quality. Jia (2023) identified an asymmetric equilibrium between job substitution and job creation, suggesting that productivity gains from digitalization expand employment overall. Yan (2022) found a "matching upgrade effect," with the elasticity of high-quality job growth reaching 1.8[8]. Wu (2023) documented a "dual polarization" pattern, with high-skill jobs growing 12.3 percentage points faster than low-skill jobs[9]. Su et al. (2024) further quantified this skill-biased process, showing that a one-unit increase in digital economy development raises the share of high-skill labor by 0.35 units. By contrast, much of the international literature adopts a case-based orientation[10]. Autor et al. (2020) demonstrated that a 10% increase in industrial-robot penetration in U.S. manufacturing reduces employment by 1.7%[11]. Bessen (2019) showed that e-commerce reduced retail jobs by 14% but increased logistics employment by 23%, illustrating sectoral reallocation[12]. Theoretically, Acemoglu (2021) proposed a productivity–substitution model to explain labor-market impacts, though a comprehensive framework for regional disparities remains underdeveloped compared with domestic research[13].

2.4 Synthesis and Research Gap

Taken together, the literature demonstrates a convergence around the transformative role of the digital economy, while revealing several important contrasts. First, definitions have expanded from technology-centric views to systemic and statistical frameworks, with domestic work emphasizing ecosystem integration and international organizations stressing measurement standards. Second, in terms of measurement, Chinese scholars highlight multidimensional adaptability through entropy and principal component methods, while international work leads in global comparability and frontier monitoring techniques. Third, employment studies show that domestic research contributes systematic frameworks such as "scale–structure–quality," whereas international research provides rich but fragmented sectoral case evidence. The gap lies in integrating these approaches: future work can combine multidimensional indices with high-frequency monitoring technologies to analyze the heterogeneous labor-market effects of digitalization. This study contributes to this literature by applying a spatial panel framework to assess the differentiated impacts of the digital economy on workers with varying educational levels, thereby extending both the methodological toolkit and the substantive understanding of employment restructuring.

3 RESEARCH FRAMEWORK

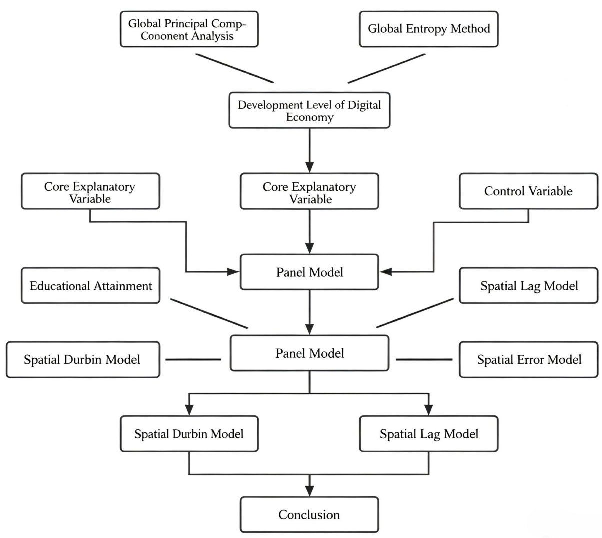

Figure 1 Research Process Flowchart

This study first conducts a comprehensive evaluation of the digital economy development levels across 31 provincial-level administrative regions in China. Subsequently, based on the digital economy development levels of each province, it analyzes the impact of the digital economy on labor employment structures. Initially, panel models are employed for the analysis. To account for spatial factors, four spatial panel models are comprehensively compared: the spatial Durbin model, spatial Durbin error model, spatial lag model, and spatial error model. Ultimately, the spatial Durbin model and spatial error model are selected for the analysis to derive conclusions. The specific process is illustrated in Figure 1.

4 MEASUREMENT OF DIGITAL ECONOMY LEVELS ACROSS CHINESE PROVINCES

4.1 Selection of Digital Economy Indicators

This study comprehensively integrates cutting-edge domestic and international literature, adhering to the principles of scientific rigor, systematicity, comparability, and practicality to meticulously construct an evaluation index system for digital economy levels, as detailed in Table 1. The system takes digital inputs, digital outputs, and digital infrastructure construction as entry points, encompassing ten key dimensions for in-depth analysis:

Proportion of Information Industry Personnel: This indicator directly reflects the scale of human resource investment in the digital economy, with its trends accurately indicating the direction of industry development and talent demand; R&D Expenditure of Large-Scale Enterprises: An increase in R&D funding typically signifies greater corporate investment in core technologies, providing foundational technical support for digital transformation (e.g., industrial Internet, AI, and big data analytics); Digital Inclusive Finance Index: This index effectively and precisely measures the penetration of financial services empowered by digital technologies; Number of Artificial Intelligence Enterprises: This directly reflects the development of enterprises in cutting-edge digital economy sectors, where prosperity inevitably generates numerous new job opportunities, profoundly impacting the employment structure of workers with different educational levels; Number of Patent Applications: This vividly demonstrates innovation vitality in the digital economy, with sustained innovation outcomes often fostering new industry models and creating novel employment opportunities; Per Capita Telecommunications Revenue: As a key indicator of digital information transmission activity, this reflects the vibrancy of the digital communications sector, closely tied to digital economy development; Mobile Phone Penetration Rate, Internet Broadband Access Rate, and Mobile Phone Users per 100 People: These core indicators of digital infrastructure determine the speed and coverage of information transmission, serving as the hardware foundation for the robust development of the digital economy and playing a critical role in supporting industrial digital transformation and employment structure optimization; Mobile Phone Users per 100 People: This fully reflects the penetration of mobile digital devices among the general population, profoundly influencing the participation and application scope of the digital economy at the grassroots level, and closely relating to employment scenarios and opportunities for workers with varying educational levels.

Through comprehensive analysis of these indicators, this study provides a thorough and insightful understanding of the current state of digital economy development and its underlying mechanisms affecting labor employment structures, laying a solid data and theoretical foundation for subsequent research and policy formulation.

Table 1 Digital Economy Development Level Index System

Primary Indicator	Secondary Indicator
Digital Inputs	Proportion of Information Industry Personnel
	R&D Expenditure of Large-Scale Enterprises
	Digital Inclusive Finance Index
Digital Outputs	Number of Artificial Intelligence Enterprises
	Number of Patent Applications
	Per Capita Telecommunications Revenue
Digital Infrastructure	Internet Broadband Access Users/Population
	Mobile Phone Penetration Rate
	Mobile Phone Users per 100 People

4.1.1 Data sources

In this chapter, considering the representativeness and availability of data, the study selects data from 31 provinces and autonomous regions in China from 2013 to 2022 as the analysis sample. The SPSS analysis tool is employed to quantify the digital economy levels of these regions. Data are primarily sourced from the annual statistical yearbooks published by the National Bureau of Statistics, provincial statistical yearbooks, and digital economy-related data provided by the CSMAR database.

4.1.2 Measurement methods

Table 2 compares the advantages and limitations of different weight determination methods. After comprehensively reviewing domestic and international studies on weight determination, it was found that most researchers prefer objective weighting techniques, with the entropy weight method being the most widely used. However, relying solely on objective weighting methods may overlook subjective factors such as expert knowledge and experience, leading to weights that do not fully reflect reality. Therefore, this study adopts a combined weighting strategy, integrating global principal component analysis (GPCA) and the global entropy method by taking the arithmetic mean of their weights to enhance the reliability and validity of the evaluation results.

Table 2 Comparison of Advantages and Disadvantages of Weight Determination Methods

Method	Advantages	Disadvantages
Subjective Weighting		
AHP Method	Structures multiple factors and quantifies subjective opinions, aiding comprehensive and rational decision-making.	Susceptible to subjectivity and sensitivity to initial parameters, leading to bias and uncertainty.
Delphi Method	Effectively collects and integrates diverse opinions through iterative feedback and anonymous voting, reducing bias.	
Objective Weighting		
Principal Component Analysis	Reduces data dimensionality while retaining critical information, enhancing interpretability and visualization.	Highly dependent on input data quality, requires appropriate parameter selection, and demands expertise for correct interpretation.
Entropy Weight Method	Objectively evaluates the importance of indicators and provides effective weight allocation, minimizing subjective influences.	
Machine Learning	Handles large-scale complex data, identifies patterns, and offers adaptability and flexibility.	

4.1.3 Weight determination using global principal component analysis

Prior to conducting principal component analysis, a Kaiser-Meyer-Olkin (KMO) test is performed. As shown in Table 3, the KMO value is 0.78, close to 1, indicating that the data are highly suitable for principal component analysis. The KMO test standards are presented in Table 4.

Table 3 KMO Test Results

Dimensionless Matrix	KMO	P-value
Z	0.78	0

Table 4 KMO Test Standards

KMO Value Range	Suitability
Above 0.9	Highly Suitable
0.8–0.9	Very Suitable
0.7–0.8	Suitable
0.6–0.7	Marginally Suitable
Below 0.6	Highly Unsuitable

Following principal component analysis criteria, components with an explanatory rate exceeding 80% are selected as principal components to ensure retention of core data information. Based on this standard, three principal components are extracted, as shown in Table 5, meeting the requirement of retaining most of the original data information.

Table 5 Principal Component Analysis Results

Component	Initial Eigenvalue	Variance (%)	Cumulative (%)
1	4.89	54.28	54.28
2	1.68	18.63	72.91
3	0.89	9.93	82.83
4	0.66	7.36	90.2

Based on the principal component analysis results, the weights of each indicator for the digital economy across provinces from 2013 to 2022 are calculated, as shown in Table 6.

Table 6 Indicator Weight Index

Primary Indicator	Secondary Indicator	Weight Coefficient	Primary Indicator Weight
Digital Inputs	Proportion of Information Industry Personnel	6.51%	28.01%
	R&D Expenditure of Large-Scale Enterprises	0.22%	
	Digital Inclusive Finance Index	21.28%	
Digital Outputs	Number of Artificial Intelligence Enterprises	-4.83%	19.01%
	Number of Patent Applications	-5.06%	
	Per Capita Telecommunications Revenue	28.90%	
Digital Infrastructure	Internet Broadband Access Users/Population	8.16%	52.97%
	Mobile Phone Penetration Rate	20.03%	
	Mobile Phone Users per 100 People	24.78%	

4.1.4 Weight determination using global entropy method

Based on the standardized data Zij, the information entropy values (ej) of digital economy development indicators across provinces from 2013 to 2022 are calculated. These entropy values are used to determine the information utility values, which are then employed to compute the weight coefficients for each indicator through Equations (1) to (4). The resulting weight coefficients are presented in Table 7.

$$\mathrm{e}_j = -k\sum_{n=1}^{n}\sum_{i=1}^{b} z_{ij} \ln z_{ij}^{\ n} \tag{1}$$

$$k = \frac{1}{\ln aN} \tag{2}$$

$$d_j = 1 - e_j \tag{3}$$

$$wj = \frac{1-e_j}{\sum_{j=1}^{n}(1-e_j)} \tag{4}$$

Table 7 Indicator Weights Using Global Entropy Method

Indicator	Information Entropy Value	Information Utility Value	Weight (%)
Proportion of Information Industry Personnel	0.9	0.1	13.3
R&D Expenditure of Large-Scale Enterprises	0.89	0.11	14.84
Digital Inclusive Finance Index	0.98	0.02	2.93
Number of Artificial Intelligence Enterprises	0.83	0.17	23.03
Number of Patent Applications	0.86	0.14	18.44
Per Capita Telecommunications Revenue	0.89	0.11	14.65
Internet Broadband Access Users/Population	0.94	0.06	7.79
Mobile Phone Penetration Rate	0.98	0.02	2.7
Mobile Phone Users per 100 People	0.98	0.02	2.32

4.1.5 Results of digital economy level measurement across provinces

The comprehensive evaluation is calculated using the formula:

$$\mathrm{S}=\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{x}_i \bullet w_i \tag{5}$$

where x_i represents each indicator, and w_i denotes the comprehensive weight of each indicator. The results are presented in Figures 2 and 3. The figures indicate that, overall, the digital economy levels across provinces are gradually increasing, with eastern regions leading, followed by central and western regions. A slight decline is observed in 2021, which aligns with China's national conditions, confirming the effectiveness and practicality of the methods used in this study.

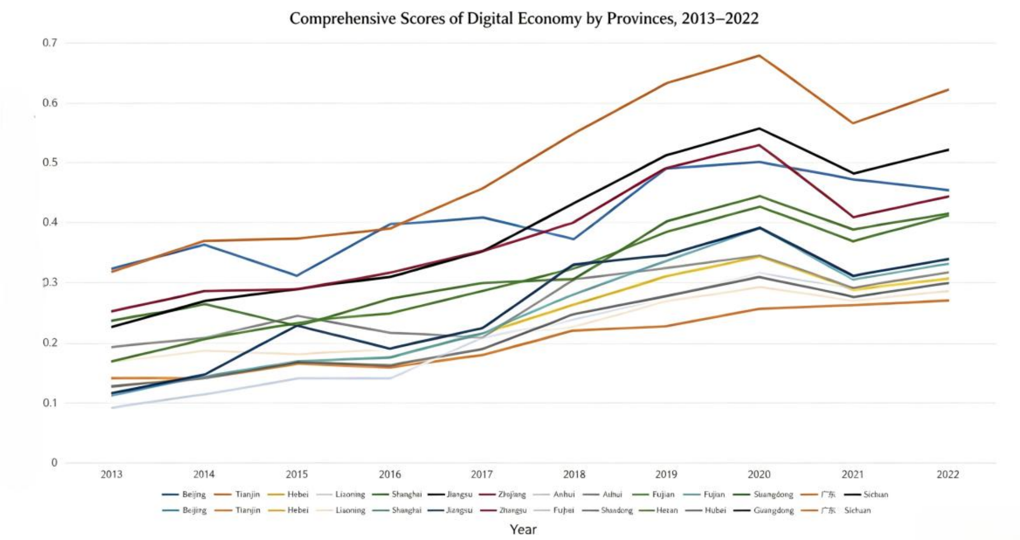

Figure 2 Comprehensive Digital Economy Scores Across Provinces (2013–2022)

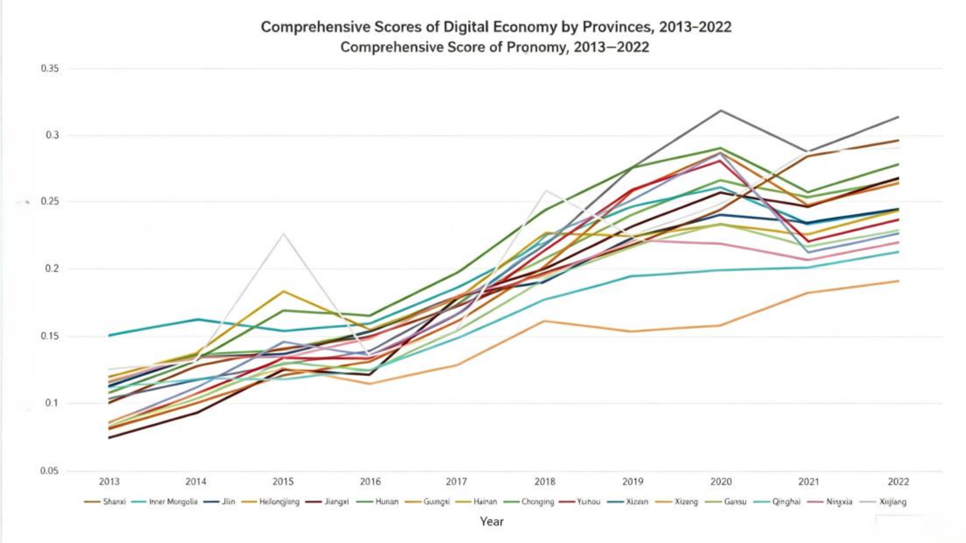

Figure 3 Comprehensive Digital Economy Scores Across Provinces (Continued)

The results from principal component analysis and the global entropy method show slight differences. To integrate the advantages of both methods, this study takes the arithmetic mean of their comprehensive scores as the final evaluation score for the digital economy. The arithmetic mean of the comprehensive scores is used to rank the digital economy levels across provinces, as shown in Table 8.

Table 8 Ranking of Digital Economy Development Levels Across Provinces

Province	Comprehensive Score	Ranking
Guangdong	0.47	1
Beijing	0.39	2
Jiangsu	0.37	3
Zhejiang	0.36	4
Shanghai	0.31	5
Shandong	0.29	6
Fujian	0.25	7
Sichuan	0.24	8
Henan	0.23	9
Hebei	0.22	10
Liaoning	0.22	11
Shaanxi	0.21	12
Hubei	0.21	13
Anhui	0.2	14
Tianjin	0.2	15
Chongqing	0.2	16
Hunan	0.2	17
Xinjiang	0.19	18
Inner Mongolia	0.19	19
Shanxi	0.18	20
Heilongjiang	0.18	21
Hainan	0.18	22
Jilin	0.17	23
Guangxi	0.17	24
Yunnan	0.17	25
Guizhou	0.17	26
Jiangxi	0.17	27
Ningxia	0.17	28
Gansu	0.15	29
Qinghai	0.15	30
Xizang	0.13	31

The ranking reveals that coastal eastern provinces significantly lead in digital economy development, occupying top positions, while central and western regions lag relatively behind. This conclusion aligns with China's current developmental context and is highly representative. The regional disparities in digital economy levels reflect the combined effects of economic foundations, resource endowments, and policy orientations. These findings provide a critical basis for subsequent analyses of the differential impacts of digital economy development on employment structures, facilitating coordinated and balanced development of the digital economy across regions.

4.2 Implications for Employment Structure Analysis

Studying the differential impacts of digital economy development on employment structures holds significant theoretical and practical value. With the rapid penetration of digital technologies and the rise of platform economies, traditional industry boundaries are continuously reshaped, giving rise to new employment forms and occupational types. This technology-driven economic transformation not only alters the demand structure of labor markets but also reshapes employment patterns across regions, industries, and population groups through technological substitution and creation effects. Investigating these differential impacts helps reveal the dynamic evolution of labor markets during digital transformation, identifying structural contradictions in skill adaptation and occupational transitions among different groups. This provides empirical evidence for formulating differentiated employment promotion policies and optimizing vocational education resource allocation, while also offering theoretical support for mitigating the risk of employment polarization caused by technological changes and promoting inclusive digital economy development.

5 ANALYSIS OF FACTORS INFLUENCING THE LABOR EMPLOYMENT STRUCTURE IN THE DIGITAL ECONOMY

5.1 Construction of Econometric Models

Building on the previous chapter, this section establishes the following regression model to identify the impact of digital economy development levels on China's labor employment structure:

$$Y = AX_1 + BX_2 + CX_3 + DX_4 + EX_5 + \varepsilon \tag{6}$$

where Y represents different skill levels of workers, X_1 is the core explanatory variable, X_2 - X_5 are control variables, ε is the random error term, and A - E are the coefficients of the respective variables.

5.2 Data Sources and Indicator Selection

This chapter employs Chinese provincial panel data for econometric analysis, covering the period from 2013 to 2022. Data are sourced from the following: China Statistical Yearbook and China Labor Statistical Yearbook (2013–2022), the CSMAR database, and the China Industrial Economy website.

5.2.1 Dependent variable: Educational attainment of the labor force

Drawing on existing literature and data availability, this study uses the proportion of employed individuals with different educational attainment levels relative to the total employed population to measure the labor employment structure. Education, as a core component of human capital, directly reflects the selection mechanisms of technological change on the labor force, providing clear targets for policy interventions. While multidimensional analysis incorporating industry and occupational indicators is necessary, the stratification of educational levels is irreplaceable in revealing the "skill-job" matching contradictions in the labor market under the digital economy. The specific classification rules are presented in Table 9.

Table 9 Educational Attainment Levels of the Labor Force

Educational Level	Category
Primary School or Below	Low to Medium Education
Junior High School	
Senior High School	
Junior College	Higher Education
Undergraduate Degree	

This study categorizes educational attainment into five levels: the proportion of workers with primary school education or below, junior high school, senior high school, junior college, and undergraduate degrees. This classification enables the effective identification of the impact of digital economy development on the employment of workers with different educational levels. In regression analysis, the econometric model is designed to accurately capture the dynamic changes in each educational group within the labor market, mitigating potential estimation biases from artificial categorizations. This classification standard facilitates a clear analysis of the employment conditions of various educational groups in the digital economy, providing robust support for subsequent empirical analysis and policy recommendations.

5.2.2 Core explanatory variable: Digital economy development level

Currently, there is no unified standard for measuring digital economy development levels. Multiple international organizations, such as the European Union, the U.S. Department of Commerce Digital Economy Advisory Committee, the OECD, the World Economic Forum, and the International Telecommunication Union, have published their respective digital economy evaluation systems. Similarly, prominent Chinese research institutions, including the China Academy of Information and Communications Technology, the Shanghai Academy of Social Sciences, Tencent Research Institute, and New H3C Group, have developed and released digital economy development indicators in recent years. Notably, these indicator systems typically rely on historical data and internal datasets held by these institutions. As demonstrated in the previous chapter, digital economy levels across Chinese provinces exhibit a general upward trend, with particularly rapid growth between 2014 and 2020. Regionally, eastern coastal provinces (e.g., Shanghai, Zhejiang, Jiangsu, Guangdong, and Fujian) lead in digital economy development, followed by central regions, while western regions lag behind. These observations align with China's current developmental context, further validating the rationality of the digital economy measurement system constructed in this study.

5.2.3 Control variables

Referring to existing literature, this study controls for several factors that may influence regression results:

Economic Development Level: Represented by provincial GDP, higher GDP typically indicates higher living standards and economic development, reflecting regional productivity and resource allocation efficiency.

Education Investment: Measured by national fiscal expenditure on education, which includes funding for basic education, higher education, and vocational education. This indicator reflects the emphasis and financial support of national and local governments on education development.

Foreign Trade Level: Represented by the total import and export value of the region where operating entities are located. This indicator reflects the region's economic connections with external markets and its competitiveness in international trade.

Urbanization Level: Proxied by the ratio of urban population to total population in each province, this indicator reflects the depth and breadth of urbanization processes. Higher urbanization levels typically indicate greater population migration to urban areas, accelerating economic development, social transformation, and lifestyle changes.

Living Standards: Measured by the average wage of employed individuals in urban units, this indicator effectively reflects the economic conditions and quality of life of residents. It is closely related to the region's economic development, industrial structure, and employment conditions.

5.3 Panel Model Analysis

This study constructs a panel model using the dependent variable, core explanatory variable, and control variables described above. The model analysis results are as follows:

5.3.1 Panel model analysis for low to medium education levels

(1) Hausman Test Results

Table 10 Hausman Test Results

Test Name	P-value	Method Used
Hausman Test	0	Fixed Effects Model

As shown in Table 10, the Hausman test supports the use of a fixed effects (FE) model. However, despite the formal support for the FE model, this study prefers random effects (RE) estimation, primarily because RE models better reflect the data generation process when the focus is on general patterns across individuals rather than individual-specific effects.

(2) Panel Model Analysis Results for Low to Medium Education Levels

Table 11 Panel Model Analysis Results for Low to Medium Education Levels

Variable	Coefficient (Coef)	t-value	p-value
Intercept	239.683	11.779	0
Digital Economy Development Level	23.528	2.633	0.009
Average Wage in Urban Units	-13.623	-6.799	0
National Fiscal Education Expenditure	0	-2.519	0.012
Year-End Population/Land Area	-72.944	-5.364	0
Urban Population/Total Population	-0.254	-3.625	0
Regional GDP	0	3.494	0.001

The analysis of factors influencing the scale of low to medium education workers reveals that digital economy development level (Coef = 23.528, p = 0.009) and regional GDP (Coef = 0.000, p = 0.001) have significant positive effects, indicating that economic expansion and comprehensive regional development continue to rely on low-skilled labor, though the marginal effect of GDP is weak. Conversely, average wages in urban units (Coef = -13.623, p = 0.000), population density (Coef = -72.944, p = 0.000), urbanization rate (Coef = -0.254, p = 0.000, p = 0.012) exhibit significant negative effects, suggesting that rising wages may drive capital substitution for labor, high-density regions and urbanization processes tend to crowd out low-skilled jobs, and education investment suppresses the stock of low-skilled workers in the long term (Table 11).

5.3.2 Panel model analysis for higher education levels

(1) Hausman Test Results

Table 12 Hausman Test Results

Test Name	P-value	Method Used
Hausman Test	1	Random Effects Model

As shown in Table 12, the Hausman test supports the use of a random effects (RE) model, and thus, this study adopts the RE model for analysis.

(2) Panel Model Analysis Results for Higher Education Levels

Table 13 Panel Model Analysis Results for Higher Education Levels

Variable	Coefficient (Coef)	t-value	p-value
Intercept	-37.406	-2.552	0.011
Digital Economy Development Level	15.114	4.282	0
Average Wage in Urban Units	8.833	9.176	0
National Fiscal Education Expenditure	-3.349	-4.691	0
Year-End Population/Land Area	70.018	6.891	0
Urban Population/Total Population	0.123	2.935	0.004
Regional GDP	0	-2.722	0.007

The digital economy development level (Coef = 15.114, p = 0.000) and average wages in urban units (Coef = 8.833, p = 0.000) have significant positive effects on the scale of higher-educated workers, indicating that improved regional development and higher-wage job opportunities promote the concentration of such workers. Population density (Coef = 70.018, p = 0.000) and urbanization rate (Coef = 0.123, p = 0.004) also show positive effects, reflecting that densely populated areas and urbanization processes may create more high-skilled jobs through economies of scale. Conversely, national fiscal education expenditure (Coef = -3.349, p = 0.000) and regional GDP (Coef = -0.000, p = 0.007) exhibit significant negative effects, suggesting that increased education investment may reduce the supply of high-skilled labor through enhanced human capital quality, and improvements in economic growth quality (e.g., industrial upgrading) may substitute for high-skilled labor. These findings provide critical insights for formulating regional labor market policies, emphasizing the need for complementary vocational training policies to mitigate structural unemployment and attention to the differential impacts of education investment and industrial upgrading on low-skilled workers (Table 13).

5.4 Spatial Panel Model Analysis

Since traditional panel models do not account for spatial relationships, this chapter conducts a spatial panel model analysis to examine the impact of the digital economy on labor employment structures. By applying the Akaike Information Criterion (AIC), the spatial Durbin model, spatial Durbin error model, spatial lag model, and spatial error model are compared to select the optimal model for explaining the effects of the digital economy on employment structures. The model formulas are as follows:

5.4.1 Spatial Durbin model

$$Y = \rho WY + X\beta + \mu WX + \alpha l_n + \varepsilon \tag{7}$$

where ρ is the spatial autocorrelation coefficient, W is the spatial weight matrix, WY and WX represent the spatial lag terms of the dependent and independent variables, respectively, α is the constant term, In is an $N*1$ identity matrix, β and θ are regression coefficients, and ε is the error term.

5.4.2 Spatial Durbin error model

$$\begin{cases} y = \beta k * x + \theta k * Wx + u \\ \quad u = \lambda * Wu + \mu \end{cases} \tag{8}$$

where βk represents the regression coefficient of X, WX is the spatial lag of the independent variable X, θk is the regression coefficient of WX, Wu is the spatial lag of the error term u, λ is the regression coefficient of Wu, and u and μ are disturbance error terms.

5.4.3 Spatial lag model

$$Y = \rho WY + X\beta + \varepsilon \tag{9}$$

where Y is the matrix of the dependent variable, X is the matrix of explanatory variables, β is the parameter vector, ρ is the spatial effect coefficient, W is the spatial weight matrix, and ε is the error term. The spatial weight matrix W describes the proximity relationships between spatial units, typically as a binary symmetric matrix. The spatial lag term WY represents the interactions between spatial units.

5.4.4 Spatial error model

$$\begin{cases} y = \beta k * x + u \\ u = \lambda * Wu + \mu \end{cases} \tag{10}$$

where y is the dependent variable, μ is the disturbance term, Wu is the spatial lag of the error term, and λ is its regression coefficient.

5.4.5 Spatial distance matrix

This study calculates the distance between cities using the spherical cosine theorem to construct the spatial distance matrix, as follows (Figure 4):

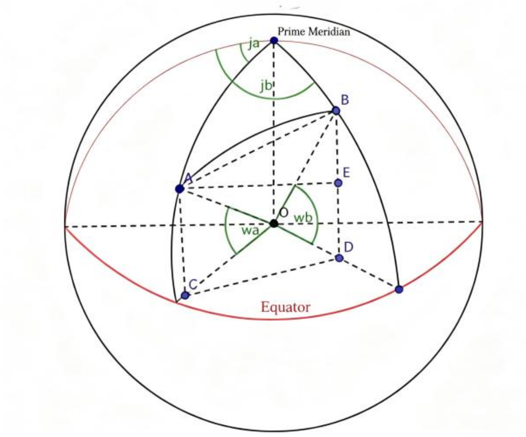

Figure 4 Diagram of Distance Calculation Between Two Points

Based on the latitude and longitude and the Earth's radius R, the coordinates of points A and B are converted into spherical three-dimensional coordinates:

$$A\begin{Bmatrix} Xa = R\,\mathrm{Cos}(wa)\,\mathrm{Cos}(ja) \\ Ya = R\,\mathrm{Cos}(wa)\,\mathrm{Cos}(ja) \\ Za = R\,\mathrm{Sin}(wa) \end{Bmatrix}$$
$$B\begin{Bmatrix} Xb = R\,\mathrm{Cos}(wb)\,\mathrm{Cos}(jb) \\ Yb = R\,\mathrm{Cos}(wb)\,\mathrm{Cos}(jb) \\ Zb = R\,\mathrm{Sin}(wb) \end{Bmatrix} \tag{11}$$

The lengths of A and B are calculated based on their three-dimensional coordinates:

$$\begin{aligned} AB^2 &= (Xa - Xb)^2 + (Ya - Yb)^2 + (Za - Zb)^2 \\ &= \cdots = 2R^2\left(1 - \mathrm{Cos}(wa)\,\mathrm{Cos}(wb)\,\mathrm{Cos}(jb - ja) - \mathrm{Sin}(wa)\,\mathrm{Sin}(wb)\right) \end{aligned} \tag{12}$$

The length between A and B is determined using the cosine theorem:

$$\begin{aligned} AB^2 &= AO^2 + BO^2 - 2AO * BO * \mathrm{Cos}\left(\triangle AOB\right) \\ \mathrm{Cos}\left(\triangle AOB\right) &= \frac{AB^2 - AO^2 - BO^2}{-2AO * BO} = \frac{AB^2 - 2R^2}{-2R^2} = 1 - \frac{AB^2}{2R^2} \end{aligned} \tag{13}$$

The arc length AB=R×∠AOB:

$$\overset{\frown}{AB} = R\arccos(\mathrm{Cos}(wa)\,\mathrm{Cos}(wb)\,\mathrm{Cos}(jb - ja) + \mathrm{Sin}(wa)\,\mathrm{Sin}(wb)) \tag{14}$$

The final calculation results are provided in the appendix. Based on the spatial distance matrix, the spatial panel model analysis is conducted as follows:

5.4.6 Spatial panel model analysis for low to medium education levels

(1) Hausman Test Results

Table 14 Hausman Test Results

Model	Hausman Test Value	Method Used
Spatial Durbin Model	1	Random Effects Model
Spatial Durbin Error Model	1	Random Effects Model
Spatial Lag Model	1	Random Effects Model
Spatial Error Model	1	Random Effects Model

As shown in Table 14, the Hausman test results for all four spatial panel models yield p-values greater than 0.05, indicating the preference for random effects (RE) models for subsequent analysis.

(2) AIC Criterion Test Results

Table 15 AIC Criterion Test Results

Model	AIC Value

Model	AIC Value
Spatial Durbin Model	1164.082
Spatial Durbin Error Model	3340.767
Spatial Lag Model	1206.028
Spatial Error Model	3045.218

Based on the AIC criterion, the spatial Durbin model has the lowest AIC value (1164.082), making it the optimal model for analysis (Table 15).
(3) Spatial Durbin Model Analysis Results

Table 16 Spatial Durbin Model Analysis Results for Low to Medium Education Levels

Variable	Coefficient(Coef)	z-value	p-value
Constant	488.059	2.61	0.009
Digital Economy Development Level	79.607	-3.469	0
National Fiscal Education Expenditure	-30.639	-4.675	0
Average Wage in Urban Units	-9.286	-0.726	0.468
Total Import and Export Value	-10.608	-3.481	0
Regional GDP	26.984	2.862	0.004
Urban Population/Total Population	-1.277	-2.042	0.001
Year-End Population/Land Area	841.55	3.414	0.001
Spatial Lag of Dependent Variable	0.72	12.621	0
Sample Size (n)	300		
Pseudo R²	0.851		
Spatial Pseudo R²	0.798		

The analysis in Table 16 indicates that the average wage in urban units is not statistically significant for low to medium education levels ($p = 0.468$). Therefore, this variable is excluded, and the analysis is re-conducted, with results shown in Table 17.

Table 17 Revised Spatial Durbin Model Analysis Results for Low to Medium Education Levels

Variable	Coefficient(Coef)	z-value	p-value
Constant	381.205	3.822	0
Digital Economy Development Level	68.604	5.068	0
National Fiscal Education Expenditure	-27.476	-6.131	0
Total Import and Export Value	-9.289	-3.866	0
Regional GDP	22.304	3.33	0.001
Urban Population/Total Population	-1.579	-3.856	0
Year-End Population/Land Area	852.049	3.617	0
Spatial Lag of Dependent Variable	0.737	14.745	0
Sample Size (n)	300		
Pseudo R²	0.851		
Spatial Pseudo R²	0.794		

As shown in Table 17, digital economy development level (Coef = 68.604, $p < 0.01$), economic growth (Coef = 22.304, $p < 0.01$), and population density (Coef = 852.049, $p < 0.01$) have significant positive effects on the scale of low to medium education workers, indicating that economic expansion and agglomeration effects in high-density regions remain key drivers for absorbing low-skilled labor. Conversely, education expenditure (Coef = -27.476, $p < 0.01$), import and export trade (Coef = -9.289, $p < 0.01$), and urbanization processes (Coef = -1.579, $p < 0.01$) exhibit significant negative effects, reflecting the substitution effect of human capital enhancement and industrial upgrading on low-skilled labor. Notably, the spatial lag term ($\rho = 0.737$, $p < 0.01$) demonstrates strong spatial dependence, suggesting that neighboring regions' labor market conditions significantly influence the local scale of low-skilled workers through spillover effects.
(4) Robustness Test
This study considers living costs as an additional factor influencing educational attainment levels, as high living costs may discourage residents from investing in education. Therefore, living costs are introduced as a new control variable to test the model's robustness, with results shown in Table 18.

Table 18 Robustness Test for Low to Medium Education Levels

Variable	Coefficient(Coef)	z-value	p-value
Constant	388.029	3.868	0
National Fiscal Education Expenditure	-27.178	-2.709	0.004
Regional GDP	22.255	-6.052	0
Urban Population/Total Population	-1.693	2.904	0
Year-End Population/Land Area	804.648	-4.08	0
Total Import and Export Value	-9.601	3.607	0.009

Variable	Coefficient(Coef)	z-value	p-value
Digital Economy Development Level	67.069	-3.934	0
Living Costs	0	5.016	0
Spatial Lag of Dependent Variable	0.736	0.106	0.005
Sample Size (n)	300		
Pseudo R^2	0.853		
Spatial Pseudo R^2	0.796		

The results in Table 18 show that the newly introduced living costs variable (Coef = 0.000, $p < 0.01$), though small in magnitude, is highly significant, suggesting that rising living costs may exert a slight influence by increasing the supply pressure of low-skilled labor. The high goodness-of-fit indicates robust explanatory power, and the minimal impact of the new variable on coefficients confirms the model's robustness.

5.4.7 Spatial panel model analysis for higher education levels

(1) Hausman Test Results

Table 19 Hausman Test Results

Model	Hausman Test Value	Method Used
Spatial Durbin Model	1	Random Effects Model
Spatial Durbin Error Model	1	Random Effects Model
Spatial Lag Model	0	Fixed Effects Model
Spatial Error Model	1	Random Effects Model

As shown in Table 19, the Hausman test for the spatial lag model supports a fixed effects (FE) model. However, despite this formal support, this study prefers random effects (RE) estimation, based on the theoretical consideration that RE models better reflect the data generation process when focusing on general patterns across individuals rather than individual-specific effects (Wooldridge, 2010). This is particularly relevant in spatial panel models, where RE settings align with the assumption that spatial correlations stem from underlying spatial processes.

(2) AIC Criterion Test Results

Table 20 AIC Test Results

Model	AIC Value
Spatial Durbin Model	1061.934
Spatial Durbin Error Model	2895.547
Spatial Lag Model	1060.893
Spatial Error Model	2923.884

Based on the AIC criterion, the spatial lag model has the lowest AIC value (1060.893), making it the optimal model for analysis (Table 20).

(3) Spatial Lag Model Analysis Results

Table 21 Spatial Lag Model Analysis Results

Variable	Coefficient(Coef)	z-value	p-value
Constant	64.75	4.492	0
Digital Economy Development Level	12.082	4.712	0
National Fiscal Education Expenditure	-4.302	-4.524	0
Total Import and Export Value	-1.329	-3.826	0
Regional GDP	2.228	2.229	0.026
Urban Population/Total Population	0.007	1.679	0.043
Year-End Population/Land Area	117.201	7.069	0
Spatial Lag of Dependent Variable	0.713	12.585	0
Phi	0.087	5.496	0
Sample Size (n)	300		
Pseudo R	0.822		
Spatial Pseudo R	0.796		

The results in Table 21 indicate that digital economy development level (Coef = 12.082, $p < 0.01$), regional GDP (Coef = 2.228, $p < 0.05$), and population density (Coef = 117.201, $p < 0.01$) have significant positive effects on the scale of high-skilled workers, suggesting that improved regional development, economic growth, and population agglomeration promote the concentration of higher-educated workers. The urbanization rate (Coef = 0.007, $p < 0.05$), though small in magnitude, is also significantly positive, reflecting the growing demand for high-skilled talent during urbanization. Conversely, national fiscal education expenditure (Coef = -4.302, $p < 0.01$) and total import and export value (Coef = -1.329, $p < 0.01$) exhibit significant negative effects, potentially due to education investment enhancing human capital quality and causing selective effects, and export-oriented economic development leading to talent outflows. The significant spatial lag term ($\rho = 0.713$, $p < 0.01$) and phi (0.087, $p < 0.01$) indicate strong spatial dependence and

heterogeneity in the high-skilled labor market. The model's pseudo R² (0.822) and spatial pseudo R² (0.796) demonstrate strong explanatory power.
(4) Robustness Test
Living costs are introduced as a new control variable to test the model's robustness, with results shown in Table 22.

Table 22 Robustness Test for Spatial Lag Model

Variable	Coefficient(Coef)	z-value	p-value
Constant	57.117	4.255	0
Digital Economy Development Level	11.733	3.976	0
National Fiscal Education Expenditure	-3.133	-4.108	0
Total Import and Export Value	0.768	-2.456	0.014
Urban Population/Total Population	0.073	1.952	0.041
Year-End Population/Land Area	96.845	6.337	0
Living Costs	0	4.887	0
Regional GDP	0.626	-2.83	0.005
Spatial Lag of Dependent Variable	0.098	9.542	0
Phi	57.117	5.5	0
Sample Size (n)	300		
Pseudo R	0.829		
Spatial Pseudo R	0.813		

The results in Table 22 show that the newly introduced living costs variable (Coef = -0.000, $p < 0.01$), though small in magnitude, is highly significant, suggesting that rising living costs may exert a slight crowding-out effect on high-skilled talent. The model's pseudo R² (0.829) and spatial pseudo R² (0.813) indicate excellent explanatory power, and the minimal impact of the new variable on coefficients confirms the model's robustness.

6 CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

The empirical analysis reveals that the development level of the digital economy in China demonstrates a clear regional gradient, with the eastern regions exhibiting prominent advantages, followed by the central and western regions. However, under the influence of macroeconomic fluctuations, the digital economy indices across provinces experienced a slight decline in 2021. This finding not only reflects the uneven pattern of regional development but also validates the rationality of the model construction.
Second, the digital economy exerts heterogeneous impacts on the employment structures of different groups. For workers with low to medium educational attainment, digital economy development (Coef=68.604), economic growth (Coef=22.304), and population density (Coef=852.049) significantly expand their employment scale through mechanisms such as economic expansion and agglomeration effects. At the same time, education expenditure (Coef=-27.476), import and export trade (Coef=-9.289), and urbanization (Coef=-1.579) generate substitution effects, revealing the crowding-out pressures faced by low-skilled positions due to industrial upgrading and human capital enhancement.
For high-skilled groups, the digital economy (Coef=12.082), regional GDP (Coef=2.228), and population agglomeration (Coef=117.201) positively drive their spatial concentration. Nevertheless, the negative impacts of education investment (Coef=-4.302) and foreign trade dependence (Coef=-1.329) highlight a dual screening mechanism characterized by talent quality upgrading and intensified international competition.
Third, the labor market exhibits significant spatial dependence. The spatial lag coefficients of employment for low to medium-skilled workers and high-skilled workers are 0.737 and 0.713 ($p<0.01$), respectively, indicating that changes in employment structures in neighboring regions substantially affect local labor supply-demand balances through factor mobility and technology diffusion. Furthermore, the spatial heterogeneity coefficient of the high-skilled labor market ($\varphi=0.087$, $p<0.01$) underscores the asymmetric and competitive nature of inter-regional talent flows.

6.2 Recommendations

6.2.1 Construction of a differentiated policy framework

(1) For Low to Medium-Skilled Groups
To address employment challenges in the digital economy era, targeted support measures should be strengthened:
Regional Industrial Collaboration Platforms: Establish "enclave economy" models to facilitate the transfer of technology-intensive industries from the eastern to the central and western regions, while guiding manufacturing clusters to county-level zones through policy tools such as tax sharing and land quota exchanges. This will promote industrial gradient transfer and equalization of employment opportunities.
Employment Carrying Capacity Assessment: Develop negative lists for industrial access based on resource endowments and ecological red lines, thereby preventing redundant low-end constructions and minimizing employment volatility risks.

Digital Training Platforms: Build modular course libraries covering manufacturing, services, and emerging industries by leveraging the “Internet + Vocational Skills” model. A credit bank system should be established to enable cross-regional skill certification, fostering the digital adaptability of low to medium-skilled workers.
Enterprise–Community Linkage Mechanisms: Encourage enterprises and vocational institutions to co-establish “skill service stations” to provide targeted job-transition training for high-unemployment-risk groups, with government subsidies tied to training outcomes.
National Unified Labor Information Platform: Integrate data from multiple departments (human resources, social security, industry, and information technology) to release real-time information on labor demand and skill gaps. Normalized “cloud recruitment” and “remote interviews” should be promoted to improve labor market matching.
Rights Protection for Migrant Workers: Pilot a “one-card” system for cross-provincial social security settlements and explore coordinated work injury insurance schemes for new employment forms such as delivery drivers and ride-hailing workers.
Safety-Net and Developmental Protections: Expand unemployment insurance coverage in industrial transfer recipient areas and establish “employment buffer funds” for temporary subsidies. Meanwhile, implement integrated “skill poverty alleviation + public welfare positions” programs to prevent poverty relapse and skill degradation.
(2) For High-Skilled Groups
To attract and retain high-level talent, a more comprehensive development environment should be created:
Talent Living Circles: Establish “scientist communities” and “engineer towns” in central cities, supported by international-standard medical, educational, and cultural facilities to reduce settlement costs.
Flexible Talent Policies: Promote models such as “migratory experts” and “weekend scientists,” enabling talents to hold concurrent roles across major urban clusters (e.g., Beijing–Tianjin–Hebei, Yangtze River Delta) to enhance mobility and flexibility.
Empowered Innovation Consortia: Support leading enterprises in forming “industrial innovation alliances,” granting autonomy in technical decision-making and benefit distribution, thereby accelerating the commercialization of research outcomes and stimulating talent vitality.
Talent Sharing Pools: Establish “talent revolving door” systems across enterprises and universities in strategic fields such as integrated circuits and artificial intelligence, removing barriers related to staffing quotas and household registration.
Targeted Attraction Plans: Implement “green channels” for foreign scientists in chokepoint technology areas, streamline permanent residency approvals, and allow collective team settlement to draw high-end overseas talent.
Offshore Innovation Bases: Set up offshore innovation and entrepreneurship bases in free trade pilot zones, providing cross-border intellectual property services and tax consultation to enhance global talent integration.
Compensation Funds for Talent Export Regions: Introduce an “intellectual compensation” mechanism, where eastern talent-importing regions compensate central and western regions for outflowing talents based on talent levels and service years, thereby supporting local cultivation infrastructures.
Backflow from R&D Centers: Encourage eastern enterprises to establish synchronized R&D branches in central and western regions, fostering local high-skilled job creation through technological spillovers and industry–academia cooperation.

6.2.2 Spatial governance innovations

To achieve coordinated development of regional labor markets, spatial governance mechanisms should be innovated:
Spatial Monitoring and Early Warning Systems: Establish integrated monitoring platforms combining satellite remote sensing, big data, and grassroots grids to track real-time employment density, skill structures, and labor mobility, thereby providing scientific support for policymaking.
Designated Employment and Skill Enhancement Zones: Identify “employment priority zones” and “skill enhancement belts” within national spatial planning, channeling infrastructure and public service resources to support industrial upgrading and talent clustering.
Blockchain-Based Data Sharing: Utilize blockchain technology to build cross-regional social security data-sharing chains, enabling traceable labor mobility trajectories, cumulative rights, and transparent dispute arbitration, thereby safeguarding the rights and interests of mobile workers.

COMPETING INTERESTS

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REFERENCES

[1] Wu Yilin, Wang Tianqi. Research on Statistical Definition and Industrial Classification of the Digital Economy. Statistical Research, 2021, 38(06): 18-29.

[2] Chen Xiaohong, Li Yangyang, Song Lijie, Wang Yangjie. Theoretical Framework and Research Prospects of the Digital Economy. Management World, 2022, 38(02): 208-224+13-16.
[3] Jia Zhuoqiang. Study on the Impact of the Digital Economy on Labor Employment. Sichuan University, 2023.
[4] Ahmad N, Ribarsky J. Towards a framework for measuring the digital economy. 16th Conference of the International Association of Official Statisticians (IAOS) OECD Headquarters, Paris, France. Paris: IAOS, 2018: 19-21.
[5] Ahmad N, Ribarsky J, Reinsdorf M. Can potential mismeasurement of the digital economy explain the post-crisis slowdown in GDP and productivity growth?, 2017.
[6] Li Z, Liu Y. Research on the spatial distribution pattern and influencing factors of digital economy development in China. IEEE Access, 2021, 9: 63094-63106.
[7] Ma D, Zhu Q. Innovation in emerging economies: Research on the digital economy driving high-quality green development. Journal of Business Research, 2022, 145: 801-813.
[8] Yan Miaomiao. Research on Achieving High-Quality Employment for Workers under the Background of the Digital Economy. Tianjin University of Finance and Economics, 2022.
[9] Wu Kedong. Study on the Impact of the Digital Economy on Labor Employment Structure and Employment Quality. Guangxi University, 2023.
[10] Su Pei, He Daxing. The Impact of Digital Economic Development on Employment: An Analysis Based on Panel Data from 279 Prefecture-Level Cities. Shanghai Economic Research, 2024(10): 53-74.
[11] Acemoglu D, Restrepo P. Robots and jobs: Evidence from US labor markets. Journal of Political Economy, 2020, 128(6): 2188-2244.
[12] Bessen J. Automation and jobs: when technology boosts employment. Economic Policy, 2019, 34(100): 589-626.
[13] Acemoglu D, Restrepo P. Tasks, automation, and the rise in US wage inequality. Cambridge: National Bureau of Economic Research, 2021: NBER Working Paper No.28920, 2026-09-08. https://www.nber.org/papers/w28920.