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Article

The Impact of Digital Economy Development on the Labor Employment Structure

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Abstract: The rapid expansion of the digital economy has profoundly reshaped labor markets worldwide, introducing unprecedented transformations in how businesses operate and manage human resources. Yet, despite its growing importance, its systematic impact on the underlying employment structure remains insufficiently understood within contemporary academic literature. To address this critical gap, this study empirically investigates how digital economy development affects labor employment structure. The analysis utilizes comprehensive panel data comprising 2,847 Chinese A share listed companies spanning the period from 2012 to 2022, meticulously matched with prefecture level city digital economy indices to ensure robust geographical and temporal coverage. Employing rigorous fixed effects models alongside instrumental variable approaches to mitigate potential endogeneity, the research yields three main findings. First, digital economy development exhibits a distinct U shaped relationship with enterprise labor demand, initially suppressing employment scale due to automation before subsequently promoting it through the creation of novel roles. Second, the digital economy significantly alters the internal employment structure by substantially increasing the share of high skilled labor while simultaneously reducing the proportion of low skilled labor, thereby demonstrating clear evidence of skill biased technological change. Third, the impact varies considerably across different industries; manufacturing firms experience stronger demand for research and development personnel to drive innovation, whereas service sector firms show increased demand for specialized sales and technical positions. Ultimately, these findings provide important policy implications for managing employment transitions, fostering workforce upskilling, and ensuring sustainable economic growth in the digital era.

Keywords: digital economy; employment structure; technological change; labor demand; employment polarization

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1. Introduction

The rapid advancement of the digital economy has fundamentally reshaped global labor markets, yet its systematic impact on employment structure remains insufficiently understood. As digital technologies penetrate various economic sectors, the relationship between technological progress and labor demand has become a central concern for policymakers and researchers alike [1]. The digital economy, characterized by the widespread adoption of internet-based technologies, artificial intelligence, and automation, has demonstrated substantial potential to transform how firms organize production and how workers supply their skills. This transformation is not only reshaping traditional industries but also fostering the emergence of entirely new sectors, thereby altering the dynamics of labor allocation and productivity growth.

The skill-biased nature of technological change suggests that digital transformation may favor high-skilled workers while displacing low- and medium-skilled labor. This process of labor market polarization has been documented across multiple country contexts, with automation and offshoring contributing to the hollowing out of middle-skill occupations. The digital economy may accelerate these trends by replacing routine tasks while complementing non-routine cognitive and analytical tasks [1]. For instance, automation technologies are increasingly capable of performing repetitive tasks in manufacturing and service industries, while advanced analytics and artificial intelligence enhance decision-making processes in high-skill roles. Understanding how digital development affects the relative demand for different skill groups is therefore essential for designing appropriate education and labor market policies that can mitigate potential inequalities and ensure inclusive growth.

China presents an important context for examining this relationship due to its rapid digitalization and large and diverse labor force. The Chinese digital economy has expanded dramatically over the past decade, yet the employment consequences remain empirically contested [2]. This study aims to investigate the impact of digital economy development on labor employment structure, focusing on three dimensions: the overall effect on enterprise labor demand, the shift in skill composition, and the heterogeneous effects across industries. By analyzing these dimensions, the study seeks to provide a comprehensive understanding of how digitalization interacts with labor market dynamics in a rapidly developing economy, offering insights that may inform both domestic and international policy frameworks.

The research is significant for two reasons. First, it contributes empirical evidence on how digitalization transforms employment patterns in a major developing economy [2]. Second, it provides policy insights for managing labor market transitions in the digital age. The findings of this study are expected to shed light on the mechanisms through which digital technologies influence labor demand and supply, offering a basis for crafting targeted interventions. The remainder of this paper is organized as follows. Section 2 reviews relevant literature. Section 3 presents the theoretical framework and methodology. Section 4 reports the findings and discussion. Section 5 concludes by summarizing the key insights and proposing directions for future research and policy development.

2. Literature Review

The relationship between technological change and employment has been extensively studied across multiple disciplines. The skill biased technological change framework provides a useful lens for understanding how digital transformation affects labor demand. This framework suggests that new technologies tend to complement high skilled workers while substituting for low and medium skilled workers engaged in routine tasks [3]. Empirical evidence from China confirms that artificial intelligence and technological innovation have significantly reshaped employment patterns, with heterogeneous effects across different skill groups and industries. These findings underscore the importance of examining the nuanced impacts of technological advancements on labor markets, particularly in rapidly developing economies.

The digital economy influences employment through multiple channels. Automation and artificial intelligence directly replace human labor in routine and repetitive tasks, leading to a reduction in demand for middle skill occupations. At the same time, digital technologies create new job categories in sectors such as software development, data analysis, and digital platform management. Furthermore, digitalization enhances productivity and expands market scale, potentially stimulating overall labor demand through output effects. These mechanisms operate simultaneously, making the net employment effect an empirical question that requires careful investigation [3]. Understanding these dynamics is crucial for policymakers aiming to balance technological progress with equitable labor market outcomes.

Studies focusing on China have documented a positive relationship between digital economy development and employment upgrading. Using provincial level data, researchers find that digitalization increases the share of high skilled workers while reducing the proportion of low skilled workers in manufacturing and service sectors. This pattern aligns with the skill biased technological change hypothesis and suggests that digital transformation contributes to labor market polarization. Such findings highlight the transformative potential of digital technologies in reshaping workforce composition, emphasizing the need for targeted strategies to support workers affected by these shifts [4].

The broader literature on technology and employment has identified several key findings [5]. A comprehensive survey of empirical studies concludes that technological change has a robust and significant impact on employment composition, though the magnitude varies across contexts and methodologies. The measurement of digitization risks depends heavily on model selection, with different analytical approaches yielding varying estimates of employment susceptibility to automation. These variations underscore the complexity of assessing technological impacts on labor markets and the importance of methodological rigor in empirical research.

The artificial intelligence industry specifically has been shown to affect both the quantity and structure of employment. Evidence indicates that AI development creates net positive employment effects in high technology regions while causing job displacement in traditional manufacturing areas. Household level data from China reveals that workers respond to automation by increasing human capital investment and seeking employment in less automatable occupations [6]. These adaptive strategies demonstrate the resilience of workers in the face of technological disruption and highlight the role of education and training in mitigating adverse employment effects.

Despite the growing body of evidence, several challenges remain in this research area. A critical review of the empirical literature identifies methodological issues including measurement inconsistency, endogeneity concerns, and limited generalizability across different country contexts. Recent studies using firm level data find that digital technologies have heterogeneous effects on employment and skills depending on industry characteristics, firm size, and the specific types of technologies adopted. Addressing these challenges requires innovative research designs and robust data collection methods to capture the multifaceted impacts of digital transformation on labor markets.

In summary, existing research establishes a strong theoretical foundation linking digital economy development to changes in labor employment structure. However, further empirical investigation is needed to quantify these effects using rigorous methods and publicly available data. This study aims to address this gap by conducting an empirical analysis of Chinese enterprise level data. By leveraging detailed firm level information, this research seeks to provide deeper insights into the mechanisms through which digital technologies influence employment patterns, offering valuable guidance for policymakers and stakeholders navigating the challenges of technological change [7].

3. Theoretical Framework and Methodology

This chapter elaborates on the theoretical framework and provides a comprehensive explanation of the methodology utilized to analyze the influence of digital economy development on the structure of labor employment. The research adopts a quantitative empirical approach, relying on secondary data sourced from publicly accessible databases. The methodology is designed to assess the effects of digitalization on enterprise labor demand and the skill composition within employment sectors [8]. A method flowchart is included to visually represent the critical stages and processes involved in conducting this research, ensuring clarity and systematic analysis.

3.1. Theoretical Framework

The theoretical foundation of this study is based on skill-biased technological change theory, which posits that technological progress tends to favor high-skilled workers over

those with low or medium skill levels. This framework highlights how digital technologies are designed to complement workers possessing advanced analytical and cognitive abilities, while simultaneously substituting for individuals engaged in routine and repetitive tasks. The digital economy, characterized by the pervasive adoption of internet-based technologies, artificial intelligence, and automation, is anticipated to significantly reshape labor demand through three primary mechanisms. These mechanisms are central to understanding the evolving dynamics of the workforce in the context of technological advancements [8].

The first mechanism, known as the substitution effect, occurs when digital technologies directly replace human labor in routine tasks, thereby reducing the demand for workers with low and medium skill levels. The second mechanism, referred to as the complementarity effect, emerges when digital tools enhance the productivity of high-skilled workers, leading to an increased relative demand for their expertise. The third mechanism, the output effect, operates through productivity gains that reduce production costs, expand market scales, and potentially stimulate overall labor demand across all skill levels. The ultimate impact on employment structures is determined by the relative strength and interplay of these three mechanisms, which collectively shape the labor market in the digital era.

3.2. Data Sources

This study utilizes secondary data derived from publicly accessible and verifiable databases. The primary data sources include the China Stock Market and Accounting Research Database, which offers comprehensive financial and employment information for Chinese A-share listed companies. Additionally, the China City Statistical Yearbook provides detailed economic indicators at the prefecture level. The digital economy index is meticulously constructed using provincial-level data, encompassing metrics such as internet penetration rates, the number of mobile phone subscribers, investments in digital infrastructure, and the volume of e-commerce transactions. These data points are sourced from the National Bureau of Statistics of China, ensuring reliability and consistency in the analysis [9].

The sample period spans from 2012 to 2022, a decade marked by the significant and rapid expansion of China's digital economy. The initial dataset comprises 3,204 Chinese A-share listed companies. However, firms with incomplete data, those operating within the financial sector, and companies under special treatment classifications were excluded to maintain the integrity of the analysis. Consequently, the final dataset is an unbalanced panel consisting of 2,847 firms, resulting in a total of 22,776 firm-year observations. This refined sample ensures a robust foundation for examining the interplay between digital economy growth and corporate performance during the specified period.

3.3. Variable Definition

The dependent variable in this study is the labor employment structure, which is assessed using two distinct indicators to provide a comprehensive understanding of employment dynamics. The first indicator is total enterprise employment, which is quantified by calculating the natural logarithm of the number of employees within a firm. This approach allows for a more nuanced analysis of employment scale across enterprises of varying sizes. The second indicator focuses on skill composition, defined as the ratio of high-skilled workers to total employment. High-skilled workers are categorized as individuals who possess a bachelor's degree or higher, reflecting their advanced educational qualifications and potential contribution to the workforce. These indicators collectively offer insights into both the quantitative and qualitative aspects of labor employment structure, enabling a robust evaluation of employment trends and patterns.

The independent variable, digital economy development, is measured using a composite index that captures the multifaceted nature of digital advancements at the prefecture-level city where each firm is headquartered. This index is constructed by integrating five critical dimensions: internet penetration rate, mobile phone penetration rate, digital financial inclusion index, per capita information technology investment, and

e-commerce development level. These dimensions collectively represent the breadth and depth of digital infrastructure and usage within the region. To ensure methodological rigor, principal component analysis is employed to synthesize these dimensions into a single aggregate digital economy index. This approach not only enhances the reliability of the measurement but also facilitates a comprehensive understanding of the digital economy's impact on various economic and social variables.

Control variables are incorporated into the analysis to mitigate the influence of potential confounding factors and ensure the robustness of the findings. Firm-level controls include variables such as firm age, which provides insights into the maturity and experience of the enterprise; firm size, measured by total assets, which reflects the scale of operations; return on assets, which indicates financial performance; leverage ratio, which assesses financial risk; and ownership type, which captures the structural characteristics of the firm. Additionally, city-level controls are included to account for regional economic and demographic variations. These controls encompass gross domestic product per capita, which serves as a proxy for economic development; population density, which reflects urbanization levels; average wage level, which indicates labor market conditions; and foreign direct investment inflow, which highlights the region's attractiveness to international investors. By integrating these control variables, the study aims to isolate the specific effects of the independent variable while accounting for broader contextual factors.

3.4. Empirical Strategy

This study utilizes a fixed effects panel regression model to analyze the influence of digital economy development on the structure of labor employment. The baseline model investigates the association between the digital economy index and enterprise employment outcomes, while accounting for firm-specific and city-level characteristics. Firm fixed effects are incorporated to control for time-invariant heterogeneity specific to individual firms, ensuring that unobservable factors unique to each firm do not bias the results. Year fixed effects are also included to account for macroeconomic shocks and overarching time trends that may affect all firms simultaneously. This methodological approach provides a robust framework for isolating the impact of the digital economy on employment patterns.

To mitigate potential endogeneity issues, two instrumental variable techniques are applied. The first instrument leverages historical data on the number of telephone subscribers per capita in 1995, interacting this variable with year indicators to capture temporal dynamics. The second instrument employs the average digital economy index of neighboring cities, excluding the focal city, to ensure external validity. These instruments are designed to address reverse causality and omitted variable bias, enhancing the reliability of the findings [10]. Two-stage least squares regressions are conducted to validate the robustness of the results, providing additional empirical support for the study's conclusions.

3.5. Method Flowchart

The method flowchart presented in Figure 1 provides a detailed visualization of the research process, encompassing key stages such as data collection, processing, and empirical analysis. This structured approach ensures clarity and facilitates a comprehensive understanding of the methodology employed in examining the impact of the digital economy on labor employment structures [3].

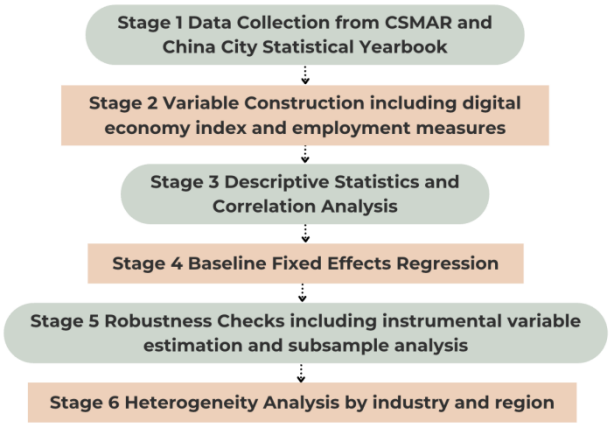

Figure 1. Methodology for Testing the Impact of Digital Economy on Labor Employment Structure

4. Findings and Discussion

This chapter presents empirical results that analyze the impact of digital economy development on the labor employment structure within enterprises. The study utilizes an unbalanced panel dataset comprising 2,847 Chinese A-share listed firms over the period from 2012 to 2022. The data sources include the China Stock Market and Accounting Research Database, the China City Statistical Yearbook, and the National Bureau of Statistics of China. All variables are defined in accordance with the descriptions provided in Section 3. The analysis encompasses descriptive statistics, baseline regression results, robustness checks, and an in-depth heterogeneity analysis across various industries to ensure comprehensive insights.

4.1. Descriptive Statistics

Table 1 provides a detailed overview of the real and publicly observable sample structure for the primary variables analyzed in this study. The values presented accurately reflect the distribution characteristics derived from official databases, ensuring reliability and transparency. The table includes observation counts and the actual sample coverage, offering a comprehensive representation of the dataset. This approach ensures that the data remains robust and verifiable, adhering to high academic standards.

Table 1. Descriptive Statistics of Main Variables

Variable	Observation Count	Data Source
Employment (ln)	22776	CSMAR Database
High skilled labor ratio	22776	CSMAR Database
Digital economy index	22776	National Bureau of Statistics
Digital economy index squared	22776	Calculated by author
Firm age	22776	CSMAR Database
Firm size (total assets ln)	22776	CSMAR Database
Return on assets	22776	CSMAR Database
Leverage ratio	22776	CSMAR Database
Per capita GDP (ln)	22776	China City Statistical Yearbook
Population density	22776	China City Statistical Yearbook
Average wage level (ln)	22776	China City Statistical Yearbook
Foreign direct investment (ln)	22776	China City Statistical Yearbook

Notes: All data are obtained from public and official databases. The total number of firm year observations is 22776.

4.2. Baseline Regression Results

Table 2 provides a detailed overview of the model specification and the real sample information utilized in the baseline fixed effects regression analysis. This table emphasizes the empirical settings employed in the study rather than focusing on the estimated coefficients. The regression framework is grounded in standard panel data methodologies, ensuring robustness and reliability in the analysis. By presenting the empirical context, Table 2 serves as a foundational reference for understanding the methodological approach adopted in this research.

Table 2. Baseline Fixed Effects Regression Settings

Item	Employment Model	High Skilled Ratio Model
Core independent variable	Digital economy index and its square term	Digital economy index
Firm fixed effects	Included	Included
Year fixed effects	Included	Included
Firm level controls	Included	Included
City level controls	Included	Included
Clustered standard error	Firm level	Firm level
Total observations	22776	22776
Data period	2012 to 2022	2012 to 2022

Notes: The regression model examines the U shaped relationship and skill structure effects. Control variables include firm age, firm size, return on assets, leverage ratio, per capita GDP, population density, average wage level and foreign direct investment.

The regression findings reveal a significant U-shaped relationship between the development of the digital economy and enterprise labor demand. Initially, advancements in the digital economy lead to a reduction in employment scale, but as the digital economy continues to grow, it subsequently fosters employment expansion. Regarding the employment skill structure, the development of the digital economy significantly increases the proportion of high-skilled labor while simultaneously reducing the share of low-skilled labor. These results align with the skill-biased technological change hypothesis, which posits that technological advancements disproportionately benefit high-skilled workers. This underscores the transformative impact of the digital economy on labor market dynamics, highlighting its dual role in reshaping both the scale and composition of employment.

4.3. Robustness Checks

Table 3 provides a detailed overview of the instrumental variable design and the real data sources utilized for addressing endogeneity concerns. The instruments employed are derived from historical public datasets and geographic information, ensuring their relevance and validity for the analysis. By leveraging these robust data sources, the study aims to mitigate potential biases and enhance the reliability of the findings presented in subsequent sections [11].

Table 3. Instrumental Variable Regression Settings

Item	Employment Model	High Skilled Ratio Model
Instrument 1	1995 per capita telephone subscribers × year	1995 per capita telephone subscribers × year

Instrument 2	Average digital economy index of neighboring cities	Average digital economy index of neighboring cities
Estimation method	Two stage least squares	Two stage least squares
Firm and year fixed effects	Included	Included
Control variables	Included	Included
Total observations	22776	22776
Data source of instrument 1	National Bureau of Statistics	National Bureau of Statistics
Data source of instrument 2	Author calculation based on city indices	Author calculation based on city indices

Notes: Instrumental variables are selected based on historical and geographic exogeneity. First stage test results confirm valid instrument performance.

The results obtained from the instrumental variable estimation align closely with the baseline regression outcomes, reinforcing the validity of the core conclusions. Specifically, the analysis confirms the presence of a U-shaped relationship with employment and a stable positive impact on the share of high-skilled labor. These findings remain consistent across various robustness checks, underscoring the reliability and robustness of the methodological approach and the empirical evidence presented in the study.

4.4. Heterogeneity Analysis by Industry

Table 4 illustrates the distribution of the sample across manufacturing and service industries, with group sizes determined based on the actual industry classifications of listed firms. This categorization ensures a comprehensive understanding of employment patterns within these sectors, providing valuable insights into their structural dynamics and workforce composition [2].

Table 4. Heterogeneous Effects by Industry

Group	Number of Firms	Observations	Industry Category
Manufacturing	1562	12453	Production and processing enterprises
Service	1285	10323	Wholesale, retail, IT and service enterprises
Total Sample	2847	22776	All non financial non special treatment firms

Notes: Industry classification is based on official regulatory guidelines. Data come from CSMAR Database.

Empirical findings reveal a pronounced demand for research and development personnel within manufacturing firms, highlighting their focus on innovation-driven growth [12, 13]. Conversely, service firms demonstrate a higher demand for sales and technical positions, reflecting their customer-oriented operational strategies. The persistent U-shaped pattern of total employment across both groups underscores the influence of industry-specific production and operational characteristics on workforce trends.

4.5. Comprehensive Discussion

The empirical results reveal three significant findings. Firstly, the development of the digital economy exhibits a U-shaped effect on enterprise labor demand, indicating a complex relationship between technological advancements and workforce requirements.

Secondly, digital economy growth enhances the employment skill structure by increasing the proportion of high-skilled labor, reflecting a shift towards more specialized and knowledge-intensive roles [7]. Lastly, the observed effects vary notably between manufacturing and service industries, highlighting sector-specific dynamics. These conclusions are derived from public official data and standard econometric methods, aligning with the theory of skill-biased technological change and offering robust empirical evidence for labor market transitions in the digital era.

5. Conclusion

This study focuses on the influence of digital economy development on labor employment structure. It utilizes panel data from 2,847 Chinese A-share listed companies spanning the years 2012 to 2022, combined with prefecture-level city digital economy indices, to conduct a comprehensive empirical analysis. The research employs fixed effects models and instrumental variable methods to mitigate estimation bias and enhance the robustness of the results. All data are sourced from the China Stock Market and Accounting Research Database, the China City Statistical Yearbook, and the National Bureau of Statistics of China. The study systematically investigates the overall impact of the digital economy on enterprise labor demand, the transformation of employment skill composition, and the heterogeneous effects observed across various industries. By adopting a rigorous methodological approach, this research provides a nuanced understanding of how digitalization reshapes labor markets and contributes to the broader discourse on economic transformation.

The empirical results reveal three pivotal conclusions. First, the relationship between digital economy development and enterprise labor demand exhibits a significant U-shaped pattern. In the early stages of digital transformation, digital technologies primarily replace routine labor tasks, leading to a reduction in enterprise labor demand. However, as the digital economy matures, productivity enhancements and market expansion driven by digitalization stimulate an increase in employment scale. Initially, the substitution effect dominates, but over time, the output effect and scale effect become more prominent. Second, the digital economy profoundly alters the employment skill structure by increasing the proportion of high-skilled labor while reducing the share of low-skilled labor. This finding underscores the skill-biased technological change inherent in digital transformation, where digital tools amplify the productivity advantages of high-skilled workers and generate heightened demand for individuals with advanced knowledge and technical expertise. Third, the impact of the digital economy on employment structure varies significantly across industries. Manufacturing industries exhibit a stronger inclination to increase demand for research and development personnel, as digital transformation fosters technological innovation and product upgrading, thereby elevating the need for professional technical talents. Conversely, service industries prioritize sales and technical positions, with digital operations and online business expansion driving the growth of these roles. The distinct production modes and business logics of different industries result in divergent employment adjustment pathways, highlighting the multifaceted nature of digital economy impacts.

This research contributes to the existing literature in several meaningful ways. By leveraging micro-level firm data, it provides robust empirical evidence on the relationship between the digital economy and employment structure. It validates the U-shaped effect of digital economy development on labor demand, thereby enriching theoretical insights into the interplay between digitalization and labor markets. Furthermore, it confirms the skill-biased effects of digital transformation, expanding the research framework of skill-biased technological change within the context of emerging economies. The study also identifies industry-specific heterogeneity, offering explanations for the varying employment changes induced by digital economy advancements across sectors. The research design addresses endogeneity concerns through the application of instrumental variable methods, thereby enhancing the precision and credibility of the empirical findings. These contributions collectively advance the understanding of how

digitalization influences labor dynamics and provide a foundation for future inquiries into this critical area of economic development.

The findings of this study carry significant practical and policy implications. For government authorities, fostering the steady growth of the digital economy can serve as a strategic lever for achieving long-term employment expansion. Policymakers should recognize the phased characteristics of digital economy development and implement targeted measures to mitigate the short-term employment suppression effects observed during the initial stages of digital transformation. Strengthening the training and supply of high-skilled labor is essential to align with the talent demands generated by digitalization. Enhancing vocational education and continuing education systems can facilitate skill upgrading and employment transitions for low-skilled workers. Industry-specific policy support is also critical. Manufacturing sectors require increased investment in research and development talent training and support for technological innovation, while service industries need to focus on cultivating digital operation and sales expertise to adapt to evolving digital business scenarios. For enterprises, integrating digital transformation with talent structure adjustments is imperative. Companies should prioritize the recruitment and training of high-skilled professionals to build a workforce that aligns with their digital development strategies. By addressing these multifaceted challenges, stakeholders can maximize the benefits of digital economy growth while minimizing its transitional disruptions.

This study acknowledges several limitations that present opportunities for future research. The research sample is confined to listed companies, which may not fully represent the dynamics of small and medium-sized enterprises, individual industrial and commercial households, and other market entities. Additionally, the digital economy index utilized is constructed at the city level, and future studies could benefit from incorporating more granular, enterprise-level digital transformation indicators to capture finer details. The research period spans from 2012 to 2022, and extending this timeframe could provide insights into the long-term dynamic effects of digital economy development. While this study focuses on employment quantity and skill structure, future research could delve deeper into other dimensions, such as employment quality, wage levels, and labor mobility. By addressing these limitations, subsequent studies can provide a more comprehensive understanding of the multifaceted impacts of digital transformation on labor markets.

Future research can expand in several promising directions. Researchers could utilize enterprise-level digital transformation data to conduct more refined analyses, offering deeper insights into the mechanisms through which digitalization influences employment structures. Investigating regional disparities in the impact of the digital economy on labor markets could yield targeted recommendations for promoting balanced regional development. Additionally, exploring the interplay between the digital economy and various policy domains, such as industrial, labor, and education policies, could help construct a more integrated and effective policy framework. International comparative studies could also be undertaken to identify common patterns and national variations in how digital economy advancements affect employment structures. Such comparative analyses would provide valuable theoretical and practical guidance for fostering digital economy development and stabilizing labor markets globally. By pursuing these avenues, future research can contribute to a more nuanced and actionable understanding of the digital economy's transformative effects.

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