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The Influence of Digital Literacy on Non-Agricultural Employment

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Digital technologies and the Internet are playing increasingly important roles in people's daily activities. The competence to utilize these technologies has created a new type of literacy, known as digital literacy. Meanwhile, non-agricultural employment is an essential source of income, especially for those living in rural areas. Researchers find that Internet usage encourages household entrepreneurship. We also posit that digital literacy enables people to look for and obtain non-agricultural employment opportunities. Using Chinese data gathered in 2017, we first study the factors influencing digital literacy. We then determine the relationship between digital literacy and non-agricultural employment. We also examine the influence of digital literacy on the income of people working in non-agricultural sectors. Quantitative results indicate that digital literacy has a positive impact on non-agricultural employment for both urban and rural residents. For those employed in non-agricultural sectors, digital literacy is positively associated with income. We suggest that people's income can be increased by equipping them with digital literacy. We also propose policies for improving digital literacy.

Keywords: digital literacy; non-agricultural employment; income

1. INTRODUCTION

During the past thirty years, the utilization of information technologies and the Internet has become more and more significant in our daily activities. Digitalization enables us to look for and obtain information, share ideas, and collaborate with others using new technologies.

Regardless of the great advantages offered by digitalization, people have not been benefitting from it on an equal footing (Manovich, 2002). People have different capabilities. Accessing digital devices and the Internet connection turns out not the sufficient condition for people to participate in the digital universe. The competence to utilize information technologies has given rise to a new type of literacy, known as digital literacy.

Recently, in China, employment in a non-agricultural sector has become an essential source of income, especially in rural areas. According to a report by China News (2019), in 2018, the annual income of farmers was 5996 yuan, with an increase by 498 yuan compared with the previous year, representing an increase of 42.0%; the net operating income was 5359 yuan, with an increase by 331 yuan compared with the previous year, contributing 27.9% to the increase of farmers' income.[1]

Nowadays, non-agricultural employment is greatly influenced by the use of digital tools. For instance, social media provide people with platforms which enable users to search for and find employment opportunities in non-agricultural sectors. Furthermore, some researchers claim that Internet usage encourages household entrepreneurship (Zhou and Fang, 2018).

With digital tools as the intermediaries, we posit that digital literacy enables people to discover and obtain more employment opportunities in non-agricultural sectors. We study the correlation between digital literacy and non-agricultural employment at the individual level, where non-agricultural employment can be either self-employment or being employed by others. We also study the association between digital literacy and income of those working in non-agricultural sectors.

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[1] Please refer to https://baijiahao.baidu.com/s?id=1632039625870438376&wfr=spider&for=pc [in Chinese].

The paper is organized as follows: Section 2 presents a review of three streams of literature: the concept of digital literacy, the factors influencing digital literacy, and the relationship between digital literacy and economic behaviors. Section 3 provides data descriptions, variables, and descriptive statistics. Section 4 presents econometric models as well as empirical results. The conclusions are drawn in section 5.

2. LITERATURE REVIEW

We intend to examine the impact of individual level of digital literacy on non-agricultural employment. We summarize three streams evident in the literature: the concept of digital literacy; factors that impact on individual levels of digital literacy; relationships between digital literacy and economic behaviors. For the last stream, we focus on three types of economic behaviors: performance of workers and enterprises, investment and resilience-building financial behaviors, and employment.

2.1 The Conception of Digital Literacy

Previous researchers have offered various definitions of digital literacy. The European Commission (2006) defines it as "the confident and critical use of ICT for work, leisure, learning and communication". This implies that digital literacy includes both operational uses of digital devices and cognitive skills. The American Library Association (ALA, 2013) defines the concept as "the ability to use information and communication technologies to find, understand, evaluate, create, and communicate digital information, an ability that requires both cognitive and technical skills". Wang et al. (2021) note that digital literacy concerns one's ability to obtain and comprehend information on various digital platforms, and is evaluated by one's ability to apply technologies to create different forms of media. Li and Li (2022) also present a definition of the concept. They propose that digital literacy covers operational skills, cognitive skills, critical thinking, creating and sharing digital contents, and communicating on the Internet.

In summary, we say that digital literacy covers the following abilities at least: Operating digital devices; seeking and finding information on the Internet; verifying the authenticity of digital contents; creating and sharing contents on digital media; collaborating with others in the digital world; protecting one's personal privacy.

2.2 Factors Affecting Digital Literacy

Researchers have examined various factors influencing individual levels of digital literacy. Park and Nam (2014) studied the case of Korea and found that disability, gender, and educational attainments influenced production literacy.

Urbančíková et al. (2017) studied social and economic factors of digital literacy in the context of Slovakia. They noted that the educational level and income were important factors determining the level of digital literacy.

Dong et al. (2021) conducted interviews with a sample of children from central China and noted that all the interviewees could access various digital devices at home, with smart phones being the device most frequently used for digital activities. Child age, household income, digital resources, parental attitudes and parental intervention were significant predictors of children's digital literacy.

2.3 Relationships between Digital Literacy and Economic Behaviors

2.3.1 Performance of Workers and Enterprises

Mohammadyari and Singh (2015) discovered that digital literacy positively affected individual performance expectancy; moreover, performance expectancy had positive effects on people's performance at work.

RVSPK et al. (2020) investigated whether digital literacy affected business uncertainty and the performance of small enterprises in Sri Lankan. They recognized that digital literacy greatly reduced business uncertainty, thereby increasing the profits of small enterprises.

2.3.2 Investment and Resilience-Building Financial Behaviors

Previous studies found that the development of digital technologies could mitigate financial market frictions and encourage family participation in financial investment. Zhou and Liang (2018) used Chinese data and noted a positive impact of Internet use on family investment in risky financial tools. This effect could arise from reduced transaction costs, more participation opportunities, and stronger social interactions.

Munari & Susanti (2021) analyzed the effects of digital literacy and financial literacy on the usage of e-banking by a group of students. They showed that both digital literacy and financial literacy had significant influences on the usage of e-banking.

Kass-Hanna et al. (2022) used data from seven Asian and African countries and investigated the relation between digital and financial literacy and financial behaviors such as saving, borrowing, and risk management. They showed that both digital and financial literacy contributed to building financial resilience.

2.3.3 Employment

Bejakovic and Mrnjavac (2020) carried out a country-level quantitative study of EU member states and found that employment rates among the laborers aged 25 to 54 and percentages of people with at least low digital skills are positively correlated.

Kikulwe et al. (2014) examined the effects of mobile money usage on entrepreneurial activities of smallholder farmers in Kenya. They showed that mobile money users sold a larger proportion of their outputs to the market and made more profits than non-users. Sekabira and Qaim (2017) studied the effect of mobile money use on off-farm activities of small coffee farmers in Uganda. They found that mobile money users marketed a larger portion of their coffee to buyers in high-value markets rather than in local regions.

Zhou and Fang (2018) explored the channels through which Internet usage promoted family entrepreneurship, including the facilitation of information flow and less-constrained liquidity.

2.4 Contributions of the Paper

Our paper makes several contributions. First, we determine quantitatively the impact of digital literacy on non-agricultural employment at the individual level. We use data from China. Previous studies focused mainly on the effect of digital literacy on household entrepreneurial activities. However, entrepreneurship is only one type of non-agricultural employment, whilst non-agricultural employment in a broader sense is an important source of income in China. Second, we examine the impact of digital literacy on the income of those employed in non-agricultural sectors. We expect that digital literacy not only affects the likelihood of obtaining of non-agricultural employment, but also impacts on the income after derived from non-agricultural employment. Third, we study the influence of digital literacy on non-agricultural employment for different groups of people. Specifically, we posit that digital literacy helps people to acquire non-agricultural employment irrespective of where they reside or their level of education.

3. DATA

3.1 The CGSS Data

We use the data of China General Social Survey (CGSS). The surveys by CGSS involve almost all provinces in China and contain information on demographic, economic, and social characteristics. Since the survey implemented in the year of 2017 offers information on people's digital competencies, we use data from the 2017 survey. Henceforth in this paper, this survey is referred to as CGSS 2017.[2]

3.2 Estimation Sample

CGSS carried out face-to-face interviews with people who are 16 years old or older. Initially, 12,582 people were interviewed by the CGSS 2017. Our sample comprised residents living in both rural and urban areas. We focused on people aged between 20 and 65. After discarding observations with missing value sfor important variables of the paper, we retained 2,578 individuals for our final sample. We name this sample the 'benchmark sample'.

[2]To obtain the data, please see http://www.cnsda.org/index.php?r=projects/view&id=94525591. The data are free of charge.

3.3 Definitions of Variables

Firstly, we examine the factors influencing digital literacy at the individual level. To measure the digital literacy, we construct an index using ten variables representing individual digital skills following Li and Li (2022). Specifically, we build a single index by computing the mean of the ten variables. Greater values on the index imply greater levels of digital literacy.

The control variables that we consider to have an impact on digital literacy include gender, age in years, education, marital status, number of children aged below 18, whether having a local registration, total income, health condition, being a member of a minority group or not, having used internet for at least five years or not, uses internet for at least five hours per week or not, living in the urban or not, living in the central region or not, and living in the eastern region or not (with the western region as the reference). The gender variable is a dummy which takes the value of 1 if the gender is male and 0 otherwise. Education variable is given a value ranging from 1 to 13, with higher values implying higher levels. Health status values range from 1 to 5, indicating the worst to the best health conditions.

Secondly, we investigate whether digital literacy has an impact on employment in non-agricultural sectors. The respondents were asked about their employment status. We define the non-agricultural employment variable to be 1 if the respondent was employed in a non-agricultural sector at the time of the interview, and 0 otherwise. Unfortunately, we cannot tell from CGSS 2017 whether the respondent is self-employed or employed by others.

Other control variables that may potentially affect one's employment status considered in the paper are gender, age in years, education, marital status, number of children aged under 18, having a local registration or not, health status, being a member of a minority group or not, living in an urban area or not, living in the central region or not, and living in the eastern region or not (with the western region as the reference).

Thirdly, we examine the effect of digital literacy on the income of those employed in non-agricultural sectors. Control variables that we consider to affect the income are the same as those that may affect the employment status.

3.4 Basic Statistics

Using the benchmark sample for computation, the mean of the digital literacy index is 3.32. Approximately 45% of respondents are employed in non-agricultural sectors. The average annual income of those employed in non-agricultural sectors is 62,622 yuan, whilst the average income of the remaining respondents is 18,876 yuan.

Table 1 gives a summary of the variables relevant to the paper based on the employment status of the respondent. Column 1 shows the means for those who are employed in non-agricultural sectors and column 2 shows the means for those who are not (e.g., either working in the agricultural sector or unemployed).

People who show greater levels of digital literacy tend to be employed in non-agricultural sectors. This is in accordance

Table 1 Descriptive statistics.

	Non-agricultural employment	
	No	Yes
	(1)	(2)
Digital literacy	3.05	3.67
Gender	0.42	0.59
Age	52.23	40.08
Education	4.36	6.96
Married	0.82	0.80
Number of kids < 18 years old	0.38	0.68
Has a local registration	0.76	0.57
Health condition	3.26	3.95
Minority	0.08	0.05
Urban	0.52	0.81
West region	0.26	0.15
Central region	0.41	0.35
Eastern region	0.33	0.50
Number of observations	1,418	1,160

with our expectation. Regarding the other controls, those more likely to work in non-agricultural sectors are: males, younger, better educated, those without a local registration, those in better health, and the non-minorities. Moreover, respondents who are living in urban areas and those who are living in the eastern region of China are more likely to be employed in non-agricultural sectors.

4. ECONOMETRIC ANALYSES

4.1 Models

We set up three models. The first is intended to evaluate factors that may impact on digital literacy. The second investigates the effect of digital literacy on non-agricultural employment. The third determines the relationship between digital literacy and the income of those who work in non-agricultural sectors.

We first build the following model.

$$Digital_i = \alpha_0 + \alpha' \mathbf{X}_i + u_i \qquad (1)$$

Where i denotes a respondent of CGSS 2017. *Digital* represents digital literacy. As mentioned earlier in the paper, we use a single index to measure the digital literacy.

X contains other control variables relating to individual characteristics, namely gender, age in years, education, being married or single, number of children aged under 18, having a local registration or not, total income, health status, being a member of a minority group or not, living in the urban or not, living in the central region or not, and living in the eastern region or not (with the western region as the reference). **X** also contains two dummies to reflect experiences with the Internet: having used the Internet for at least five years and using the Internet for at least five hours per week.

We apply Equation (1) to our sample and apply an OLS estimator.

Secondly, we construct the following model.

$$Nonagr_i = \beta_0 + \beta_1^* \, Digital_i + \beta' \mathbf{Z}_i + \varepsilon_i \qquad (2)$$

Where i denotes a respondent of CGSS 2017. *Nonagr* is a dummy to indicate whether the individual is employed in non-agricultural sectors. The essential explanatory variable *Digital* is digital literacy. A positive estimate of β_1 indicates that digital literacy positively affects an individual's probability of working in non-agricultural sectors.

Z contains other control variables concerning individual characteristics: gender, age in years, education, married or single, number of children aged under 18, whether or not the respondent has a local registration, health status, being a member of a minority group or not, living in an urban areas or not, living in the central region or not, and living in the eastern region or not (with the western region as the reference).

We apply Equation (2) to our sample. We apply a Probit model and compute the marginal effect of each independent variable.

Lastly, we build the following model.

$$Income_i = \gamma_0 + \gamma_1^* \, Digital_i + \gamma' \mathbf{Z}_i + v_i \qquad (3)$$

Where i denotes a respondent of CGSS 2017. *Income* is total annual income measured in ten thousand yuan. Independent variables in Equation (3) are the same as those in Equation (2).

We apply Equation (3) to our sample. We adopt an OLS estimator and use two subsamples: those who work in non-agricultural sectors and those who do not.

4.2 Factors Influencing Digital Literacy

We examine the factors that could potentially influence digital literacy. We report in Table 2 results obtained through Equation (1).

The digital literacy index shows that males score higher than their female counterparts. Also, the younger males have better digital literacy. Higher levels of education are associated with people who score higher on the digital literacy index. Incomes and health conditions are positively associated with digital

Table 2 Influencing Factors of Digital Literacy.

	Dependent variable: Digital Literacy
Gender	0.050*
	(0.091)
Age	−0.014***
	(0.001)
Education	0.056***
	(0.001)
Married	−0.002
	(0.943)
Number of kids $<$ 18 years old	0.006
	(0.758)
With a local registration	−0.054
	(0.113)
Total income	0.003*
	(0.080)
Health condition	0.040***
	(0.006)
Minority	−0.029
	(0.629)
Experience with internet for $>$ 5 years	0.374***
	(0.001)
Uses internet for $>$ 5 hours each week	0.110***
	(0.006)
Urban	0.046
	(0.213)
Central region	0.031
	(0.434)
Eastern region	0.110**
	(0.013)
Number of observations	2,578

Note: Coefficient estimates and p-values in brackets are reported. ***, **, and * mean significance at 1%, 5%, and 10% level, respectively.

literacy. Internet use experience impacts on digital literacy in a positive way, indicating that the more time one spends on the Internet, the higher is his or her level of digital literacy.

There is no significant difference between rural and urban residents. The difference between residents living in the central region and those in the western region are insignificant. However, residents living in the eastern region have higher scores on the digital literacy index than those in the western region.

4.3 The Effects of Digital Literacy on Non-agricultural Employment

First, we apply Equation (2) to the entire benchmark sample. Second, we utilize two subsamples of the benchmark sample according to the residential status of the respondents. Results for rural and urban residents are given in columns 2 and 3, respectively.

Figures in Table 3 indicate that, for the entire sample, digital literacy increases the possibility of non-agricultural employment, as we expected.

Looking at column 2, we see that digital literacy has a significant positive impact on the likelihood of non-agricultural employment for rural residents. Figures in column 3 show that digital literacy also positively influences the possibility of non-agricultural employment for urban residents. In addition, the magnitude of the effect is quite similar for the rural and the urban residents.

Thus, we propose that digital literacy effectively helps people to find and obtain non-agricultural employment opportunities in both rural and urban areas.

In terms of other controls, those who are more likely to work in non-agricultural sectors are male, younger, and better educated. From Table 2, we see that education is positively correlated with digital literacy. Hence, we suggest that education helps people to acquire non-agricultural employment both directly and indirectly through higher levels of digital literacy. Those who are married and who are healthier are more likely to work in non-agricultural sectors. Whether or not people have local registration does not significantly affect their employment status. People living in the urban areas have more opportunities of obtaining non-agricultural employment. Moreover, people living in the central and eastern regions show are more likely to be employed in the non-agricultural sector than those living in the western region.

Next, we divide the benchmark sample according to the respondents' level of education. t We apply Equation (2) using both respondents whose education levels are lower than

Table 3 Impacts of digital literacy on non-agricultural employment.

	Entire sample	Rural residents	Urban residents
	(1)	(2)	(3)
Digital literacy	0.034***	0.032**	0.036**
	(0.006)	(0.041)	(0.032)
Gender	0.208***	0.126***	0.217***
	(0.000)	(0.000)	(0.000)
Age	−0.014***	−0.005***	−0.016***
	(0.001)	(0.001)	(0.001)
Education	0.023***	0.031***	0.021***
	(0.000)	(0.002)	(0.002)
Married	0.175***	0.022	0.237***
	(0.000)	(0.599)	(0.000)
Number of kids <18 years old	0.008	0.011	0.009
	(0.592)	(0.583)	(0.652)
With a local registration	−0.021	−0.051	−0.011
	(0.391)	(0.324)	(0.686)
Health condition	0.069***	0.062***	0.058***
	(0.000)	(0.000)	(0.000)
Minority	−0.061	−0.046	−0.037
	(0.166)	(0.276)	(0.550)
Urban	0.225***		
	(0.000)		
Central region	0.093***	0.056*	0.107**
	(0.003)	(0.080)	(0.011)
Eastern region	0.095***	0.264***	0.069***
	(0.004)	(0.000)	(0.009)
Number of observations	2,578	890	1,688

Table 4 Impacts of digital literacy on non-agricultural employment.Table 4

	Less educated	Better educated
	(1)	(2)
Digital literacy	0.037**	0.145***
	(0.024)	(0.001)
Gender	0.221***	0.073**
	(0.000)	(0.046)
Age	−0.015***	−0.008***
	(0.000)	(0.000)
Education	0.033***	0.002
	(0.000)	(0.912)
Married	0.074**	0.260***
	(0.025)	(0.000)
Number of children <18 years old	−0.009	0.004
	(0.575)	(0.903)
With a local registration	−0.030	0.012
	(0.280)	(0.750)
Health condition	0.071***	0.015
	(0.000)	(0.495)
Minority	−0.029	−0.120
	(0.521)	(0.126)
Urban	0.205***	0.093
	(0.000)	(0.204)
Central region	0.072**	0.111
	(0.023)	(0.142)
Eastern region	0.087**	0.069
	(0.014)	(0.226)
Number of observations	2,002	576

undergraduate and respondents whose education levels are equal to or higher than undergraduate. Results are presented in Table 4.

Figures in Table 4 show that digital literacy positively affects non-agricultural employment for both poorly and well-educated residents. Nevertheless, the impact is much greater for those who have a good education.

4.4 The Effects of Digital Literacy on Annual Income

Now we examine the association between digital literacy and individual annual income. For comparison purposes, we look at the respondents who work in the non-agricultural sectors and those who do not. The results, after applying Equation (3), are given in Table 5.

As is shown in column 1, digital literacy is positively correlated with higher annual income of those who work in non-agricultural sectors, but has no significant effect on those who do not. We suggest that higher levels of digital literacy not only help people to acquire non-agricultural employment, but also contribute to higher incomes of people working in non-agricultural sectors.

In regard to other controls, in both groups, the males on average earn more than the females. Income is positively correlated with age and level of education. People with higher incomes are likely to have more children. In terms of those who work in the agricultural sector or are unemployed, people living in the central region earn more than those living in the western region. For both groups, people living in the eastern region earn more than those living in the western region.

To sum up, we find that the level of digital literacy is positively associated with individual's employment in non-agricultural sectors. This is true for people living in both rural and urban areas, and for people both poorly or well educated. In addition, higher levels of digital literacy generally mean higher incomes for people who work in non-agricultural sectors.

Based on the information of CGSS 2017, 55% of respondents aged between 20 and 65 do not work in non-agricultural sectors. According to the digital literacy index, 58% of these people have a digital literacy lower than the sample mean. We infer that more people would be able to secure employment in non-agricultural sectors if they were equipped with digital literacy.

Table 5 Effects of digital literacy on total annual income.

	Work in non-agricultural sectors	The rest
	(1)	(2)
Digital literacy	1.218***	0.061
	(0.009)	(0.701)
Gender	1.923***	1.813***
	(0.000)	(0.000)
Age	0.095***	0.076***
	(0.004)	(0.000)
Education	0.722***	0.436***
	(0.000)	(0.000)
Married	0.620	0.812**
	(0.463)	(0.034)
Number of children $<$18 years old	0.896**	0.336*
	(0.023)	(0.089)
With a local registration	−0.828	−0.320
	(0.301)	(0.374)
Health condition	0.161	0.267**
	(0.608)	(0.044)
Minority	−1.419	−0.206
	(0.234)	(0.704)
Urban	−0.032	0.165
	(0.964)	(0.647)
Central region	0.441	0.756**
	(0.595)	(0.036)
Eastern region	3.260***	1.441***
	(0.000)	(0.001)
Number of observations1,160	1,418	

5. CONCLUSIONS

The utilization of information technologies and the Internet has become quite significant in our daily activities. The competence to utilize the information technologies has given rise to a new type of literacy, known as digital literacy.

Currently, in China, non-agricultural employment provides a source of income that is significant. Therefore, the employment of both rural and the urban residents in non-agricultural sectors is an efficient means of increasing household income.

We posit that people with digital literacy have more opportunity to seek and obtain employment in non-agricultural sectors, either working for others or in a self-employed capacity. In this paper, we use data from China to examine the effect of digital literacy on individual employment in non-agricultural sectors. Empirical results indicate that digital literacy has a positive impact on employment in non-agricultural sectors. This is true for people living in both rural and urban areas, and applies to those with either low or high levels of education. Also, having a local registration does not affect the possibility of obtaining non-agricultural employment. To sum up, we suggest that in China, the lack of or low levels of digital literacy can be a significant obstacle for people who wish to be employed in non-agricultural sectors. Improving people's digital literacy can potentially increase their chances of finding employment in non-agricultural sectors.

After investigating the factors that impact on digital literacy, we discover that the experiences of Internet users are positively correlated with digital literacy. We propose that digital skills can be acquired through training. We also found that people living in the eastern region have better digital skills than those living in the western region. Thus, public policies should be designed to reduce the gap between the two areas in terms of their population's digital literacy.

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