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The Impact of Differentiated Development of the Digital Economy on Employment Quality—An Empirical Analysis Based on Provincial Data from China

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Abstract: In the context of the digital age, the digital economy, as a new economic model that the Chinese government is currently committed to developing, has played a positive role in driving consumption and creating employment opportunities. However, the differential development characteristics of the digital economy are becoming increasingly evident. The level of digital infrastructure and the application of digital facilities in China's eastern regions are superior to those in the central and western regions. The increasing level of differential development in the digital economy will further accelerate the cross-regional mobility of labor. For the more developed eastern regions in China, in terms of the digital economy, the ability to empower employment is relatively high, which can create more job opportunities and attract a larger labor force seeking employment opportunities. In contrast, the central and western regions face slower development in the digital economy and relatively insufficient employment-empowering capacity, leading to labor force outflow. Proper cross-regional labor mobility can enhance the efficiency of labor resource allocation. However, excessive labor force mobility can lead to imbalanced labor resource allocation, causing job shortages and reduced employment quality in regions with an excess of labor force, while labor loss regions face labor shortages and talent drain, resulting in a loss of economic vitality in those regions. Therefore, clarifying and addressing the various negative impacts brought about by the differential development of the digital economy are crucial for improving the overall employment quality in the digital economy era. However, there is currently limited research focused on the influence of differential development levels of the digital economy on employment quality. This study delves into the impact of the differential development levels of the digital economy on employment quality and analyzes the underlying mechanisms. Based on panel data from 31 provinces and cities in mainland China from 2011 to 2020, this study uses the entropy method to calculate both the employment quality index and the digital economy index. Building upon the digital economy index, the Gini coefficient of the digital economy development level in various regions in China is calculated using the Gini coefficient formula. Subsequently, a two-way fixed-effects model empirically analyzes the impact of China's differential development levels in the digital economy on employment quality. The research finds that the improvement in China's differential development level in the digital economy significantly reduces employment quality. After re-calculating the Gini coefficient and the employment quality index using principal component analysis, it is found that the Gini coefficient of the digital economy still has a significantly negative impact on the employment quality index. After conducting 2SLS regression using instrumental variables, it is confirmed that there is still a significant negative correlation between the Gini coefficient of the digital economy and the employment quality index. According to the regression results, for every 1% increase in the Gini coefficient of the digital economy, the employment quality index will decrease by 0.111% to 0.361%. Through a regression analysis of the mechanism of action, it is found that the industrial structure plays an intermediary role in the impact of the differential development levels of the digital economy on employment quality. The improvement in the differential development levels of the digital economy is unfavorable for the transformation and upgrading of the industrial structure in the central and western regions, as well as the rational development of China's overall industrial structure, thereby affecting the improvement

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of employment quality. Based on the above empirical results, the following policy recommendations are proposed: 1. The Chinese government should increase fiscal support for digital infrastructure construction in the central and western regions, continuously narrowing the gap in digital economy development levels between regions. 2. Regional governments in China should actively guide the healthy upgrading of industrial structures based on the actual conditions of each region. 3. In the digital economy era, the government should introduce relevant labor protection and social security policies based on the characteristics of emerging professions to further improve the employment quality of workers in the digital economy era.

Keywords: digital economy; digital differentiation; employment quality; industrial structure

1. Introduction

Employment, as the greatest livelihood project, has been highly valued by Chinese governments. The fundamental solution to the employment problem lies in maintaining steady economic growth. Economic growth serves as the driving force behind increasing the employment scale and the number of job opportunities. Meanwhile, improving the quality of employment requires continuous growth in workers' incomes, optimization of the working environment, and effective protection of workers' legitimate rights and interests. In October 2022, at the 20th National Congress of the Communist Party of China, it was explicitly stated that China's objective is to attain employment that is more abundant and of higher quality. The implementation of an employment priority policy was emphasized, highlighting the significance of both "quantity" and "quality" in the advancement of employment, with the ultimate goal of achieving high-quality full employment.

In recent years, rapid advancements in digital technologies, such as artificial intelligence, cloud computing, and big data, have propelled China's economy and society into the fast track of digital economic advancement. The incorporation of the digital economy into the Chinese government's work report initially transpired in 2017, and then the prevalence of the digital economy has been steadily escalating. According to the "China Digital Economy Development White Paper (2021)," China's digital economy surged to a magnitude of CNY 45.5 trillion by 2021, constituting 38.8% of the GDP for that year. In stark contrast, the extent of China's digital economy stood at a mere CNY 2.6 trillion in 2015, signifying 14.2% of the total GDP during that period. Currently, the digital economy has emerged as a pivotal impetus propelling high-quality progress within China's economy. The "Insights into the Current Situation and Trends of China's Digital Economy Development", released by the China Academy of Information and Communications Technology, anticipates that by 2025, China's total data volume is projected to encompass 30% of the global data volume, positioning China as the nation boasting the most extensive array of data types and the largest data volume. The amalgamation of digital technology with the real economy has engendered novel employment modalities, with the digital economy progressively assuming a momentous role in employment promotion, thereby constituting a vital impetus for fostering high-quality employment.

The emergence of the digital economy has led to the creation of numerous new employment opportunities. Apart from a smaller proportion of positions related to digital research and development, most employment opportunities in the digital economy are characterized by flexible employment arrangements [1]. These flexible employment positions primarily rely on internet platforms, such as freelancers, platform food delivery drivers, ride-sharing drivers, and so on. These flexible employment groups are often considered independent contractors rather than employees. The relationship between digital platforms and these flexible workers tends to be more of a business partnership rather than a traditional employment relationship. Compared to the protection of workers' rights under ordinary civil law, this business partnership provides limited labor protection for flexible workers [2]. This means that they are not legally considered employees and they do not enjoy the traditional labor protections afforded to full-time employees, such as limits on working hours, overtime pay, paid leave, and workers' compensation benefits [3]. This makes them vulnerable to potential exploitation and unfair treatment. The lack of a fixed employment relationship can result in a deterioration of labor rights [4], and most workers in the digital economy, including freelancers, platform food delivery drivers, and ride-sharing drivers, do not have labor protection contracts with the digital platforms they work for. These platforms cannot be regarded as genuine employers. Therefore, the increase in employment positions does not necessarily reflect a significant improvement in the welfare levels of these groups of workers. In this study, the assessment of employment quality does not solely rely on the quantity of employment positions but also takes into consideration labor protection and employment environment factors. A comprehensive employment quality index is constructed to assess the quality of employment. This approach aims to provide a more holistic understanding of the well-being and job security of workers in the digital economy, acknowledging that mere job quantity may not fully represent the effective enhancement of their welfare.

However, the digital economy development level in various regions in China demonstrates distinctive features. Innovation capacity and telecommunications services serve as important indicators for measuring the level of digital economy development, and these two indicators show significant variations across different regions in China. Taking the data on patent applications in various regions as an example, according to the "China Statistical Yearbook (2021)," [5] the top three provinces in terms of patent applications are Guangdong, Jiangsu, and Zhejiang, with 967,204, 719,452, and 507,050 applications, respectively. In contrast, Qinghai, the province with the lowest ranking, has only 6736 applications, a difference of approximately 143 times between the first and last place. In terms of telecommunications services, the top three provinces are Guangdong, with CNY 1502.53 billion, followed by Jiangsu with CNY 918.87 billion and Zhejiang with CNY 830.99 billion. The province with the lowest ranking is Tibet, with CNY 42.909 billion, whereas Guangdong's is 35 times that of Tibet's. The divergent growth of the digital economy poses challenges to the sustainable and healthy development of the overall economy. Regional disparities in digital economic advancement impede the integration and allocation of labor and capital resources, resulting in imbalances and hampering the enhancement of employment quality. Therefore, the main goal of this study is to empirically analyze the influence of differentiated development of the digital economy on employment quality, and the secondary goal is to find out the underlying mechanism between the differentiated development of the digital economy and employment quality. Finally, based on the empirical results, we propose policy advice.

2. Literature Review, Theoretical Analysis, and Research Hypotheses

2.1. Literature Review

Tapscott initially introduced the concept of the digital economy, highlighting its differentiation from the traditional economy. Tapscott emphasized that the digital economy is characterized by the transmission of information through digital means [6]. Mesenburg pointed out that the digital economy encompasses the establishment of e-commerce infrastructure and its associated commercial activities [7]. Guo and Liang [8] argue that internet technology serves as the fundamental driving force behind the digital economy.

The development pattern of the digital economy differs significantly from the economic laws under traditional industries, and there are significant differences in the path of productivity enhancement [9]. Existing research has examined the optimization effects of the digital economy on productivity. On the one hand, the impact of industrial digitalization has driven the transformation of traditional industries through the application of digital technologies, aiming to increase production efficiency and output. The adoption of digital technologies by businesses helps reduce operational costs [10], which is due to the existence of spatial and temporal barriers to traditional employment methods. The development of the digital economy has considerably expanded the temporal and spatial boundaries of employment, facilitating the optimization of labor resource allocation [11].

On the other hand, it refers to the digital industries, which have a spatial spillover effect driven by the development of information and communication technology (ICT) and the internet industry [12]. Yang and Jiang [13] pointed out that this spillover effect plays a substantial driving role in the high-quality economic development of surrounding regions. Furthermore, the communication network infrastructure, which serves as the backbone of the digital economy, offers a robust basis for the functioning of digital business models, ultimately bolstering operational effectiveness for enterprises [14].

However, the presence of regional disparities in technological innovation talent absorption capacity, economic development levels, and digital economic policies has resulted in imbalanced regional characteristics in China's digital economy development. These disparities can hinder the sustainable and robust growth of the digital economy. Li [15], utilizing the Dagum Gini coefficient method, conducted a study on output efficiency, regional disparities, and the dynamic evolution of the digital economy in different regions in China. The findings indicated that regional disparities in the digital economy have been widening over time. Jiao [16] examined the regional disparities of the digital economy in eight comprehensive economic zones in China, revealing significant variations among them. Han et al. [17], employing Kernel density estimation and the Dagum Gini coefficient, evaluated the development of the digital economy in China's three major regions. The study concluded that the provincial-level development of the digital economy in China demonstrates a fluctuating upward trend with non-equilibrium or differentiated growth. In summary, the existing literature highlights substantial regional disparities in the level of digital economy development in China, yet there is a relative scarcity of literature analyzing the economic impacts brought about by this differentiated development level.

Employment quality is a multidimensional and comprehensive concept. Lai et al. [18] constructed an employment quality evaluation system based on certain criteria, such as worker compensation, social security, labor relations, employment conditions, and the work environment. Zhu et al. [19] developed an employment quality evaluation system based on employment capability, employment security, employment services, and employment level.

The existing literature has mainly examined the relationship between the digital economy and employment quality from a micro-level perspective, focusing on industries and enterprises. Some studies have indicated that the application of intelligent technologies generated by the digital economy may replace labor employment [20]. Others have pointed out that the emergence and widespread use of new communication technologies, such as computers and the internet, have weakened constraints on working hours and locations, potentially leading to longer working hours and decreased employment quality for workers [21,22]. Furthermore, the development of the digital economy, while increasing employment requirements, may also lead to structural unemployment, which could hinder the improvement of employment quality [23,24]. However, some studies argue that the advancement of the digital economy can improve productivity, alleviate labor intensity, and foster emerging job opportunities, which are beneficial for enhancing employment quality [25,26]. These two arguments have not yet reached a consensus in the existing research.

The majority of research has approached the correlation between the digital economy and employment quality from a micro-level viewpoint. Currently, there is no consensus as to whether the digital economy has a positive or negative effect on employment quality. Hence, it is crucial to comprehend the connection between the digital economy and employment at both the macro and micro levels, investigate its underlying mechanisms, and gain a deeper insight into the intrinsic impact of the digital economy on employment quality. Understanding this is pivotal for enhancing the digital economy to bolster employment quality. The existing literature predominantly focuses on the association between the digital economy and employment quality, with limited consideration given to the influence of China's diversified digital economy development on employment quality. Consequently, the marginal contribution of this study lies in examining the influence of varied digital economy development on employment quality from a macro perspective.

2.2. The Direct Effects of Differential Development Levels in the Digital Economy on Employment Quality

2.2.1. Differentiated Characteristics of Digital Infrastructure

We aim to assess the varying degrees of digital economy development in different regions in China by analyzing the distinctive characteristics of digital infrastructure and the levels of digital applications.

Digital infrastructure plays a crucial role in the development of the digital economy, and its key functions can be seen from the following perspectives. Firstly, digital infrastructure provides robust data storage and processing capabilities, supporting the data-driven nature of the digital economy. The modern digital economy relies on technologies, such as big data analytics, artificial intelligence, and machine learning, which require vast data resources. Digital infrastructure serves as the backbone for these technologies. Secondly, digital infrastructure facilitates cross-regional connectivity through the internet, promoting the formation of interregional markets. Businesses can easily expand their operations across regions using digital infrastructure, accelerating trade and cooperation between regions. Additionally, digital infrastructure provides strong support for innovation and entrepreneurship, giving rise to numerous startups and technological innovations. Technologies like cloud computing, open data, and APIs enable more convenient product and service development. Furthermore, digital infrastructure helps improve the efficiency of business operations and reduces operational costs, enhancing a company's competitiveness. It also creates conditions for the generation of employment opportunities. In summary, digital infrastructure is an indispensable pillar of digital economy development, providing a solid foundation for economic growth, innovation, and employment.

The differentiated development of digital infrastructure has the potential to exacerbate disparities between regions, affecting the balanced growth of the digital economy. This situation can result in a widening wealth gap [27], hindering the overall sustainable development of the digital economy. In cases where there is an imbalance in digital economy development, regions with existing capital advantages are more likely to adopt modern intelligent production equipment at a faster rate, thus strengthening their capacity to attract investments. Consequently, this further amplifies the disparities in production capital proportions between regions with relatively weaker capital [28].

The length of fiber optic cables and the number of broadband internet access ports are relevant indicators of digital infrastructure because they reflect two crucial aspects of digital infrastructure: the coverage and capacity of communication networks, which are vital for the development of the digital economy. Firstly, the indicator of fiber optic cable length is of paramount importance because it signifies the availability of high-speed and stable data transmission. Fiber optic communication is a high-bandwidth, low-latency transmission method that, in comparison to traditional copper wires or wireless communication, can support larger data transmission capacities. Consequently, the extent of fiber optic network coverage directly impacts the performance of various data-intensive applications in the digital economy, including online video streaming, cloud computing, big data analysis, and remote work. Extensive coverage of fiber optic networks in a region can provide faster and more reliable internet connections, thus facilitating the widespread adoption and use of digital services. Secondly, the number of broadband internet access ports is another critical indicator because it reflects the capacity and availability of digital infrastructure. Broadband internet access ports refer to communication interfaces that allow individuals and businesses to connect to the internet. With the continuous development of the digital economy, an increasing number of devices and applications require fast and stable internet connectivity. This necessitates a greater number of broadband internet access ports. Having an adequate quantity of broadband internet access ports can meet users' demands and support a wide range of online activities, including e-commerce, online education, telemedicine, and the connectivity of smart home devices. Therefore, the quantity of broadband internet access ports is a key metric that indicates whether a region's digital infrastructure is sufficient to support the development and innovation of the digital economy. In summary, the length of fiber optic cables and the number of broadband internet access ports are pivotal indicators of digital infrastructure. They are essential for the successful development of the digital economy, ensuring efficient data transmission, enabling data-intensive applications, and supporting a wide range of online activities. Improvements in these indicators can enhance the competitiveness of the digital economy, foster economic growth, and create employment opportunities.

Figures 1 and 2 illustrate the distribution of optical fiber length and the number of broadband internet access ports from the 31 provinces (autonomous regions and municipalities directly under the central government) in China. In 2020, as shown in Figure 1, Jiangsu had a total optical fiber length of 3,990,069 km, Zhejiang had 3,497,879 km, and Sichuan had 3,535,457 km. On the other hand, the three regions with the lowest rankings were Tibet, with only 201,862 km, followed by Ningxia with 269,378 km, and, slightly higher, was Qinghai with 375,296 km. In terms of internet access port numbers by 2020, in Figure 2, Guangdong had the highest with 86.5323 million ports, followed by Jiangsu with 72.2486 million ports, and, finally, Shandong with 67.5676 million ports, ranking in the top three. Conversely, Tibet had only 2.1898 million ports, and Qinghai had 4.1282 million ports. The unequal development of digital infrastructure between regions will have a negative impact on the overall employment quality. Uneven development of digital infrastructure will put workers in underdeveloped regions at risk of unemployment and inadequate employment opportunities. This is because the digital economy increasingly relies on high-speed internet and digital technologies. In regions with relatively weak digital infrastructure, people have fewer opportunities to access remote work, online learning, and digital entrepreneurship. This exacerbates the digital divide, limiting the participation of businesses and individuals in the digital economy in areas with relatively weak digital infrastructure. Furthermore, digital skills have become crucial in the digital economy, and regions with insufficient digital infrastructure development will lack opportunities to provide digital skills training and education for workers, leading to a skills gap. Moreover, individual entrepreneurship and business development in regions with relatively weak digital infrastructure will be constrained. Areas lacking digital hardware support struggle to attract digital companies and achieve the digital transformation of traditional companies, which hinders local job growth and employment quality improvement. This situation can result in an influx of labor into areas with advanced digital infrastructure, leading to job shortages in those regions. In contrast, underdeveloped areas with weak digital infrastructure struggle to drive the digital transformation of their economies, making it difficult to improve the employment environment and wage levels for local workers. Therefore, the differential development of digital infrastructure will overall hinder the improvement of employment quality. It creates disparities in job opportunities, digital skills acquisition, and economic growth potential between regions, which, in turn, affect the quality of employment available to individuals in those areas.

2.2.2. Differentiated Development of Digital Applications

The potential positive mechanism of the digital economy and employment quality is shown in Figure 3. As the digital economy continues to evolve, it has created new market demands and further spawned new types of occupations. Examples of these emerging employment groups include platform food delivery drivers, ride-sharing drivers, and online service providers. These emerging employment groups have distinct characteristics in the digital realm, reflecting the profound impact of the digital economy and technological developments on work patterns and the job market. Firstly, digital tools provide these emerging employment groups with greater flexibility. They can work anytime and anywhere through mobile applications, and they are no longer confined to traditional offices or work locations. This digital flexibility allows them to better balance work and life, adapting to different schedules and demands. Additionally, digital platforms offer these employment groups more extensive market opportunities. Digital platforms connect suppliers and demanders, enabling them to provide and access services over a broader range, creating more employment opportunities.

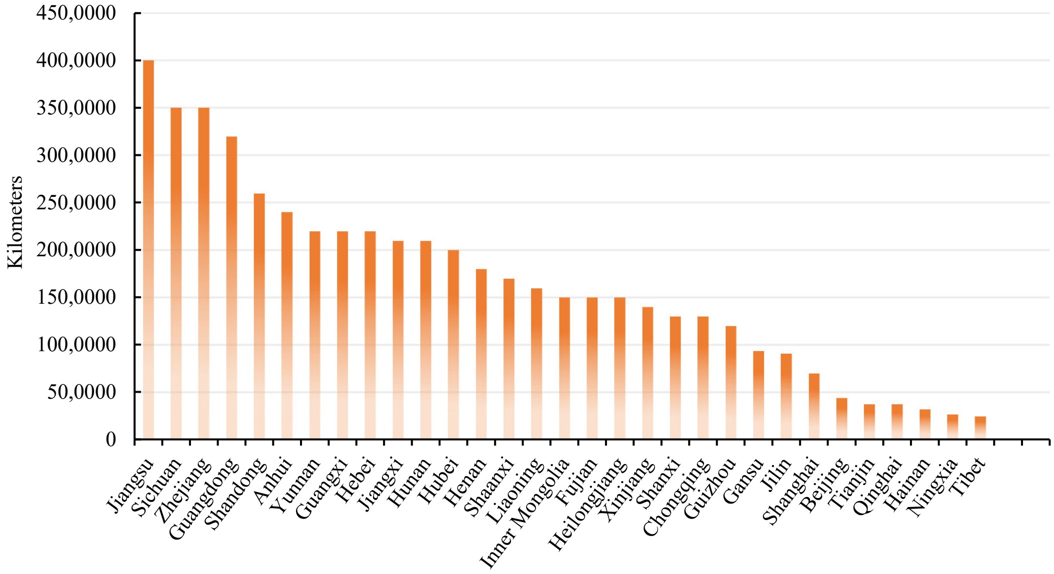

Figure 1. Fiber optic cable length in each region by 2020. (Data source: China Statistical Yearbook (2021)) [5].

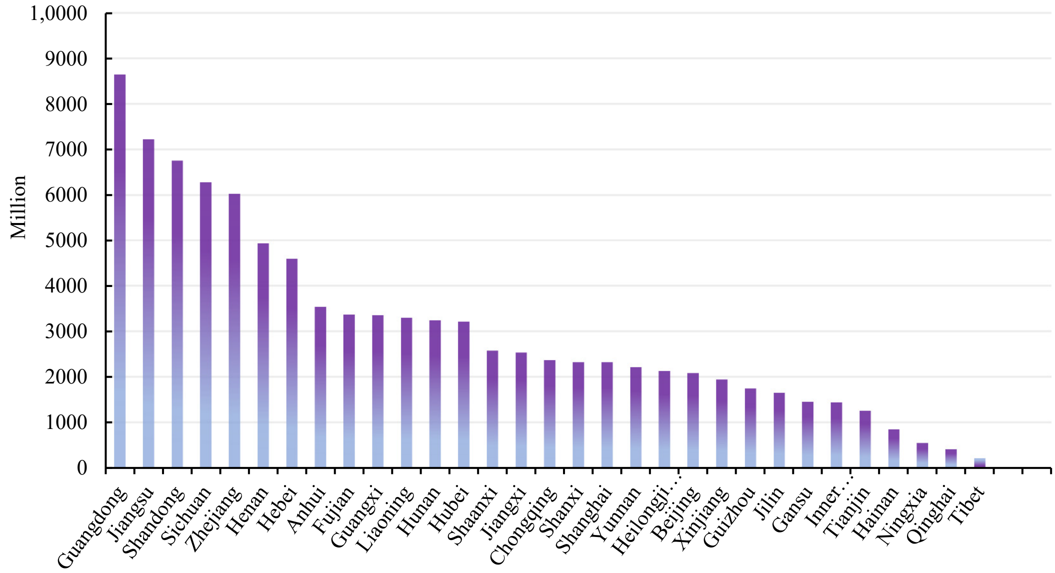

Figure 2. The number of internet access ports in each region by 2020. (Data source: China Statistical Yearbook (2021)) [5].

However, digitization also presents some challenges. These occupations may involve a certain degree of digital divide, as individuals with lower digital literacy might face exclusion. Furthermore, the instability of the digital economy to some extent affects the stability of these professions. Their income is often dependent on fluctuations in the number of orders and market demand. Digitization is one of the primary occupational characteristics of these emerging employment groups, granting them greater flexibility, market opportunities, and efficiency. However, it also brings challenges, such as the digital divide and instability. The people, due to a lack of the ability to use the digital device, can be isolated from the digital economy and its opportunity for employment. The difference in people's ability to use the digital application can be seen as the individual differences of the digital application, and those regions with relatively lower human capital may have a relatively lower level of digital applications.

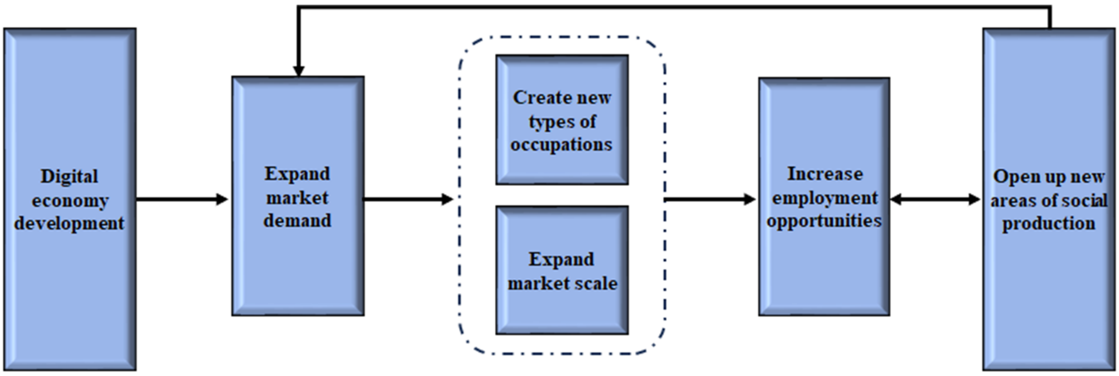

Figure 3. Mechanisms of the impact of the development of the digital economy on employment.

E-commerce can be seen as an initiative application of digital applications in people's lives, and e-commerce has become a crucial component of China's contemporary digital economy, exerting a profound influence on economic growth and employment quality. Driven by the global wave of digitization, the Chinese e-commerce market has rapidly risen to become one of the world's largest online retail markets. This trend has not only altered business models but also presented new opportunities and challenges for China's job market. Firstly, the rise of e-commerce has propelled the vigorous development of China's digital economy. Through digital means, such as online shopping, digital payments, and e-commerce platforms, China's business ecosystem has been upgraded and expanded. This has provided businesses with broader markets and more efficient operational methods, thereby powerfully driving the growth of China's digital economy. Simultaneously, the Chinese government has actively supported the development of the digital economy, further unleashing the market potential of this sector through policy guidance. Secondly, the ascent of e-commerce has had a profound impact on the quality of employment in China. E-commerce platforms have created new employment opportunities, including for platform food delivery drivers, warehousing and logistics workers, and e-commerce platform operators, among others. These emerging forms of employment typically offer flexibility, allowing individuals to choose their work hours according to their schedules. However, they also come with a degree of instability and issues related to social security. Therefore, e-commerce is of utmost importance for China's job market, requiring a balance between increasing job opportunities and improving employment quality. However, as e-commerce has rapidly developed in China, its level of development varies across different regions. Some major cities and coastal areas have rapidly adopted and promoted e-commerce, while other regions may face challenges, such as insufficient digital infrastructure, limited market access, and talent drain. This has resulted in significant disparities in the development of e-commerce across China. Firstly, first-tier cities and eastern coastal regions in China are typically e-commerce hotspots, benefiting from stronger digital infrastructure, higher internet penetration rates, and more market opportunities. In these areas, e-commerce platforms thrive, attracting significant investments and corporate participation, thus driving the growth of the digital economy. Secondly, relatively less-developed inland regions may encounter challenges related to inadequate digital infrastructure, limiting the development of e-commerce. The lack of high-speed internet connectivity and support for digital technologies makes it difficult for residents in some regions to fully access the opportunities offered by the digital economy, exacerbating the digital divide. Due to the uneven development characteristics of e-commerce, it has implications for employment quality in different regions. E-commerce creates a substantial number of job opportunities in first-tier cities and coastal regions but may offer fewer opportunities in China's central and western regions. In this context, this section will delve into the phenomenon of the uneven development of e-commerce across various regions in China, analyze its impact on the digital economy and employment quality, and explore ways to address this imbalance to ensure that the opportunities of the digital economy are more broadly distributed nationwide, promoting fair and sustainable employment quality growth.

Using the e-commerce industry in various regions in China as an illustration, Figure 4 presents the percentage of enterprises engaged in e-commerce for the total number of enterprises in 2020, and these data represent the proportion of e-commerce enterprises to the total enterprises.

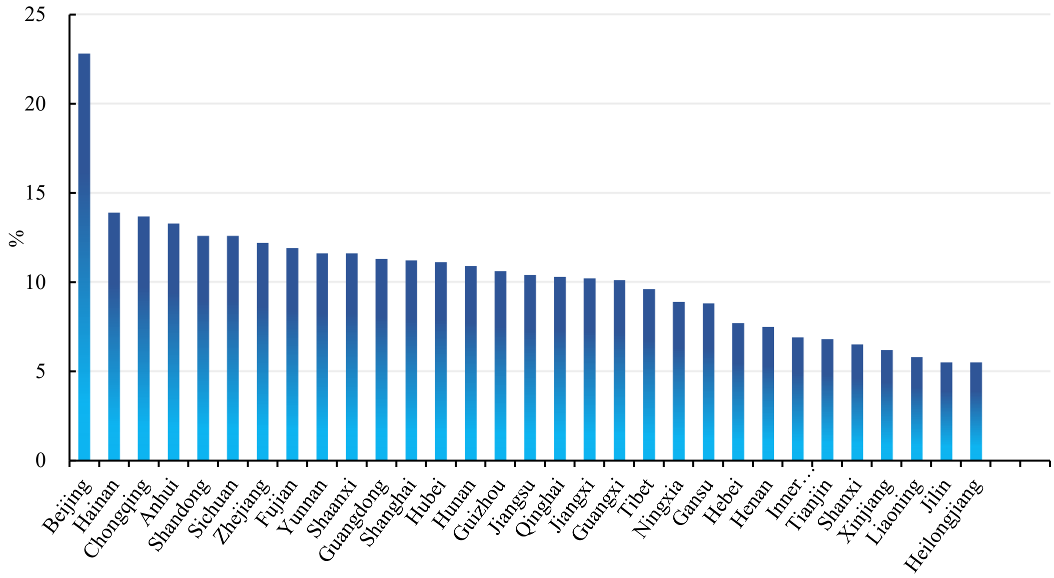

Figure 4. The proportion of e-commerce enterprises to the total enterprises in each region by 2020. (Data source: China Statistical Yearbook (2021)) [5].

In 2020, the percentage of enterprises engaged in e-commerce trading activities varied across different regions in China. Heilongjiang accounted for 5.5% of total enterprises, Liaoning accounted for 5.8%, Xinjiang accounted for 6.2%, and Henan accounted for 7.5%. In contrast, Chongqing accounted for 13.7% and Zhejiang accounted for 12.2%. The percentage level of participation in e-commerce and the quality of employment are closely related in China. The uneven development of e-commerce across different regions and industries has resulted in varying degrees of e-commerce participation, thereby influencing the diversity of employment conditions. Regions with high levels of e-commerce participation typically create more job opportunities, particularly in certain areas, such as e-commerce platform operations, logistics, digital marketing, and customer support. These fields of work often require digital skills and online sales experience. Therefore, individuals employed in more developed e-commerce regions are more likely to secure jobs related to the digital economy and enjoy relatively higher average salary levels.

Firstly, regions with advanced digital economies typically have more sophisticated digital infrastructure, attracting the presence and investments of businesses related to the digital economy. This provides these regions with more job opportunities. Secondly, these advanced digital economy regions have a greater demand for advanced digital skills and specialized knowledge, requiring workers to undergo higher-level digital skills training. The availability of educational resources and labor mobility makes digitally developed regions more attractive. However, this attractiveness can also pose risks of over-competition and “burnout” among job seekers, as the labor supply may exceed the actual demand for positions. Job seekers may resort to long working hours or even accept lower wages to gain a competitive edge, ultimately lowering employment quality. In contrast, less-developed regions in the digital economy may receive less attention from digital-centric businesses, leading to fewer job opportunities related to the digital economy. These regions may also have limited capacity to absorb labor. Additionally, wage levels in these regions tend to be lower than in digitally developed areas. Less-developed digital economy regions often engage in low-end industries within the digital economy, such as e-commerce warehousing and logistics, while high-end industries, like software and hardware development and financial promotion, are concentrated in digitally developed regions. If the disparities in digital economic development levels between regions continue to widen, the disparities in employment levels will become more pronounced. Mismatches in labor resources between regions will lead to a decrease in employment quality. The employment situation in digitally developed regions will become increasingly challenging, while the employment levels in digitally less developed regions will remain stagnant, ultimately hindering the overall improvement of employment quality in China.

Based on the above theoretical analysis, this paper proposes the following hypothesis.

Hypothesis 1. *The higher the level of differentiated development of the digital economy, the more detrimental it is to the improvement of employment quality*.

2.3. The Indirect Effects of Differential Development Levels in the Digital Economy on Employment Quality

Digital Economy, Industrial Structure, and Employment Quality

Existing research has confirmed that advancements in internet technology optimize the employment structure, and the widespread application of digital technology creates new job opportunities in the tertiary sector [29]; it has partially substituted employment positions in labor-intensive and medium-to-low technology-intensive industries [30]. Meanwhile, the digital transformation of traditional enterprises can significantly improve productivity [31]. Hu et al. [32] have found that the advancement of digital technology is associated with consistent growth in employment, contributing positively to the restructuring of industries and the creation of job opportunities. Guo [33] has pointed out that the increasing adoption of artificial intelligence is expected to drive the expansion of digital finance, consequently influencing the structure of industries. Wang [34] showed that the industrial intelligence in China expands the absorptive capacity of the service sector for employment, thus contributing to the improvement of employment quality. Ye et al. [35] conducted an empirical analysis using panel data at the provincial level in China during 2001–2017. Their study examined the impact of digital economic development on employment structure, considering various aspects, such as industry, sector, and skills. Their findings suggest that the digital economy has played a significant role in reshaping China's employment structure, leading to a shift towards a manufacturing-oriented, high-tech, and high-skilled direction.

The convergence of digital technology and traditional industries has revolutionized information transfer and knowledge acquisition, effectively reducing production costs for enterprises and achieving more efficient resource allocation. It has also enabled economies of scale and precise resource allocation, thus driving the transformation and upgrading of industrial structures [36]. However, the differentiated development of the digital economy leads to variations in the integration between digital technology and the real economy in terms of speed, quality, and extent across different regions [37]. This disparity creates imbalances in supply and demand, information transmission, and knowledge acquisition. Consequently, there is a misalignment of labor resources, which impedes the enhancement of employment quality. Moreover, the differential development of the digital economy hinders the balanced development of emerging industries across regions, obstructing the overall progression of the industrial structure towards the mid-to-high end [38].

Therefore, the differentiated development of the digital economy poses a constraint on the transformation and upgrading of the overall industrial structure. The industrial structure and employment structure are two complementary systems, where the advancement of the industrial structure drives improvements in the employment structure. However, the speed of upgrading the employment structure often lags behind that of the industrial structure. According to Zong et al. [39], the upgrading of the industrial structure generates numerous emerging job positions. This upgrading process has a positive impact on employment quality, but the differential development of the digital economy hampers the transformation and upgrading of the industrial structure, thus adversely affecting employment quality. As the digital economy advances, workers in the primary sector gradually transition away from agricultural work and move into manufacturing, services, and other related industries. Simultaneously, the upgrading and transformation of the secondary industry through digital technology will improve the production efficiency of this sector, promote new social divisions of labor, and, consequently, increase the demand for emerging service industries. As a result, the tertiary industry will continue to develop. Therefore, sustained progress in the digital economy facilitates the gradual shift of labor from the primary industry to the secondary and tertiary industries, ultimately leading to an improvement in employment quality through the upgrading of the industrial structure. If the digital economy develops in a balanced manner across different regions in China, it will drive the overall industrial structure towards higher levels.

However, the differential development of the digital economy has significant disparities in the adjustment speed of the industrial structure among regions, thereby impeding the transformation and upgrading of the overall industrial structure [40]. Furthermore, it distorts the rationalization level of the industrial structure within each region. This ultimately hinders the enhancement of employment quality and inhibits the healthy development of the industrial structure [41,42]. Skilled labor in regions with relatively backward industrial structures and relatively lower levels of digital economy may migrate to regions with relatively better industrial structures and higher levels of digital economy. This migration pattern results in regions with better industrial structures attracting a greater number of high-skilled and low-skilled workers. However, the excessive concentration of talent can lead to a mismatch in labor resources. The over-concentration of labor in regions with developed industrial structures and digital economies may transform the healthy labor market competition into a state of involution, ultimately undermining the overall improvement of employment quality.

Based on the theoretical analysis presented above, this paper proposes the following hypothesis.

Hypothesis 2. *The differentiated development of the digital economy affects the quality of employment by influencing the industrial structure of each region.*

3. Model and Data

3.1. Evaluation System Construction and Measurement of the Digital Economy

The digital economy, as a burgeoning economic form, encompasses industrial digitization, digital industries, and data valorization with internet information technology as a carrier, which is an emerging economic form that promotes resource reorganization of traditional factors to achieve optimal resource allocation and regeneration [43]. The development of ICT is crucial for the realization of the digital economy [44]; thus, the development of digital infrastructure in various regions in China should be included as a measuring indicator. The extensive adoption of digital technology enables the digital economy to permeate various facets of societal existence, while traditional industries are also integrating with the advancements of the digital economy. Simultaneously, the digital economy undergoes constant evolution through its practical implementation. Therefore, the extent to which digital technology is widely adopted should be integrated into the evaluation system for the digital economy. Additionally, the research and innovation capacities are crucial for fostering the rapid advancement of the digital economy, and evaluating these capabilities is of utmost importance. Therefore, this study assesses the level of digital economy development in different regions by considering digital infrastructure, the widespread application of the digital economy, and innovation capabilities. The evaluation system and indicators are shown in Table 1.

Table 1. Digital economy development indicators evaluation system.

	Primary Indicators	Secondary Indicators	Tertiary Indicators
The evaluation system of digital economy indicators in various regions in China	Digital infrastructure	Fiber optic density	Length of fiber optic/Area of administrative regions
		Internet coverage density	Number of internet broadband access ports/Permanent resident population
		Mobile phone penetration rate	Mobile phone penetration rate
		Number of internet domain names	Number of internet domain names
	The widespread application of digital technology	Telecommunication service volume per capita	Total telecommunication service volume/Permanent resident population
		Depth of digital financial usage	Depth of digital financial usage
		Breadth of digital financial coverage	Breadth of digital financial coverage
		Digital finance digitization degree	Digital finance digitization degree
	Innovation capability	Intensity of research and development investment	Research and development expenditure of industrial enterprises above designated size/Permanent resident population
		Innovation activity	Number of patent applications/Permanent resident population

Based on the above indicators, this study uses the entropy method to calculate the weight of each indicator and subsequently generate the digital economy index for various regions in China. The advantage of using the entropy method lies in the fact that it does not require assigning subjective weights to each indicator. In situations where the exact weights for each indicator are not known, the results of the entropy method are more objective. The specific calculation steps are as follows:

Firstly, the indicators are subjected to a standardization process. Because all the indicators in Table 1 are positive indicators, the standardization formula used is as shown in Equation (1):

$$x_{ij}^{1} = \frac{x_{ij} - \min\{x_{ij}\}}{\max\{x_{ij}\} - \min\{x_{ij}\}} \tag{1}$$

where x_{ij} in Equation (1) is the "j" indicator of each region "i" in Table 1; $j = 1,\ 2,\ 3\cdots\cdots 10$.

The second step is to calculate the weights accounted for by each indicator in each region, and it represents the weight proportion of each indicator to the total indicators. The calculation formula is shown in Equation (2):

$$P_{ij} = \frac{x_{ij}^{1}}{\sum_{i=1}^{30} x_{ij}^{1}} \tag{2}$$

The third step is to find the information entropy based on the calculation result of the second step, which is calculated as shown in Equation (3):

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^{31} P_{ij} * \ln(P_{ij}) \tag{3}$$

In the fourth step, the coefficient of variation of each index is calculated according to Equation (3), and the calculation formula is shown in Equation (4):

$$d_j = 1 - e_j \tag{4}$$

The fifth step is to normalize the coefficient of variation by calculating the weight proportion of each indicator's coefficient of variation, as shown in Equation (5):

$$w_j = \frac{d_j}{\sum_{j=1}^{10} d_j} \tag{5}$$

In the sixth step, the comprehensive index of the digital economy in each region is calculated based on the weights, as shown in Equation (6):

$$Digital_i = \sum_{j=1}^{10} w_j * x_{ij}^1 \tag{6}$$

Based on the data of various indicators in Table 1 and the calculation process using the entropy method mentioned above, this study has computed the digital economy index for different regions in China and presented the spatiotemporal distribution in Figure 5. According to Figure 5, the digital economy index of each region in China has a significant increasing trend from 2011 to 2020. The average index value for all regions in 2011 was 0.085, while it increased to 0.194 in 2015 and further to 0.371 in 2020. From 2011 to 2020, China's digital economy index increased by an average of 0.029 annually. Specifically, in the eastern region, the digital economy index grew from 0.151 in 2011 to 0.475 in 2020, with an average annual increase of 0.032. In the central and western regions, the digital economy index increased from 0.043 in 2011 to 0.273 in 2020, with an average annual increase of 0.023. Overall, the digital economy index in various regions in China has been steadily rising, but there are significant differences among regions. The eastern region has a relatively higher average and growth speed of the digital economy index, while the central and western regions have relative lower averages and growth speeds compared to the overall average, indicating a trend of increasing disparity in the development of the digital economy. In terms of regional distribution, significant variations exist in the progress of the digital economy throughout China. Some regions, such as Beijing, Tianjin, Shanghai, Zhejiang, and Guangdong, have consistently held a leading position in digital economy advancement, while other areas have been striving to catch up. This indicates a significant disparity in the development of the digital economy across regions, highlighting the presence of differentiated growth.

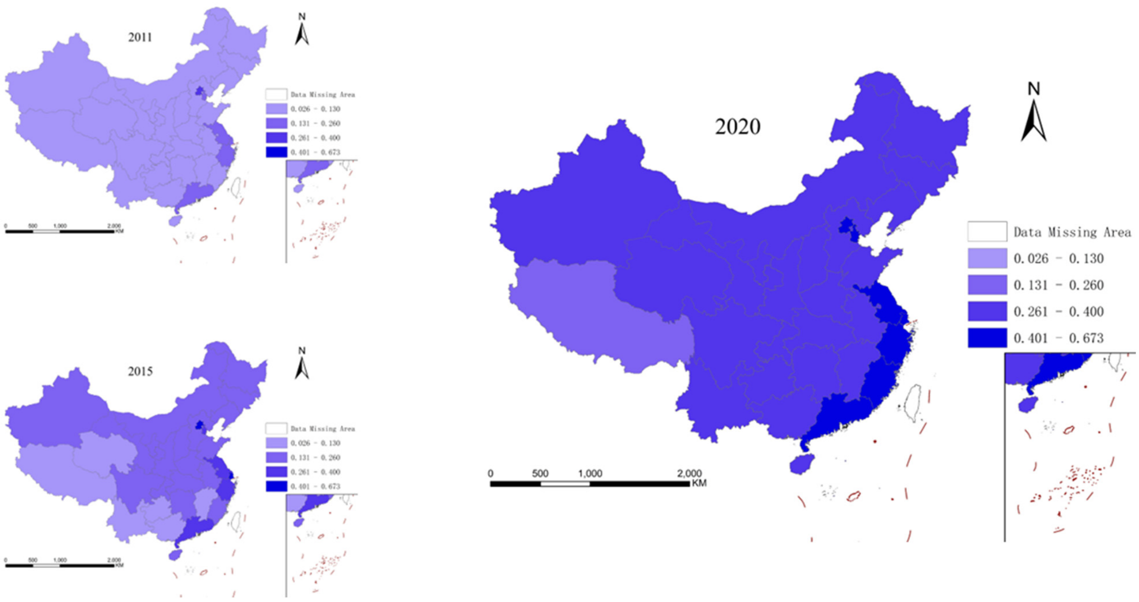

Figure 5. Spatial–temporal distribution of the digital economy index in various regions in China.

To measure the degree of digital economy differentiation among various regions in China, the Gini coefficient is calculated based on the results of the digital economy index, and the Gini coefficient calculation formula is shown in Equation (7). The range of the calculated results is from 0 to 1, where a value closer to 1 indicates a higher level of imbalance, and vice versa.

$$Gini = \frac{1}{2\overline{Digital}} \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{|Digital_j - Digital_i|}{n(n-1)} \quad (7)$$

3.2. Construction and Measurement of Employment Quality Evaluation System

This paper constructs an evaluation system for employment quality based on the concept of decent labor. According to the existing research, the evaluation system of employment quality of 31 provinces in China is constructed from three dimensions of labor remuneration, labor protection, and employment conditions. Nine specific indicators are used in the evaluation system. Labor remuneration reflects the total remuneration received by workers for their participation in productive activities, which embodies the social value created by labor [45]. It is measured by five secondary indicators: average wages of urban employed persons, the proportion of total wages to GDP, accumulated surplus of unemployment insurance fund (in CNY 100 million), accumulated surplus of urban and rural residents' social pension insurance fund (in CNY 100 million), and accumulated surplus of work injury insurance fund (in CNY 100 million). The primary indicators of labor protection reflect the specific conditions of workers in terms of seeking fair treatment, and they are measured by three secondary indicators: labor dispute settlement rate, number of fund trade unions, and success rate of union mediation. Employment conditions are measured by the urban registered unemployment rate. The secondary indicators in Table 2 are derived from the original data of the "China Statistical Yearbook (2012–2021)" [5] and do not involve any calculations; hence, Table 2 does not include tertiary indicators. The specific evaluation system for employment quality is presented in Table 2.

Table 2. Evaluation system of employment quality by region in China.

	Primary Indicators	Secondary Indicators
Evaluation system of employment quality	Labor remuneration	Average wage of urban employed person Proportion of total wages to GDP Accumulated surplus of unemployment insurance fund (in CNY 100 million) Accumulated surplus of urban and rural residents' social pension insurance fund (in CNY 100 million) Accumulated surplus of work injury insurance fund (in CNY 100 million)
	Labor protection	Labor dispute settlement rate Number of fund trade unions Success rate of union mediation
	Employment conditions	Urban registered unemployment rate

In this study, the quality of employment is assessed using the entropy value method, and the results are shown in Figure 6.

Figure 6 illustrates significant variations and unstable temporal changes in employment quality across various regions in China. Except for the southeastern coastal areas, most regions exhibit a fluctuating trend in employment quality. Non-coastal regions have been unable to sustain continuous growth in employment quality, and some areas even experienced a decline in employment quality in 2020 compared to 2015.

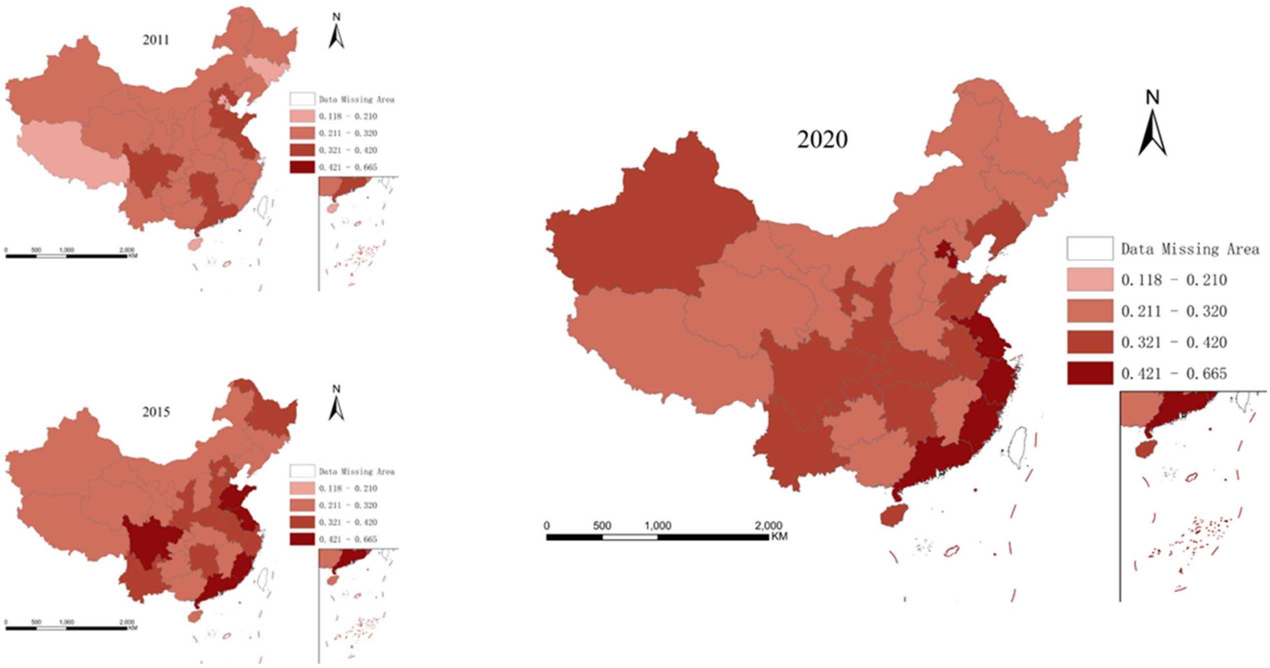

Figure 6. Spatial–temporal distribution of employment quality in various regions in China.

3.3. Variable Selection and Descriptive Statistics of the Data

3.3.1. Dependent Variable

The dependent variable in this study is employment quality, which is a comprehensive indicator. Based on the employment quality evaluation system constructed earlier, the employment quality score is calculated using the entropy method, ranging from 0 to 1. Employment quality is positively correlated with its values.

3.3.2. Independent Variable

The core independent variable is the level of differentiated development in the digital economy. It is also based on the digital economy development evaluation system constructed earlier. The level of differentiated development in the digital economy is calculated using the entropy method. Subsequently, the level of differentiated development in the digital economy for each region in China is calculated using Equation (7). The range of the core independent variable is 0 to 1. A value closer to 1 indicates a greater imbalance in digital economy development among regions and a higher level of differentiated development, or vice versa.

3.3.3. Control Variables

The following control variables are selected in this paper: regional GDP per capita ($lnpgdp$), human capital level in each region (*lnhc*), number of foreign-invested enterprises ($lnfie$), road infrastructure ($lnrinf$), urbanization level (*Urban*), technological progress level (*Tech*), policy regime (*Policy*), and labor force structure (*Labrstr*).

The regional GDP per capita ($lnpgdp$) is adjusted using the GDP deflator with the base year of 2011 and then transformed into a logarithmic value. The human capital level in each region (*lnhc*) is expressed by the logarithm of the number of students enrolled in higher education per hundred thousand people. The number of foreign-invested enterprises ($lnfie$) is expressed as the logarithm of the number of foreign-invested enterprises in each region. Road infrastructure ($lnrinf$) is the logarithmic value of road area in each region. Urbanization level (*Urban*) is the proportion of registered urban population to the total population in each region. Technological progress level ((*Tech*) is the ratio of the number of granted patents to the number of patent applications in each region. The policy regime (*Policy*) is expressed by the proportion of fiscal expenditure to GDP in each region. Labor force structure (*Labrstr*) is calculated as the ratio of the proportion of high-skilled labor to the combined proportion of low-skilled and medium-skilled labor (high-skilled labor: education level of bachelor's degree or above; medium-skilled labor: education level of high school or college; low-skilled labor: education level below high school).

3.3.4. Mechanism Variables

Based on the previous theoretical analysis, the authors contend that the differentiated advancement of the digital economy has repercussions for employment quality by influencing the structure of industries. In this study, the Theil index is employed to gauge the rationalization level of the industrial structure [46], while the transformation and upgrading level of the industrial structure are utilized as additional mechanism variables. The calculation formula for the rationalization level of the industrial structure in each region is as follows:

$$indr = \sum_{i=1}^{3}\left(\frac{y_i}{y}\right)\ln\left(\frac{\frac{y_i}{l_i}}{\frac{y}{l}}\right) \tag{8}$$

In Equation (8), y_i represents the output value of the i (primary; secondary; tertiary) industry in each region, and l_i represents the number of employees in the i (primary; secondary; tertiary) industry of each region. The variables y and l represent the total economic output and total employees across industries in each region, respectively. The calculation method of this index reflects whether the allocation of labor resources is reasonable. When the per capita GDP of the i (primary; secondary; tertiary) industry is higher than the overall per capita GDP, the proportion of employees in the i (primary; secondary; tertiary) industry should be higher. Therefore, this value is a positive indicator. An increase in this index can be considered an indication that the overall industrial structure is moving towards a more rational level. Conversely, if this index decreases, it suggests the opposite.

To determine the transformation and upgrading level of the industrial structure, weights are assigned to the primary, secondary, and tertiary industries, followed by calculating their weighted average [47]. The formula is shown as Equation (9), where x_i represents the proportion of the i (primary; secondary; tertiary) industry's output to the GDP. This index assigns the highest weight proportion to the tertiary industry. An increase in this index reflects the development of the industrial structure towards a more advanced level, indicating a continuous upgrading of the industrial structure. Conversely, if this index decreases, it suggests the opposite. The definitions, data sources, and descriptive statistics of each variable are shown in Tables 3 and 4.

$$indt = \sum_{i=1}^{3} x_i \times i \tag{9}$$

Table 3. Variable definition and data source.

Category	Variable	Symbol	Definition	Source	UoM
Dependent variable	Employment quality	*Empqlty*	The employment quality in various regions in China from 2011 to 2020 was calculated according to the evaluation index system in Table 2.	China Statistical Yearbook; China Population and Employment Statistical Yearbook	
Independent variable	Digital Economy Differentiation Index	*Gini*	The Gini coefficient of the digital economy in each region in China from 2011 to 2020 was calculated according to the evaluation system in Table 1 and the entropy method. Subsequently, it was recalculated according to Equation (7).	China Statistical Yearbook; Yearbook of China Communications; Institute of Digital Finance Peking University (IDF)	

Table 3. *Cont.*

Category	Variable	Symbol	Definition	Source	UoM
Control variables	The regional GDP per capita	$lnpgdp$	The logarithmic value of GDP (in CNY) per capita in each region in China.	China Statistical Yearbook [5]	
	Level of human capital	$lnhc$	The logarithm of the number of students enrolled in higher education per hundred thousand people in each region in China.		
	The number of foreign-invested enterprises	$lnfie$	The logarithm of the number of foreign-invested enterprises in each region.		
	Road infrastructure	$lnrinf$	The logarithmic value of road area in each region in China.		
	Urbanization level	$Urban$	The proportion of registered urban population to the total population in each region in China.		%
	Technological progress level	$Tech$	The ratio of the number of granted patents to the number of patent applications in each region in China.		
	Policy regime	$Policy$	The proportion of fiscal expenditure to the total GDP in each region in China.		
	Labor force structure	$Labrstr$	The ratio of the proportion of high-skilled labor to the combined proportion of low-skilled and medium-skilled labor. (High-skilled labor: education level of bachelor's degree or above; medium-skilled labor: education level of high school or college; low-skilled labor: education level below high school).	China Labour Statistical Yearbook	
Mechanism variables	The rationalization level of the industrial structure	$indr$	The rationalization level of the industrial structure in each region in China was calculated based on Equation (8).	China Statistical Yearbook [5]	
	The transformation and upgrading level of the industrial structure	$indt$	The transformation and upgrading level of the industrial structure in each region in China was calculated using Formula (9).		

Table 4. Descriptive statistics of variables.

Category	Symbol	N	Mean	Std. Dev.	Min	Max
Dependent variable	$Empqlty$	310	0.328	0.085	0.119	0.665
Independent variable	$Gini$	310	0.008	0.005	0.003	0.038
Control variables	$lnpgdp$	310	10.780	0.448	9.691	12.013
	$lnhc$	310	7.823	0.292	6.987	8.633
	$lnfie$	310	8.813	1.407	5.338	12.097
	$lnrinf$	310	9.741	0.922	6.489	11.535
	$Urban$	310	0.574	0.134	0.222	0.942
	$Tech$	310	0.554	0.102	0.251	0.835
	$Policy$	310	0.284	0.210	0.023	1.379
	$Labrstr$	310	0.110	0.110	0.027	0.778
Mechanism variables	$indr$	310	0.204	0.127	0.012	0.598
	$indt$	310	2.379	0.127	2.166	2.836

According to Table 4, the differentiation index of the digital economy ranges from 0.003 (minimum value) to 0.038 (maximum value). There is a significant difference between the above values, indicating that the digital economy varies widely among different regions. The average employment quality value is 0.328, and it ranges from a minimum of 0.119 to a maximum of 0.665. This reveals a certain disparity in employment quality among regions.

3.4. Empirical Model Setting

The baseline regression model for this paper is set as follows:

$$lnEmpqlty_{it} = \alpha_0 + \beta_1 lnGini_{it} + \sum_{k=1}^{8} \beta_k X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (10)$$

In Equation (10), i and t represent the province and the year, respectively. $lnEmpqlty_{it}$ represents the logarithm value of the employment quality index for i region in t year. $lnGini_{it}$ represents the level of differentiation in the digital economy for i region in t year, which is the logarithm value of the calculated result from Equation (7), while $lnGini_{it}$ is the core independent variable in this paper. β_1 reflects the marginal impact of the core independent variable on employment quality. X_{it} represents a series of control variables, whereas β_k denotes the estimated coefficients of each control variable. μ_i represents the unobservable province individual fixed effects for the i province, λ_t represents the time effects, ε_{it} represents the random disturbance term, and α_0 represents the intercept term of the model.

4. Empirical Results

4.1. Baseline Regression Results

In order to further determine whether the model set in this paper should use fixed effects, the Hausman test should be conducted first, as shown in Table 5. For the Hausman test results of Equation (10), the test results show that the Hausman value is 26.940, and the corresponding p-value is 0.0007, which means that the random effect can be rejected from the 1% confidence level, and this paper chooses that it is reasonable to use the fixed effect model after the test.

Table 5. Hausman test.

Variables	FE	RE
lnGini	−0.154 *** (0.042)	−0.167 *** (0.029)
lnpgdp	0.161 (0.130)	0.078 (0.076)
Urban	0.961 *** (0.164)	0.403 *** (0.111)
lnhc	−0.182 * (0.099)	−0.235 *** (0.076)
lnfie	−0.071 (0.051)	0.043 (0.028)
lnrinf	0.011 (0.066)	0.210 *** (0.036)
Policy	0.277 (0.233)	0.478 *** (0.123)
Labrstr	−0.592 * (0.311)	0.149 (0.198)
cons	−0.340 (1.265)	−2.324 *** (0.899)
Hausman	26.940 ***	
$p - value$	0.0007	

Note: *** and * represent 1% and 10% levels of statistical significance, respectively; standard errors are in parentheses.

As shown in Table 6, (8) reports the results of model estimation of Equation (10), where (1) is a univariate regression without the inclusion of control variables, and (2) to (7) are regression results with the stepwise inclusion of control variables based on (1). Table 6 shows that the estimated coefficient between the level of differentiation in the digital economy and employment quality is significantly negative. The results support hypothesis one, which suggests that the differentiated advancement of the digital economy has a negative effect on employment quality. The negative impact on employment quality can be attributed to the disparities in the level of digital economic advancement among regions, leading to significant differences in the empowerment of the digital economy on economic advancement, as manifested in the different degrees of digital infrastructure advancement and the introduction of advanced production equipment and machinery, resulting in different rates of capital accumulation. This leads to a widening gap in the level of emerging productivity represented by the digital economy. Such disparities directly impact the enhancement of employment quality, as regions with lower digital economic development are unable to fully harness the potential benefits and opportunities offered by the digital economy. Furthermore, the differentiation of the digital economy will result in varying digital application development, therefore preventing the generation of new market demand, and the differentiation of the digital economy will make the emerging market share related to the digital economy vary greatly from region to region, causing the employment environment to form a polarized situation. The digital economy in relatively developed regions is more able to attract foreign talent to enter, thus making the employment situation gradually one of "involution", while the digital economy in relatively underdeveloped regions is facing talent outflows, and the "quantity" and "quality" of emerging jobs are both hindered, thus preventing the improvement of the overall employment quality.

Table 6. Estimation results of the baseline regression.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lnGini	−0.060 * (0.036)	−0.064 * (0.037)	−0.117 *** (0.045)	−0.110 ** (0.044)	−0.120 *** (0.044)	−0.118 *** (0.044)	−0.117 ** (0.045)	−0.117 ** (0.053)
lnpgdp		0.081 (0.037)	0.041 (0.095)	0.133 (0.010)	0.165 (0.101)	0.187 * (0.107)	0.182 (0.126)	0.182 (0.127)
Urban			0.375 ** (0.184)	0.518 *** (0.189)	0.495 *** (0.189)	0.541 *** (0.202)	0.538 ** (0.207)	0.538 ** (0.212)
lnhc				−0.270 *** (0.099)	−0.239 ** (0.101)	−0.231 ** (0.102)	−0.230 ** (0.103)	−0.230 ** (0.105)
lnfie					−0.089 * (0.053)	−0.088 (0.053)	−0.088 (0.054)	−0.088 (0.054)
lnrinf						−0.043 (0.066)	−0.042 (0.066)	−0.042 (0.066)
Policy							−0.018 (0.244)	−0.018 (0.247)
Labrstr								0.005 (0.346)
cons	−1.103 *** (0.028)	−1.937 ** (0.966)	−1.269 (1.015)	−0.031 (1.101)	0.174 (1.105)	0.314 (1.127)	0.357 (1.272)	0.353 (1.308)
Individual fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y	Y	Y	Y
F	2.77 *	1.76	2.57 *	3.82 ***	3.64 ***	3.09 ***	2.64 **	2.30 **
R^2	0.885	0.885	0.887	0.890	0.891	0.891	0.891	0.891
N	310	310	310	310	310	310	310	310

Note: ***, **, * represent 1%, 5% and 10% levels of statistical significance, respectively; standard errors are in parentheses. Y represents YES.

4.2. Robustness Tests

This section conducts robustness tests using three different ways to enhance the robustness and reliability of the regression results mentioned above. The first way includes calculating the digital economy index using principal component analysis (PCA) to replace the core independent variable, and then the differentiated characteristics index of the digital economy is calculated according to the Gini coefficient calculation Equation (7), which serves as the core independent variable for the robustness test. The second way replaces the dependent variable by using the employment quality calculated through principal component analysis, and it is used as the core dependent variable for the robustness test. The third way simultaneously replaces both the dependent and core independent variables, with both being calculated using principal component analysis. The results of the robustness regression tests are presented in Table 7. By analyzing the regression results, it can be noted that, even after employing the three different methods for variable replacement, the estimated coefficients linking the core independent variable and the dependent variable persistently exhibit a significantly negative trend. This further indicates that the level of differentiation in the advancement of the digital economy has a major significantly negative effect on employment quality.

Table 7. Robustness tests of the baseline regression.

	Substitution of Independent Variable	Substitution of Dependent Variable	Substitution of both Independent and Dependent Variables
lnGini	−0.013 * (0.088)	−0.341 *** (0.103)	−0.111 *** (0.050)
Control variables	Y	Y	Y
Individual fixed effect	Y	Y	Y
Time fixed effect	Y	Y	Y
F	25.95 ***	54.90 ***	53.38 ***
R^2	0.642	0.791	0.887
N	310	310	310

Note: *** and * represent 1% and 10% levels of statistical significance, respectively; standard errors are in parentheses. Y represents YES.

4.3. Endogenous Discussion

There may be endogeneity issues in the baseline regression of Equation (10), which could lead to biased estimation results. Although control variables and fixed effects are included in the baseline regression for control, there may still be a problem of reverse causality affecting the estimation results. It is possible that there exists a reciprocal causal relationship between the differentiation of the digital economy and employment quality, where differentiated advancement of the digital economy negatively affects the improvement of employment quality, and the decrease in employment quality may lead to labor force outflow to economically developed regions, aggravating the differentiation in the digital economy across regions. This mutual reverse causality gives rise to endogeneity issues. Therefore, this paper uses historical data as an instrumental variable (IV) to deal with the endogeneity issue according to Huang et al. [48].

The internet is a continuation of traditional communication technologies, and the digital economy itself is based on the internet. Thus, the development of telecommunications infrastructures in various regions during their historical development would, to some extent, influence the subsequent application of digital technologies, meeting the requirement of instruments' variable relevance to the core independent variable. Then, the impact of traditional telecommunications tools on current employment quality is minimal, satisfying the exogeneity requirement of the IV. However, the data selected for IVs are cross-sectional and cannot be directly used with panel data. Therefore, according to Zhao et al. [49], we use the product of the number of local telephone users in 1990 and the internet penetration rate from 2003 to 2012 in each region to construct the interaction term as the IV. Meanwhile, we use the two-stage least squares (2SLS) method for estimation. The data for the number of local telephone users in 1990 and the internet penetration rate from 2003 to 2012 are obtained from the "China Compendium of Statistics 1949–2008" and the China Internet Network Information Center (CNNIC), respectively.

Table 8 reports the regression results after using IVs. From the results, it can be observed that the IV is significantly negative with the core independent variable at a significance level of 1%. In the second-stage regression, the coefficient estimates of the core independent variable remain consistent with the sign in the baseline regression, and the core variables are still significantly negative with the dependent variables.

Furthermore, according to the results of $Anderson\ canon.\ corr.\ LM\ statistic$ and $Cragg-Donald\ Wald\ F\ statistic$, the hypotheses of unidentifiable and weak IVs of IVs are significantly rejected, indicating that all instrumental variables are uncorrelated and exogenous, so the IVs selected in this paper are reasonable and valid. Therefore, we consider the results of the baseline regression to be valid, which further verifies the hypothesis of this study that the differentiated advancement of the digital economy has a significant negative impact on employment quality.

Table 8. Regression results of the IV.

	First-Stage Regression *lnGini*	Second-Stage Regression *lnEmpqlty*
IV	−0.892 *** (0.188)	
$lnGini$		−0.361 *** (0.178)
$Control\ variables$	Y	Y
$Provincial\ fixed\ effect$	Y	Y
$Time\ fixed\ effect$	Y	Y
$Anderson\ canon.\ corr.\ LM\ statistic$		24.614 ***
$Cragg-Donald\ Wald\ F\ statistic$		22.511 [16.38]
N		310

Note: *** represents 1% level of statistical significance; standard errors are in parentheses. Y represents YES.

5. Further Discussion

5.1. Heterogeneity Analysis

For a long time, there have been significant regional disparities in economic development in China, with the eastern region having a stronger economic foundation compared to the central and western regions [50]. The development of the digital economy varies significantly depending on the supporting environment, resulting in differences in its impact on employment quality. This study further considers the issue of regional heterogeneity by dividing the 31 provinces of China into three parts: eastern, central, and western regions (eastern regions include Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; central regions include Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; western regions include Inner Mongolia, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang). The regression analysis is conducted by interacting the index of differentiated development of the digital economy, which is the Gini coefficient of the digital economy, with the dummy variables of the eastern, central, and western regions.

According to Table 9, the varied progress of the digital economy has a significant negative effect on employment quality in the eastern region, whereas it demonstrates a non-significant positive impact on the central and western regions. The eastern regions attract workers from the central and western regions due to its highly developed digital economy. However, an excessive influx of labor may intensify employment competition in the eastern region, leading to a phenomenon known as "involution" and a decline in employment quality in that region.

Table 9. Heterogeneity regression results.

	Eastern Regions	Central Regions	Western Regions
$lnGini\#i.area$	−0.099 ** (0.042)	0.147 (0.100)	0.167 (0.111)
$Control\ variables$		Y	
$Provincial\ fixed\ effect$		Y	
$Time\ fixed\ effect$		Y	
F		2.85 ***	
R^2		0.896	
N		310	

Note: *** and ** represent 1% and 5% levels of statistical significance, respectively; standard errors are in parentheses. Y represents YES.

5.2. Mechanism Analysis

Table 10 illustrates the estimation results of the mechanism regression. In (9), the dependent variable is the rationalization level of the industrial structure, which is calculated as shown in Equation (8). In (10), the dependent variable is the transformation and upgrading level of the industrial structure, while the core independent variables are the interaction term with the Gini coefficient of the digital economy and the regional dummy variables. The regression results of (9) in Table 7 indicate that a higher degree of differentiation in the development of the digital economy is not beneficial for improving the rationalization level of the industrial structure. The regression results of (10) indicate that the divergent growth of the digital economy will have a substantially negative effect on the transformation and upgrading of the industrial structure in the central and western regions of China. However, the impact on the eastern region, although positive, is not statistically significant.

Table 10. Mechanism variable regression.

	(9)*indr*	**(10)*indt***
$lnGini$	−0.041 ** (0.021)	
$lnGini\#i.area$		
Eastern regions		0.002 (0.004)
Central regions		−0.042 *** (0.008)
Western regions		−0.029 *** (0.009)
$Control\ variables$	Y	Y
$Provincial\ fixed\ effect$	Y	Y
$Time\ fixed\ effect$	Y	Y
F	15.40 ***	8.00 ***
R^2	0.931	0.964
N	310	310

Note: *** and ** represent 1% and 5% levels of statistical significance, respectively; standard errors are in parentheses. Y represents YES.

The differentiated development of the digital economy across regions in China distorts the rationalization level of their industrial structures. With an excessive influx of labor resources into digitally developed regions, the industrial structure in these regions tends to become overly advanced, resulting in the waste of resources allocation. Conversely, regions with relatively underdeveloped levels of digital economy development experience resource losses related to the tertiary industry, including capital and high-skilled labor outflows. This will further exacerbate the imbalance in the industrial structure. This situation ultimately impedes the enhancement, transformation, and advancement of the industrial structure. So, the incongruity of labor resources across regions, resulting from the unevenness of the industrial structure, will gradually lead to the "involution" of employment conditions in developed advanced regions and the outflow of labor from relatively underdeveloped regions in the digital economy. Therefore, it can be inferred that the imbalanced development of the digital economy has led to a decline in employment quality by distorting the industrial structure. This verifies hypothesis two.

6. Conclusions and Policy Implications

This study analyzes the influence of the level of differentiated development of the digital economy on employment quality based on panel data of 31 provinces in China from 2011 to 2020. It explores the underlying mechanisms and demonstrates that the differentiated development of the digital economy in each region in China has a significant negative effect on employment quality. Through a series of robustness tests, it is revealed that the negative impact of differentiated development of the digital economy on employment quality remains significant. Furthermore, the mechanism regression analysis reveals that the influence on employment quality is mediated by its impact on the industrial structure.

Based on the above empirical tests, the following policy recommendations are proposed in this paper:

First, improve the rectification of regional disparities in digital economy development to foster equitable progress across regions. The government should increase financial support for underdeveloped regions in digital economy development, enhance investments in infrastructure construction, promote the interconnection and interoperability of the information infrastructure, facilitate the sharing of information resources, make an effort to reduce the disparities in the digital economy among regions, provide employees more and better options, and contribute to the improvement of employment quality.

Second, focus on optimization, transformation, and upgrading of the industrial structure while driving stable growth in employment. Each region should adopt appropriate strategies and gradually develop the tertiary industry. The regions where the primary industry is the main industry should promote the modernization of traditional agriculture, and the regions where the secondary industry is the main industry should actively introduce local technology and equipment, promote the upgrading of traditional industries to automation and intelligence, and develop more high-tech industries [51–53]. And, the regions where the tertiary industry is the main industry should provide strong support to relevant industries and undertake the responsibility of labor force transition between the primary and secondary industries.

Third, explore flexible employment systems and promote the social security institution. This is due to the fact that the evaluation system for employment quality in this study primarily focuses on public service and social security. The expansion of the digital economy has led to the emergence of a wider range of employment prospects in the labor market; however, it has also resulted in heightened job instability. The emerging employment modes generated by the digital economy are more flexible, but they are not within the existing social security system. Therefore, the government needs to establish new employment management methods, set up a normative governance system based on various issues, such as labor compensation and social insurance, and further strengthen social security for flexible employment under the continuous innovation and development of the digital economy model, thereby improving the quality of employment.

7. Limitations and Future Improvement

The major constraint of this study is the availability of data. The digital financial inclusion index provided by the IDF is only available up to the year 2020, which means that the data after 2020 have not yet been published, so this study is unable to capture the influence of the differentiated level of digital economy development on employment quality in 2021 and 2022. During this period, China was marked by the profound impact of COVID-19, which caused substantial shock to economic and social development. Since then, there have been significant changes in production and lifestyle, with the gradual rise of online work through the internet. Hence, it remains to be discussed whether workers in regions with a relatively developed digital economy during this period would have better employment quality, or whether workers in regions with a relatively undeveloped digital economy experienced a decline in employment quality. These questions require further exploration. Therefore, in future research, once the new edition of the Digital Inclusive Finance Index is released, the author will use the new data to extend the panel data in the temporal dimension for further in-depth analysis or re-select relevant indicators instead of the Digital Inclusive Finance Index for further exploration.

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