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Digital Revolution and Employment Choice of Rural Labor Force: Evidence from the Perspective of Digital Skills

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Abstract: The practical implementation of the employment promotion effect of the digital economy is closely linked to rural laborers' digital skills (DS). Therefore, this study uses the Mprobit model to empirically test the impact of DS on rural labor employment choices. The results show that: (1) the acquisition of DS by the rural labor force significantly increases the rate of off-farm employment and entrepreneurship but has no significant effect on farm employment, with work skills having the most significant positive impact on the rural labor force off-farm employment and online business skills having the most significant positive impact on rural labor force entrepreneurship. (2) The mechanism test reveals that DS influences the employment choices of the rural labor force by alleviating the information access constraint and financing constraints faced by rural labor. (3) Heterogeneity analysis shows that males and rural laborers in rich regions can benefit from entrepreneurship. In contrast, females and low-skilled and rural laborers in middle and poor regions can benefit more from off-farm employment. Our findings provide empirical evidence on effectively cultivating DS to increase the diversity of employment choices for the rural workforce and highlight the importance of improving DS.

Keywords: digital economy; digital skills (DS); employment choice; off-farm employment; entrepreneurship

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1. Introduction

In recent years, with the development of the digital economy, the rapid sinking of the digital economy in rural areas, represented by the Internet and e-commerce, has not only had a comprehensive impact on the production, life, and ecology of the rural workforce but has also had a profound impact on the employment market of the rural workforce [1–5]. According to the Digital China Construction and China Taobao Village Study Report, as of December 2021 there were 284 million Internet users in rural China, with a 57.6% Internet penetration rate. Moreover, the size of the digital economy reached 45.5 trillion yuan in 2018, with 191 million jobs created in the digital economy. The number of digital economy jobs is expected to reach 379 million by 2025. The digital economy can offer new opportunities for the full employment of the vast rural workforce.

It is worth noting that while the digital economy has brought huge employment dividends to all, it has placed higher demands on the DS for the workforce [6]. Scholars have carried out considerable research on the definition of digital skills, but no consensus has yet been reached. Digital skills, according to Eshet [7], are the abilities of individuals to perform tasks such as producing, living, and learning in a digital environment. From a developmental standpoint, Martin et al. classified residents' digital skills into three stages [8]. The first stage is the capacity to utilize digital tools and devices correctly, while the second is the ability to use digital tools and devices to access digital resources. The third stage is the ability to use digital tools to innovate and create new knowledge and resources. Due to China's lagging digital skills education system, rural residents' ability and awareness to use digital technologies to innovate expertise and resources are currently low. As a result, digital skills are currently characterized as micro-subjects' attitudes and abilities to use digital tools and devices correctly and appropriately, to utilize digital resources, to learn new knowledge, and to communicate socially with others in the evolving digital environment.

Even though digital devices such as smartphones are now widely available in rural China, the digital skills of China's rural labor force remain relatively poor. According to the data from the "Survey and Analysis Report on Digital Literacy in Rural China in the Context of Rural Revitalization Strategy", released by the Informatization Research Center of the Chinese Academy of Social Sciences in 2021, the digital skills gap between urban and rural residents in China is evident, with the average score of urban residents being 56.3 out of 100. The average score of rural residents is 35.1, a difference of up to 21.2 points, and rural residents' average score is 37.5% lower than urban residents. Rural residents have a digital literacy score of only 18.6, notably lower than other occupational groups and 57% lower than the overall population average. According to the survey, as China's rural infrastructure is rapidly digitizing and networking, the central conflict of the "digital divide" between urban and rural areas in the new era is changing from infrastructure to digital literacy and skills. In this context, the Chinese government has placed a high value on efforts to improve the overall DS of the population. As early as 2018, the "Guidance on Stabilizing and Expanding Employment in the Development of the Digital Economy" stated unequivocally the importance of "upgrading the digital skills of new farmers and new subjects", with the goal of "driving more workers to shift and improve their employment quality". In 2022, the 14th Five-Year Plan specifically advocated strengthening digital skills education and training for all people and popularizing and improving citizens' DS.

To improve rural residents' DS, it is required not only to develop network infrastructure and bridge the "access gap" but also to pay attention to network training methods and scientifically determine training contents. We should concentrate on assisting the rural labor force in mastering software such as smart agriculture and improving the rural labor force's digital application abilities. For example, giving rural workers hands-on chances such as live e-commerce training, teaching rural laborers how to utilize new media tools to capture market information promptly, and teaching rural laborers how to use mobile phone software for digital marketing to help agricultural products enter the city. At the same time, promoting and explaining digital security knowledge and skills to rural labor in batches is vital to compensate for digital security weaknesses and strengthen the rural workforce's digital skills. Digital skills are a kind of human capital, and the carrier of its function is digital technology. For the rural workforce, digital technology use is divided into two categories: accessibility and depth of use, with the former reflecting differences in access opportunities and the latter reflecting differences in digital skills [9]. Most existing studies have explored the impact of the digital technology access opportunity gap on rural labor force employment [5,10,11]. However, few have looked at the impact of rural labor force DS acquisition on their employment choices from the perspective of participants' capabilities.

This paper examines the impact of the rural labor force's acquisition of DS on their employment choices using data from the China Family Panel Studies (CFPS) from 2014 to 2018. This study contributes to the related literature in three ways. First, existing studies have primarily examined the impact of digital economy development on rural labor force employment from the perspective of application effects such as Internet use, digital infrastructure, and digital technology application [12–15]. However, minimal research has been carried out to investigate the impact of DS on the employment choices of rural labor. We are among the first to discuss the rural workforce's DS on their employment choices from the perspective of participants' abilities and broadening the exploration of the digital economy on rural labor employment research. Second, in terms of transmission mechanisms, prior research focused primarily on the impact of individual natural endowments, such as human capital and social capital, on rural labor force employment. This paper completes the impact of DS on the role of various financing channels and information accessibility from the perspective of individual financing channels and information accessibility, emphasizing that improving financial and information accessibility in the context of the digital economy also requires complementary DS. Third, regarding policy significance, this paper provides empirical evidence and path recommendations for how policymakers can effectively cultivate DS to drive diverse employment in the rural workforce.

The rest of the paper is structured as follows. Section 2 includes literature reviews and research hypothesis. Section 3 specifies our variables, data, and estimation methods. Section 4 presents our empirical results. Further analyses, such as mechanism and heterogeneity, are exhibited in Section 5. The last section concludes.

2. Literature Review and Research Hypothesis

2.1. Literature Review

Current scholarly research on the impact of rural labor force employment is primarily concerned with non-farm employment and the factors that influence non-farm employment, such as human capital, social capital, and demographic and household characteristics [16–19]. Human capital theory suggests that human capital is the most critical factor influencing rural laborers' employment and career development. Improving human capital levels can increase workers' labor-market competitiveness and thus promote rural laborers' non-agricultural employment transfer. Kurosaki and Khan used micro panel data to investigate human capital's effects on non-farm employment. The findings showed that education significantly increases the rural labor force's non-farm employment rate and wages of the rural labor force [20]. Luan et al. found that education plays an essential role in increasing the non-farm income of the rural labor force [21]. The social capital theory believes that social capital plays an essential role in the job search process of rural laborers. China is a traditional "geo-society" and "human society". Rural "human affection" can have various positive effects, including trust, dependence, and mutual aid. It is also conducive to transmitting and gathering knowledge and raising rural laborers' employment or self-employment rate [22]. Morise found that social capital contributes to the off-farm employment rate of the rural labor force and, thus, access to off-farm wages [23]. Liang et al. argued that social capital, as a social resource embedded in interpersonal networks, can facilitate the dissemination of employment information and promote rural labor's non-farm employment [24]. Finally, regarding demographic and household characteristics, Cheng and Pan found that rural laborers' individual and household characteristics considerably impacted their non-agricultural employment [25].

Many studies have been conducted to investigate the impact of digital economy development on rural laborer employment, but a consistent conclusion has yet to be reached. Two main views are presented: The first is the "creation effect", which argues that developing the digital economy will boost rural labor force employment, as Isley and Low explored the relationship between broadband and employment rates during April and May 2020 in rural U.S. counties. They discovered that broadband availability and wired broadband adoption significantly impacted rural employment rates [26]. Atasoy examinexd the impact of broadband internet access expansion from 1999 to 2007 on labor market outcomes across the United States and discovered that gaining access to broadband services in a county is associated with a 1.8 percentage point increase in the employment rate [1]. Hjort and Poulsen estimated the effect of Internet access on employment in Africa using the gradual arrival of submarine Internet cables on the coast and maps of the terrestrial cable network. The results showed that Internet access significantly increases African employment [27]. Meanwhile, Bruno also found that the digital economy increases employment demand, mainly through increased productivity, industrial sector innovation, and technology diffusion [23]. However, some scholars have argued against this, arguing that the development of the digital economy will lead to a decline in labor demand by reducing the value of current jobs, shortening the life cycle of jobs, and increasing the price of human capital, thus putting forward a second "substitution theory" view. Through theoretical analysis, Lishchuk et al. pointed out that the development of the digital economy mainly leads to the reduction of labor demand through increased productivity, the application of intelligent and innovative technologies, and the change of industrial structure [28]. From the perspective of skill differences, Acemoglu and Restrepo discovered significant differences in the impact of the digital economy on the labor force with different skills, increasing the demand for high-skilled labor and decreasing the demand for low-skilled labor [29].

In summary, previous studies have contributed to our understanding of the impact of digital economy development on rural labor force employment. However, the above literature ignores the premise of Amartya Sen's theory of "feasible ability". The individual must have the corresponding feasible abilities to achieve functional activities, provided the material conditions are met [30]. The rural labor force's lack of digital skills makes it likely to be excluded from the digital employment system, particularly in the context of the existing "same network and same speed" society in China [31]. Numerous studies have shown that digital skills, as a "gateway" to employment, can significantly impact an individual's chances of getting a job, promotion, or salary increase and workplace employability, productivity, and efficiency [32]. Therefore, while testing the impact of digital economy development on rural labor force employment choices, the rural labor force's digital skills acquisition should be considered. Thus, from a participant ability standpoint, this paper supplements the micro-reality evidence and mechanical testing of the impact of rural labor's acquisition of digital skills on their employment choices. It enriches the research on the employment aspects of the digital economy.

2.2. Research Hypothesis

There are two main reasons for the positive impact of DS on rural labor force employment choices. On the one hand, DS can increase the diversity of employment. According to human capital theory, human capital is essential to rural laborer employment. DS significantly accumulates human capital [13]. Rural laborers mastering DS can use digital platforms for online learning to improve their professional skills and reverse their attitudes toward risk, increasing their probability of diverse and high-quality employment [33]. At the same time, acquiring DS can help the rural workforce access a broader range of economic opportunities. According to the Organization for Economic Cooperation and Development's (OECD) Digital Economy Outlook 2019, rural labor can work more flexibly and conveniently through online platforms rather than being employed by a single formal employer, significantly increasing the possibility of multiple employment for rural labor and effectively improving rural employment options for the labor force [34].

On the other hand, DS has a significant spatial spillover effect on rural labor entrepreneurship, effectively promoting local rural labor entrepreneurship and significantly impacting rural labor entrepreneurship in neighboring areas [35]. According to resource-based theory, human, physical, and social capital influence entrepreneurial success. First, as an essential component of human capital, DS significantly impacts entrepreneurs' entrepreneurial capabilities, identifying entrepreneurial opportunities and integrating entrepreneurial resources, which play an essential role in driving entrepreneurial behavior. Second, rural laborers with higher DS can use the Internet to break down geographical barriers in traditional social networks, broaden the radius of social interactions, and open up new "friend circles" and social circles, which can not only provide emotional and financial support for rural laborers, but can also help to improve the accuracy and timeliness of information acquisition, boost their competitive advantages, and thus increase the entrepreneurship rate [36]. In contrast, an increase in the entrepreneurship rate can help to increase new jobs and employment opportunities, significantly improving rural laborers' employment options. All of the above analyses suggest that promoting the cultivation of DS can help rural laborers participate more extensively and effectively in the digital economy, which in turn helps to increase the diversity of employment options for rural laborers. As a result, the following hypothesis is proposed in this paper.

Hypothesis 1. *Mastery of DS can significantly improve employment options for the rural workforce.*

According to entrepreneurial resource endowment theory, resource endowment conditions significantly influence individual entrepreneurship. Numerous empirical studies have also shown that initial wealth accumulation affects individual entrepreneurial activities. Financing constraints can prevent rural laborers from crossing the entrepreneurial capital threshold or achieving the optimal amount of capital investment, inhibiting their entrepreneurial decisions [37–39]. When rural laborers are equipped with DS, on the one hand, they can increase the financing channels of rural laborers through e-commerce platforms, Alipay, and the micro-lending function of mobile payment providers to alleviate financing constraints and improve financial accessibility [40,41]. On the other hand, the effective accumulation of social capital can be accomplished by expanding and maintaining relationship networks through online communication platforms, enriching rural laborers' financing channels [42]. According to information effect theory, entrepreneurial capabilities include identifying entrepreneurial opportunities, controlling entrepreneurial risks, and reducing transaction costs. The ability of rural laborers to access information is more critical in identifying entrepreneurial opportunities in rural areas where information dissemination channels are more limited, and the cumulative effect of information generated by information access will positively impact rural laborers' employment decisions [43,44]. With the implementation of the "digital countryside" strategy in recent years, the Internet and e-commerce have rapidly declined in rural areas. When rural laborers have specific digital skills, they can communicate via the Internet and e-commerce platforms, which can help improve their information dissemination efficiency and broaden the scope of information dissemination, alleviating information constraints and increasing the likelihood of identifying entrepreneurial opportunities. Based on this, this paper puts forward the following hypothesis:

Hypothesis 2. *Mastering DS affects the rural labor force's employment choice by relieving financing and information acquisition constraints.*

The mechanism analysis is presented in Figure 1.

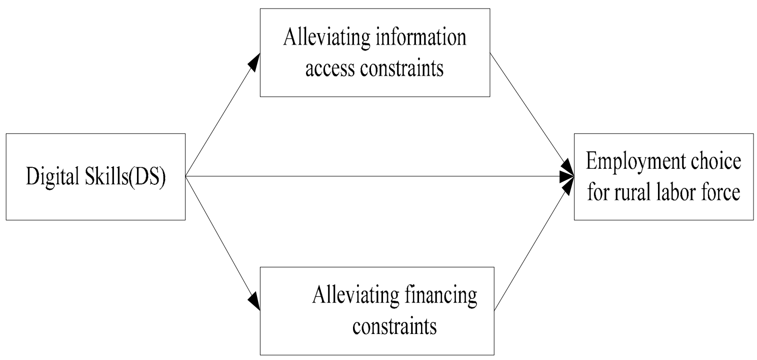

Figure 1. Mechanism analysis of DS influencing employment choice for rural labor force.

3. Data and Methods

3.1. Data Source

The empirical analysis is based on the 2014–2018 China Family Panel Studies (CFPS) dataset. This paper investigates the impact and mechanism of DS on rural labor employment choices. The survey data can provide detailed and reliable research data support.

CFPS data is a nationwide sample survey project covering 25 provinces, autonomous regions, and municipalities under the central Government of China. The database contains individual and household socio-economic information and more detailed information on household economic activities, social interactions, and demographics. Considering the research objectives of this paper, individual-level, household-level, and province-level data are to be used. Data from the CFPS 2014–2018 database are to be matched with provincial-level data in turn, and then laborers living in rural areas and aged 18–64 years old are screened out as research subjects. The missing data of key variables and data with obvious outliers were excluded, and the last panel data of 10,679 samples for three years were obtained.

3.2. Model, Variable Selection, and Description

3.2.1. Model

The following econometric model is used in this study to investigate the impact of DS on rural labor employment choice:

$$P(y_i = j \mid x_i) = \frac{\exp(b_j x_i')}{\sum\limits_{k=1}^{j} \exp(b_k x_i')} \tag{1}$$

In Equation (1), $P(y_i = j \mid x_i)$ represents the possibility of employment choice of the rural labor force, x_i represents the influencing factors on rural labor force's i choice of employment, and b_k represents the regression coefficient value. Then, assuming $y_i = k$ as a reference variable, Equation (1) can be transformed into Equation (2):

$$P(y_i = j \mid y = korj) = \frac{P(y = j)}{P(y = k) + P(y = j)} = \frac{\exp(x_i' b_j)}{1 + \exp(x_i' b_j)} \tag{2}$$

The corresponding relative risk ratio is Formula (3):

$$\frac{P(y = j)}{P(y = k)} = \exp(x_i' b_j) \Rightarrow \ln\left(\frac{P(y = j)}{P(y = k)}\right) = x_i' b_j \tag{3}$$

Putting all variables into Equation (3), the employment choice model Equation (4) is obtained:

$$\ln\left(\frac{P_j}{P_k}\right) = \alpha_0 + \alpha_1 \gamma_i + \sum_{m=2}^{n} a_m X_i + \varepsilon \tag{4}$$

Among them, P_j represents the employment status of the jth interviewee. In this paper, P_1 represent self-employed agriculture (SEA), P_2 represents agricultural employment (AE), P_3 represents non-farm employment (NFE), and P_4 represents entrepreneurship (EP), respectively assigned values of 1, 2, 3, and 4. γ_I represents the digital skills possessed by the i respondent. X represents a series of control variables, including variables of individual characteristics, family characteristics, and regional characteristics.

3.2.2. Variables Selection and Description

(1) Dependent variables. The dependent variable in this paper is employment choice. The employment choice variable is primarily based on the type of work answered by the individuals in the questionnaire, and the types of employment are divided into four categories: self-employed agriculture (SEA) = 1, agricultural employment (AE) = 2, non-farm employment (NFE) = 3, and entrepreneurship (EP) = 4. According to the CFPS questionnaire, a rural laborer is characterized as SEA if they work for themself/their own family in agriculture. The rural laborer is classified as engaged in AE if employed by another individual or company and works in agriculture.

(2) Independent variables. The independent variable in this paper is digital skills (DS), which are identified as both the access and use levels. First, at the access level, the rural

workforce is judged to have the basis for using digital tools and devices based on whether they use computers or cell phones. If yes, 1 is assigned; otherwise, 0 is assigned. Second, at the use level, the frequency of individuals' use of digital functions in the China Household Tracking Survey (CFPS) database reflects digital skills, which include "frequency of using the Internet for learning, working, socializing, entertainment, and business activities", with seven levels of frequency ranging from "never" to "almost every day" and a score of 0–6 for "never" to "almost every day". Factor analysis was used to reduce the dimensionality of the 5 dimensions, and principal component analysis was used to extract common factors with eigenvalues greater than 1. A total of 3 common factors were extracted, and their cumulative variance contribution rate reached 77%, indicating that they can reflect the changes in the 5 dimensions. Because of the negative values of the factor scores, they were transformed into values between 0 and 6 according to the standard scores. The KMO values were approximately 0.690. The significant p-values of Bartlett's test were all 0.000, indicating a good correlation between the dimensions and the validity of the factor analysis results.

(3) Control variables. To avoid the problem of omitted variables as much as possible, referring to the previous literature [41,45–47], the control variables in this paper include individual characteristics, household characteristics, and regional characteristics. Specific variables are described below, and the summary statistics of these variables are shown in Table 1.

Table 1. Variable definition and descriptive statistics.

Variables	Variables Definitions	Mean	SD
Employment choice	SEA = 1, AE = 2, NFE = 3, EP = 4	2.481	1.075
DS	Obtained from the factor analysis of the frequency of multi-dimensional functions of digital technology	3.486	1.396
Gender	Male = 1, Female = 0	0.427	0.495
Age	Age value	34.47	10.15
Age^2	Square of age	1291	761.2
Education	Years of education	8.887	3.827
Health	Healthy categorical variables 1–5	2.644	1.117
Marital status	Married = 1, other = 0	0.787	0.409
Family size	Total family size	4.763	2.010
Family upbringing burden	Number of children to total family size ratio	0.201	0.198
Industrial structure	The ratio of output value of the primary industry to GDP	0.096	0.037
Regional GDP per capita	Logarithm of regional GDP per capita	10.74	0.381
Urbanization rate	Urbanization rate	55.55	10.10

Source: Based on CFPS data in 2014, 2016, and 2018; sample size is 10,679.

4. Results and Discussion

4.1. Impact of DS on Rural Labor Force Employment Choices: Main Results

Table 2 shows the estimated impact of DS on rural labor force employment choices. The Mprobit model's explained variables are four types of employment, and the regression results use SEA as the reference group. The first three columns of Table 2, Columns (1) to (3), do not include the fixed effects of time and region. The results demonstrate that the DS coefficients are insignificant in AE, while they are all statistically significant at the 1% level in NFE and EP. The last three columns of Table 2, Columns (4) to (6), include the fixed effects of time and region. The results show a robust effect that DS can significantly increase NFE and EP but not AE. Furthermore, DS are more likely to promote NFE than EP. On the one hand, most of the information posted on Internet-based information recruitment platforms is for off-farm jobs, so even if the rural labor force masters DS, it will have little impact on AE. On the other hand, with the application of digital technologies in recent years, such as the Internet, the rural labor force's efficiency in job search and information acquisition in the labor market has improved. As a result, the rural labor force's acquisition of DS significantly promotes NFE and EP. However, the promotion effect between the two differs because EP necessitates a higher level of human capital and digital skills from the rural labor force than NFE.

Table 2. The impact of DS on rural labor force's employment choice.

Variables	(1) AE	(2) NFE	(3) EP	(4) AE	(5) NFE	(6) EP
DS	0.0003	0.0259 ***	0.0153 ***	0.0001	0.0303 ***	0.0211 ***
	(0.0009)	(0.0050)	(0.0031)	(0.0008)	(0.0047)	(0.0031)
Gender	0.0090 ***	0.0433 **	0.0313 ***	0.0092 ***	0.0424 **	0.0306 ***
	(0.0031)	(0.0170)	(0.0089)	(0.0030)	(0.0167)	(0.0082)
Age	0.0022	−0.0186 ***	0.0127 ***	0.0021	−0.0169 ***	0.0146 ***
	(0.0015)	(0.0032)	(0.0038)	(0.0014)	(0.0032)	(0.0039)
Age^2	−0.0000	0.0001 ***	−0.0002 ***	−0.0000	0.0001 ***	−0.0002 ***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0001)
Education	−0.0020	0.0807 ***	0.0046	−0.0020	0.0783 ***	0.0018
	(0.0012)	(0.0067)	(0.0049)	(0.0012)	(0.0059)	(0.0051)
Health	0.0011	−0.0071	0.0036	0.0011	−0.0066	0.0052 *
	(0.0011)	(0.0051)	(0.0030)	(0.0011)	(0.0050)	(0.0029)
Marriage	−0.0022	−0.0846 ***	0.0580 ***	−0.0029	−0.0858 ***	0.0527 ***
	(0.0059)	(0.0175)	(0.0163)	(0.0060)	(0.0182)	(0.0152)
Family size	0.0007	−0.0102 ***	0.0047 *	0.0007	−0.0098 ***	0.0049 **
	(0.0007)	(0.0029)	(0.0026)	(0.0007)	(0.0030)	(0.0025)
Family upbringing burden	−0.0059	0.0302	−0.0263	−0.0062	0.0292	−0.0214
	(0.0068)	(0.0207)	(0.0205)	(0.0070)	(0.0207)	(0.0201)
Industrial structure	0.0130	−1.5316 ***	−0.0781	−0.0071	−1.6343 ***	0.1350
	(0.0714)	(0.3955)	(0.2795)	(0.0737)	(0.3364)	(0.2432)
Regional GDP per capita	0.0208 **	0.0488	0.0623	0.0153	0.0756	0.0539
	(0.0094)	(0.0661)	(0.0470)	(0.0097)	(0.0669)	(0.0448)
Urbanization rate	−0.0002	−0.0001	−0.0023	−0.0004	−0.0013	−0.0026
	(0.0003)	(0.0034)	(0.0015)	(0.0003)	(0.0036)	(0.0019)
Time FE	No	No	No	Yes	Yes	Yes
Region FE	No	No	No	Yes	Yes	Yes
Observations	10,679	10,679	10,679	10,679	10,679	10,679

Notes: The coefficients in the table are marginal effects rather than regression coefficients; the standard errors in brackets are clustered at the provincial level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2. Impact of Different Dimensions of DS on Rural Labor Force's Employment Choice

Table 3 further disaggregates DS to examine the impact of different dimensions of DS on rural laborers' employment choices. Mou et al. [48] classified DS into five dimensions: digital learning skills, digital social skills, digital entertainment skills, digital business skills, and digital work skills, and the five dimensions of DS were regressed using a panel Mprobit model. The findings showed that, compared to SEA, rural laborers' acquisition of digital learning, social, work, and business skills had insignificant effects on individuals' choice of AE. However, all significantly increased the proportion of NFE and EP among rural laborers. Work skills had the most significant positive effect on NFE among rural laborers, and business skills had the most significant EP promotion effect. This suggests that a rural labor force with good job skills has better access to decent jobs and a higher proportion of NFE. In contrast, a rural labor force with online business skills can alleviate credit constraints, increase financial availability to promote EP, and thus increase EP. Meanwhile, the rural labor force acquisition of recreational skills reduces the proportion of AE and increases the proportion of NFE and EP. The main reason for this is that, on the one hand, rural areas lack recreational and leisure facilities and have lower levels of human capital than urban areas. At the same time, online entertainment and social interaction are more attractive to rural residents, making them more likely to engage in online games and online social platforms, squeezing out their working time and reducing the proportion employed in agriculture. On the other hand, compared with urban residents, rural laborers with limited social capital are more likely to be constrained by access to information resources. The acquisition of recreational and social skills assists rural laborers in expanding their "circle of friends" and social circle based on kinship to enhance social capital, among which the information and trust functions of social capital can significantly increase the probability of NFE and thus squeeze out the proportion of AE and increase the proportion of NFE and EP.

Table 3. Impact of different dimensions of DS on the employment of rural labor force.

Variables	(1) AE	(2) NFE	(3) EP
Digital learning skills	0.0004	0.0060 ***	0.0025 *
	(0.0006)	(0.0018)	(0.0015)
Digital social skills	0.0006	0.0132 ***	0.0041 ***
	(0.0005)	(0.0025)	(0.0013)
Digital work skills	0.0010	0.0267 ***	0.0080 ***
	(0.0007)	(0.0022)	(0.0022)
Digital entertainment skills	−0.0010 **	0.0058 *	0.0105 ***
	(0.0005)	(0.0033)	(0.0016)
Digital business skills	−0.0000	0.0181 ***	0.0223 ***
	(0.0010)	(0.0038)	(0.0020)
Control variables	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	10,679	10,679	10,679

Notes: The coefficients in the table are marginal effects; the control variables are consistent with Table 2; the standard errors in brackets are clustered at the provincial level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.3. Robustness Check

(1) Endogeneity problem. In order to test and solve the endogeneity problem of the above model due to factors such as omitted variables and reverse causality, the instrumental variables method is used in this study to overcome the possible effects of the above problem. The conditional mixed process (CMP) method proposed by Roodman was used to re-estimate the relationship between DS and rural labor force employment choices, drawing on the studies of Tian et al. and Zhang et al. [49,50]. It is worth noting that an appropriate instrumental variable must be found regardless of whether the instrumental variable method or CMP estimation is used. According to Zhou and Fan [36], whether or not families have computers in the 2014 CFPS questionnaire was chosen as an instrumental variable for DS. First, the relevance hypothesis is met because whether or not families have computers is a requirement for using the Internet and mastering DS in general, satisfying the relevance condition. Second, the exogenous criterion is met because there is no correlation between whether or not families have computers and the occupation preferences of the rural labor force. Therefore, the instrumental variables in this paper are selected more reasonably. The CMP model is used to construct a set of equations for estimation, and columns (1) and column (2) in Table 4 are the results of estimation using the probit model and Mprobit model, respectively. From column (1), the coefficient of the effect of household computer ownership on DS is 0.3443 and is significantly positive at the 1% level, indicating that it meets the hypothesis of correlation. From column (2), the effect of DS on NFE and EP is still significant and positive after using the instrumental variable, except for the non-significant effect on AE, suggesting that the acquisition of DS by rural laborers still significantly increases the likelihood that rural laborers will choose NFE and EP. In addition, in terms of the coefficients, the absolute value of the coefficient of DS becomes larger for each employment type after using the instrumental variables method, indicating that the effect of DS acquisition on NFE is underestimated due to the endogeneity

problem. However, the conclusion that the acquisition of DS can significantly contribute to the diversification of employment options in the rural labor force is still robust.

Table 4. Test results of the CMP model using instrumental variables.

Variables	(1) DS	AE	(2) NFE	EP
DS	-	0.0002 (0.0027)	0.0488 *** (0.0158)	0.0160 * (0.0097)
IV: Whether or not family have computer	0.3443 *** (0.0890)	-	-	-
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	2212		2212	

Notes: The coefficients in the table are marginal effects; the control variables are consistent with Table 2; the standard errors in brackets are clustered at the provincial level; * $p < 0.1$, *** $p < 0.01$.

(2) Omitted variable test. In the baseline regression model, this paper controls for some individual and household-level covariates that affect the employment choices of rural laborers as much as possible. However, some unobservable variables still bias the estimation results of the model. Therefore, drawing on Oster's study uses the model's results with observable variables to assess the impact of potentially missing unobservable variables on the model results [51]. Specifically, the main principle of this approach is to observe how many times the unobserved factors are the observed factors in order to have a significant effect on the initial estimation results by measuring the model in this paper. The results are shown in Table 5. First, from the result in the first row, we can see that the 95% confidence interval into which the actual calculation of numerical skill β^* falls and which does not contain 0 indicates that no unobserved variables are as important as those already observed to impact the empirical results. Second, from the result in the second row, we can see that the measurement of δ values suggests that, even if the model has the problem of omitting unobservable variables, the effect of that omitted variable is at least 2.1307 times greater than that of the observable variable in terms of having an impact on the empirical results of the model, which is less likely to occur. Therefore, it is difficult for the omitted variable to bias the empirical results, so the core findings of this paper are more robust and credible.

Table 5. Omitted variable test results.

Variables	Testing Method	Judgment Criteria	Actual Calculation Result	Whether to Pass Test
DS	(1)	$\beta^* = \beta^*(R_{max}, \delta) \in (0.1179, 0.1611)$	0.1395	Yes
	(2)	$\beta > 1$	2.1307	Yes

(3) Replace explanatory variables. In this section, DS is characterized by the degree of importance rural workers place on the various functions presented by digital devices, also known as digital attitudes. Based on the data available, this paper uses the "importance of work, study, social, recreational and business activities" to reflect rural workers' attitudes toward using digital technology online, with five levels of importance ranging from very unimportant to very important. The same principal component analysis was used to extract common factors with eigenvalues greater than one and convert them into values between 0 and 6 according to the standard score. The panel Mprobit model is then used for regression analysis. The results are shown in Panel A of Table 6. The results show that the effect of digital attitudes on AE is not significant but still significantly increases the proportion of NFE and EP among rural laborers, which is consistent with the baseline regression results, indicating that the core findings of this paper are more robust.

Table 6. Robustness tests of DS on employment choices of rural labor force.

	AE	NFE	EP
Panel A: Replace Core Explanatory Variables			
Digital attitude	0.0007	0.0259 ***	0.0195 ***
	(0.0012)	(0.0038)	(0.0024)
Control variables	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	10,679	10,679	10,679
Panel B: Exclude Regions with More Developed Internet			
DS	0.0007	0.0321 ***	0.0201 ***
	(0.0008)	(0.0049)	(0.0028)
Control variables	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	9193	9193	9193
Panel C: Replace Panel Mlogit Model for Regression			
DS	−0.0007	0.0485 ***	0.0212 ***
	(0.0007)	(0.0051)	(0.0032)
Control variables	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	10,679	10,679	10,679

Notes: The control variables are consistent with Table 2; the standard errors in brackets are clustered at the provincial level; *** $p < 0.01$.

(4) Excluding regions with more developed Internet. Given the regional unevenness of Internet development, regions with higher levels of Internet development have more developed digital network infrastructure and training. As a result, the digital technology adoption behavior of rural laborers in these regions, as well as the frequency of activities involving digital technology, are not entirely determined by the independent choices of micro subjects but are heavily influenced by the external development environment, characterizing DS solely in terms of the frequency of specific behaviors biasing the estimates. According to the document "Operation of the Internet and Related Services Industry" issued by the Ministry of Industry and Information Technology, it is clearly stated that the current level of Internet business development in five provinces, namely Guangdong, Beijing, Shanghai, Zhejiang, and Fujian, ranks highest in national Internet development. Therefore, to further verify the robustness of the core findings, this paper tries to exclude these more developed Internet regions for robustness testing, and the test results are shown in Panel B of Table 6. The results show that DS still significantly increases the proportion of NFE and EP among rural laborers, further indicating the robustness of the core findings.

(5) Replacement of estimation method. The previous benchmark regression section used the panel Mprobit model, and this section is replaced with the panel Mlogit model for regression to verify the robustness of the core findings further. Moreover, the results are shown in Panel C of Table 6, which shows that the panel Mlogit model's regression results are more consistent with the benchmark regression results, indicating that the paper's core findings are robust and credible.

5. Further Analysis

5.1. Who Can Benefit More from Digital Upskilling?

The previous analysis shows that DS significantly improves the employment choices of the rural labor force. However, it is worth noting that this is only an average effect at the whole sample level and does not account for the heterogeneity of the impact of DS on rural laborers' employment choices. In order to obtain more detailed findings, this paper further analyzes the heterogeneity of the impact of DS on rural laborers' employment choices in terms of the dimensions of regional economic development level, skill level, and gender differences.

5.1.1. Grouped by Different Economic Development Levels

Because there is a digital penetration gap and a digital capability gap in different regions [52], this paper divides provinces into three regions according to their GDP ranking: rich, middle, and poor. The regression results are shown in Table 7. DS can significantly increase the proportion of NFE in middle and poor regions. However, the effect on NFE is most significant in poor regions, while the effect on EP is most significant in wealthy regions. The main reason for this is that employment opportunities in poor regions are limited compared to those in wealthy regions. It is more difficult for individuals to obtain employment information, with less job matching. When rural laborers acquire digital skills, they can use the information dissemination function of the Internet to help them obtain more employment information. In rich regions, economic and digital development levels are higher. When rural laborers master digital skills, they can increase their probability of identifying entrepreneurial opportunities.

Table 7. The impact of DS on employment choices of rural labor force with different economic development levels.

Panel A: Dependent Variable Is NFE			
	Rich Regions	**Middle Regions**	**Poor Regions**
DS	0.0162	0.0301 ***	0.0346 ***
	(0.0141)	(0.0085)	(0.0065)
Control variables	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	1880	3313	5486
Panel B: Dependent Variable Is EP			
DS	0.0233 *	0.0123 **	0.0231 ***
	(0.0122)	(0.0055)	(0.0028)
Control variables	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	1880	3313	5486
Panel C: Dependent Variable Is AE			
DS	−0.0049 *	0.0003	0.0017 **
	(0.0028)	(0.0015)	(0.0007)
Control variables	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	1880	3313	5486

Note: The control variables are consistent with Table 2; the standard errors in brackets are clustered at the provincial level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.1.2. Grouped by Different Skill Levels

Referring to the study of Acemoglu and Restrepo [29], the impact of the digital economy on the labor force with different skills varies considerably. Therefore, it is essential to explore the skill heterogeneity of DS on the employment choice of the rural labor force. Drawing on the studies of Autor et al. and Tian and Zhang [53,54], this paper defines the rural labor force with more than 15 years of education as a high-skilled labor force, those with education levels at high school and above and below college as the medium-skilled labor force, and those with education levels below high school as the low-skilled labor force. The results of the subsample estimation are shown in Table 8. The findings show that DS has the most significant impact on NFE and EP of low-skilled rural labor, consistent with the findings of [51], implying that improving the DS of low-skilled rural labor is a prerequisite for inclusive growth in the digital era. Meanwhile, DS significantly reduced the proportion of the high-skilled rural labor force employed in agriculture, but the effects on medium-skilled and low-skilled agricultural employment were insignificant.

Table 8. The impact of DS on employment choices of the rural labor force with different skill.

Panel A: Dependent variable is NFE	**High Skill**	**Medium Skill**	**Low Skill**
DS	0.0270 ***	0.0348 ***	0.0291 ***
	(0.0099)	(0.0075)	(0.0061)
Control variables	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	1218	1870	7591
Panel B: Dependent variable is EP			
DS	−0.0048	0.0134 **	0.0265 ***
	(0.0063)	(0.0061)	(0.0048)
Control variables	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	1218	1870	7591
Panel C: Dependent variable is AE			
DS	−0.0056 **	0.0006	0.0007
	(0.0027)	(0.0032)	(0.0015)
Control variables	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Observations	1218	1870	7591

Note: The control variables are consistent with Table 2; the standard errors in brackets are clustered at the provincial level; ** $p < 0.05$, *** $p < 0.01$.

5.1.3. Heterogeneity in Gender

In a traditional "patriarchal society" in China, driven by the ideology of "men are in charge and women are in charge", there are apparent differences between rural male and female laborers regarding family roles and employment choices. Therefore, this paper investigates the heterogeneity of DS in rural laborers' NFE from a gender perspective, and the specific test results are shown in Table 9. The results show that DS has the most significant impact on female NFE and the most significant effect on male EP. The main reason for this is that, when compared with men, women face discrimination in the rural job market in terms of employment opportunities, income distribution, and financial access to services, and they have relatively fewer opportunities to go out because of their narrower scope of life and more homogeneous social relationships. However, with the recent boom in the digital economy, women can communicate with the outside world via the Internet and e-commerce platforms after acquiring digital skills, which can compensate for the "lack" of social capital and increase their employment channels, thereby increasing the proportion of NFE. Because of their higher risk tolerance, competitive awareness, human capital, and social capital, men have an advantage in entrepreneurial activities. Meanwhile, the rapid development of Internet finance in recent years has provided an opportunity to alleviate rural laborers' financing constraints. As a result, male rural laborers are more willing to start their businesses after acquiring digital skills.

Table 9. The impact of DS on employment choices of the rural labor force with different gender.

Variables	**NFE**		**EP**		**AE**	
	Female	**Male**	**Female**	**Male**	**Female**	**Male**
DS	0.0483 ***	0.0201 ***	0.0140 ***	0.0252 ***	−0.0015	0.0012
	(0.0050)	(0.0063)	(0.0036)	(0.0045)	(0.0013)	(0.0015)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4563	6116	4563	6116	4563	6116

Note: The control variables are consistent with Table 2; the standard errors in brackets are clustered at the provincial level; *** $p < 0.01$.

5.2. Mechanism Exploration

The acquisition of DS by rural laborers can significantly increase the diversity of their employment options, but how does DS influence rural laborers' employment choices? Based on the previous theoretical analysis, this paper contends that DS primarily influences rural labor's employment choices by alleviating information access constraints and financing constraints.

5.2.1. Information Channel Effect

Due to limited information, knowledge, and endowment, the rural labor force is in low-level employment. Therefore, information access ability is essential for rural laborers' participation in the digital economy. It benefits improving individual feasible ability, realizing diverse employment patterns, lowering employment search costs, and realizing efficient and accurate matching of human and job. Rural laborers with DS can use online platforms to transfer information, break down spatial and information barriers, and effectively alleviate the information constraints they face in the digital context. Because the Internet is primarily an online communication platform, it can remove barriers and gaps in the flow of information, bridge the digital inequality caused by the digital divide, and improve rural laborers' information acquisition and technology application abilities, allowing them to make better employment and entrepreneurial decisions. As a result, we used the question "The importance of the Internet, TV, newspaper, radio, and mobile SMS as information acquisition channels" from the China Household Tracking Survey (CFPS) questionnaire to examine the impact of DS on information acquisition ability, drawing on the study of Zhou and Fan [36].

Table 10 reports the results of the DS and information access mechanisms tests. The findings show that a rural workforce with DS can significantly increase the importance of the Internet, newspapers, radio, and mobile SMS as information access channels, with the Internet having the most significant impact. As the primary carrier of information technology, the Internet has the potential to improve the efficiency and breadth of information dissemination. Therefore, rural laborers with DS can improve their information acquisition ability by emphasizing the Internet as an information acquisition channel, with business skills having the most significant impact on alleviating information flow constraints, owing to the ability of rural laborers with business skills to use digital finance such as Internet platforms and mobile payment to quickly collect and filter information, thereby alleviating information flow constraints. The main reason for this is that rural laborers with business skills can use Internet platforms and mobile payment to collect and filter information quickly, thereby alleviating information constraints.

Table 10. Mechanism of action: effect of DS on information acquisition ability.

Variables	(1) TV	(2) Internet	(3) Newspaper	(4) Broadcast	(5) Mobile SMS
DS	−0.0023	0.3208 ***	0.0802 ***	0.0471 ***	0.1642 ***
	(0.0204)	(0.0165)	(0.0245)	(0.0142)	(0.0211)
Digital learning skills	−0.0182 *	0.1135 ***	0.1116 ***	0.0560 ***	0.0671 ***
	(0.0098)	(0.0109)	(0.0131)	(0.0103)	(0.0153)
Digital work skill	−0.0273 ***	0.1162 ***	0.0872 ***	0.0348 ***	0.0556 ***
	(0.0079)	(0.0091)	(0.0083)	(0.0069)	(0.0127)
Digital social skills	0.0112	0.1483 ***	0.0205 *	0.0050	0.0839 ***
	(0.0125)	(0.0120)	(0.0101)	(0.0101)	(0.0147)
Digital entertainment skills	0.0063	0.1555 ***	0.0214 **	0.0105	0.0484 ***
	(0.0122)	(0.0100)	(0.0099)	(0.0115)	(0.0108)
Digital business skills	−0.0201	0.2036 ***	0.0767 ***	0.0378 **	0.0930 ***
	(0.0164)	(0.0120)	(0.0164)	(0.0144)	(0.0140)
Control variables	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Observations	2212	2212	2212	2212	2212

Note: The control variables are consistent with Table 2; the standard errors in brackets are clustered at the provincial level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.2.2. Financing Constraint Effect

The existence of financing constraints is an important factor limiting the success of entrepreneurship, which harms the entrepreneurship of low-income people with entrepreneurial spirit but limited capital. In recent years, low-income groups excluded from traditional finance have been absorbed by inclusive digital finance derived from Internet technology due to its low cost and easy accessibility. When rural laborers master digital skills, they can effectively use inclusive digital finance to alleviate the problems of "difficult financing" and "expensive financing" they face. As a result, they equalize entrepreneurial opportunities. Therefore, in examining the impact of DS on financing constraints, this section employs a probit model to validate the impact of DS on rural laborers' borrowing behavior in terms of both formal credit (availability of bank loans) and informal credit (availability of private lending). Table 11 shows the regression results, which show that acquiring DS significantly increases the likelihood of rural laborers obtaining formal loans but has no effect on private lending. It suggests that the rural labor force's acquisition of DS ultimately improves their employment options, primarily by increasing their likelihood of obtaining loans from financial institutions. Furthermore, online business skills have the most significant impact on easing credit constraints for formal credit. The main reason for this is that rural laborers with online business skills can improve their efficiency in using digital financial technologies such as Internet platforms and mobile payments to collect information quickly and reduce financing and transaction costs, which can help make up for traditional finance's shortcomings, effectively solve the problems of "difficult" and "expensive" financing for rural laborers, improve financial accessibility, and remove formal credit's financing constraints.

Table 11. Mechanisms of action: effects of DS on financing constraints.

Variables	**(1)**	**(2)**	**(3)**	**(4)**
	Formal Credit (Bank Loans)		**Informal Credit (Private Lending)**	
DS	0.0608 ***		−0.0010	
	(0.0179)		(0.0102)	
Digital learning skills		0.0227 **		0.0048
		(0.0095)		(0.0064)
Digital work skill		0.0237 ***		−0.0012
		(0.0073)		(0.0056)
Digital social skills		0.0144		0.0022
		(0.0108)		(0.0091)
Digital entertainment skills		0.0214 ***		−0.0028
		(0.0071)		(0.0055)
Digital business skills		0.0504 ***		−0.0079
		(0.0114)		(0.0076)
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations	10,679	10,679	10,679	10,679

Note: The control variables are consistent with Table 2; the standard errors in brackets are clustered at the provincial level; ** $p < 0.05$, *** $p < 0.01$.

6. Conclusions and Policy Implications and Limitations

The rapid development of the digital economy in recent years has resulted in many flexible employment workers and a variety of new employment forms, opening up more room for development to secure employment and entrepreneurship for urban and rural laborers. Furthermore, digital technology introduces new opportunities and challenges to China's labor market as an emerging technology. The main issue is how to effectively enable more laborers in less developed rural areas to fully benefit from the digital economy's employment dividends. Bridging the "utilization gap" of the rural labor force and improving rural labor force DS are the key points and concrete approaches to overcoming this problem. Based on this, this paper examines the impact of DS on rural labor force employment choices using CFPS data from 2014 to 2018. The findings show that, first, DS can significantly contribute to rural labor force NFE and EP, with each 1% increase in DS increasing rural labor force NFE and EP by 3.03% and 2.11%, respectively, indicating that DS is an essential factor influencing rural labor force employment choice. Second, the degree to which each DS affects rural laborer employment varies, with work skills having the most significant effect on promoting the NFE of rural laborers, and online business skills having the most significant effect on promoting EP. Third, the mechanism analysis demonstrates that DS improves the rural labor force's employment options by alleviating information access and financing constraints. Fourth, the heterogeneity analysis results show that DS promotes NFE among rural laborers, particularly among low-skilled rural laborers, and that males and rural laborers in less economically developed regions can benefit from EP. In contrast, females and rural laborers in economically developed regions can benefit more from NFE.

In the context of the digital economy, improving the DS of the rural labor force and promoting fuller and higher quality employment in the rural labor force is an effective way to "stabilize employment" and achieve shared prosperity. Rural laborers' low employment level is a "passive and helpless action" due to the lack of their resources. Building the personal "resilience" of rural laborers to participate more fully in the jobs created by the digital economy is undoubtedly critical to improving their employment options. The contribution of DS to the employment options of rural laborers demonstrates that DS can play an essential role in improving the employment options of rural laborers and promoting fuller and higher quality employment of rural laborers. Therefore, in order to give full play to the role of the "reservoir" of digital economy employment, this paper proposes the following policy implications. First, a digital skills diffusion system for rural areas should be built, and efforts should be made to improve the viability of rural residents' digital skills and raise the awareness of the digital economy among rural laborers, making it a key focus of a series of policies to bridge the digital divide and achieve dividend sharing in the current and future periods. Second, emphasis should be placed on the development of digital skills, with a particular emphasis on the development of work skills, social skills, and online business skills in order to improve the viability of the rural labor force's ability to participate in employment and obtain well-paying jobs, so as to provide intrinsic motivation for the digital economy to play a greater role in "stabilizing employment" and promoting common prosperity. Third, we should adopt "precise support" measures for the disadvantaged labor force to improve digital technology adoption by the low-skilled rural labor force and rural women, narrow the "digital divide" in the use of digital technology by disadvantaged groups, and enable low-skilled rural labor force and rural women to truly learn the functions of digital technology such as information search, skill learning, and social communication, so that they can find suitable jobs.

This paper still has certain limitations. Our study discovered that digital skills significantly improve the employment choices of the rural labor force, but how much of a spillover effect does rural labor force digital skills have on the employment choices of the rural labor force in the village and surrounding villages? Will mastery of the digital skills of the rural labor force increase the income gap among rural households? These issues have not been resolved. We hope to address them in future studies as more data become available.

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