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The Impact of Digital Capabilities on Peasants' Wage Growth: Evidence from Chinese Farmer Entrepreneurs

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Abstract: The gradual integration of digital technology into traditional Chinese villages has triggered a shift in income distribution from labor to capital, posing challenges to the wage growth of employed peasants. Based on the theory of empowerment, this paper explores the mechanisms of credit availability and talent loss in the interplay between digital capabilities and wage augmentation among employed peasants. This study empirically examines or validates the mechanism of digital capabilities on wage growth for employed peasants through the entropy weight method, the OLS linear model, the mediation effect model, and propensity score matching while using survey data from 490 farmer entrepreneurs as samples. The findings are as follows. (1) The digital capabilities of farmer entrepreneurs have a significant positive impact on the wage growth of employed peasants, and this result remains robust after a series of robustness checks. In terms of hierarchical effects, digital foundational capabilities > digital application capabilities > digital innovation capabilities. (2) Credit availability and talent loss mediate the relationship between digital capabilities and wage growth for employed peasants. (3) The digital capabilities of farmer entrepreneurs who are young, highly educated, and have a low family-dependency ratio exert a more pronounced influence on the wage growth of employed peasants. Additionally, lower policy uncertainty enhances the effect of digital capabilities on wage growth for employed peasants. The study uncovers the empowerment mechanism of digital advancements embedded during the entrepreneurial journey, enriches research on digital capabilities and common prosperity, and provides a feasible path for governments to formulate reasonable entrepreneurship and digital promotion policies.

Keywords: digital capabilities; peasants' wages; credit availability; talent loss; common prosperity

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1. Introduction

Chinese farmer entrepreneurs make up an important group that drives nearby rural labor employment, increases peasants' wages, and promotes common prosperity. After the Chinese government issued the "Outline of the Digital Rural Development Strategy" in 2019, the Chinese central government departments successively released a series of policy documents, including the "Digital Rural Development Action Plan (2022–2025)" and the "Guiding Opinions on the Construction of a Digital Rural Standard System", indicating that the Chinese government highly values digital rural construction. With the gradual improvement of digital infrastructure, China's rural entrepreneurial ecosystem has changed, with the old world gradually deconstructed and a new world of digital twins established [1]. The original business model has changed, with the internet connecting farmers to large markets and connecting rural areas to cities [2]. Through diversified logical forms and low-cost digital means, spatial barriers are eliminated, trade barriers are broken down, a multi-level network-connected ecosystem is created, and the relationship between producers and consumers is reshaped [3], triggering new agricultural factor allocation and the organizational division of labor [4], leading to a new rural production and operation system. In addition, digital technology has also led to a shift in income distribution from labor to capital [5], with backward production capacity being eliminated and the average wages of low-skilled labor even declining [6], further exacerbating income inequality. However, rural areas are based on a rural acquaintance society formed by blood and geography. Whether the improvement of digital capabilities brought about by digital technology among farmer entrepreneurs will impact the continued growth of small farmers' wages remains to be further verified and answered.

Firstly, as digital countryside construction progresses, digital infrastructure is gradually improving. The internet facilitates the effective dissemination of information, enhances the demonstration effect of successful entrepreneurship, and promotes entrepreneurial behavior among rural residents [7,8]. Digital empowerment can also increase employment opportunities for labor with high human capital by expanding economic scale and improving management efficiency [9]. Concurrently, digital technology accessibility significantly promotes rural labor outflow [7]. Given the coexisting reality of increased demand for labor with high human capital and rural labor outflow, further investigation is needed to understand how the wages of employed peasants in rural areas will change. Secondly, the nature of locality and regionality in the digital age is evolving, with the boundaries of different ecosystems being transcended through digitization [10]. Digital transformation in enterprises plays a vital role in alleviating financing constraints [11]. The depth of digital inclusive finance (DIF) usage is crucial to the quality of rural entrepreneurship, and a supportive business environment strengthens this relationship [12]. Enhancing digital financial capabilities can disproportionately benefit disadvantaged groups, particularly those in rural or underdeveloped areas [13].

Meanwhile, those living in poverty, without secondary education, and in poor health are more vulnerable to digital exclusion [14]. Digital capabilities, characterized as dynamic capabilities [15], struggle to reasonably explain such contrasting realities. The dynamic capabilities of enterprises enable them to respond to the ever-changing market environment and maintain sustainable competitive advantages [16]. Different from enterprise digital capabilities, the digital capabilities of farmer entrepreneurs aim to effectively acquire and utilize information, improve agricultural production efficiency, and broaden sales channels, hoping to change the existing production and operation status, improve social status, and restore social functions. The enterprise digital capabilities representing dynamic capability characteristics cannot cover the social functions of farmer entrepreneurs' digital capabilities. Therefore, empowerment theory presents new opportunities for research development. The core essence of "empowerment" revolves around bolstering the effectiveness of agents and furnishing them with pathways, instruments, or prospects for the accomplishment of their objectives. How digital capabilities based on empowerment theory can benefit employed peasants has not yet garnered significant attention from researchers.

This study embeds the empowerment theory into the entire process of farmer entrepreneurship and integrates it with the three stages of rural entrepreneurial practice: startup, expansion, and self-renewal. It views the digital capabilities of farmer entrepreneurs as multidimensional and dynamically evolving. By learning and utilizing digital tools, they attain novel competencies to enhance entrepreneurial excellence and value generation, thus realizing the digitization or digital transformation of marketing methods, products, and services [17]. In turn, this drives rural economic development, increases farmers' income, and narrows the urban–rural gap. In the research on the development of digital technology, the study of digital capabilities has consistently garnered the attention of researchers, leading to a series of research achievements. However, the focus has primarily been on enterprises' digital capabilities, with a noticeable lack of literature examining the impact mechanism of farmer entrepreneurs' digital capabilities on the growth of peasants' wages and, particularly, the absence of a systematic theoretical framework and empirical testing. Therefore, this study has three objectives. First, it aims to investigate the direct impact of farmer entrepreneurs' digital capabilities on the wage growth of employed peasants.

Second, the objective of this study is to delve into the consequences of farmer entrepreneurs' digital capabilities on both credit accessibility and the phenomenon of talent loss; furthermore, it endeavors to validate the intermediary function hypothesis pertaining to credit availability and talent loss, ultimately elucidating the intricate mechanism through which farmer entrepreneurs' digital capabilities influence the wage augmentation of rural employees. Third, the study aims to further explore the heterogeneity effects brought by farmer entrepreneurs' groups and policy uncertainty.

In this light, leveraging survey data from 490 farmer entrepreneurs across 21 cities (prefectures) in Sichuan Province, the study employs the entropy weight method, the OLS linear model, the mediation effect model, and propensity score matching to unravel the mechanism underpinning the influence of farmers' entrepreneurial digital capabilities on the sustained growth of employed peasants' wages. Compared to existing research, the key contributions of this paper lie in elucidating the intricate dynamics between farmer entrepreneurs' digital capabilities and their multifaceted impacts, specifically addressing the enhancement of credit accessibility, the mitigation of talent exodus, and the subsequent influence on wage growth among employed peasants. By adopting a nuanced approach, this research offers fresh insights into the intricate mechanisms at play, enriching the understanding of the digital transformation's role in rural economic development. Firstly, it constructs a theoretical analysis framework linking digital capabilities to the wages of employed peasants, revealing the impact mechanisms of credit accessibility and talent loss on these wages, thereby broadening the scope of the empowerment theory. Secondly, it examines the heterogeneous effects of different levels of digital competence, heterogeneity within farmer entrepreneur groups, and policy uncertainty on the wage growth of employed peasants, clarifying the intricate relationships between digital competence and various farmer entrepreneur groups and policy environments. Thirdly, it enriches research on digital competence and common prosperity, providing quantitative evidence and empirical insights for refining digital promotion strategies and guiding entrepreneurial policies for different entrepreneurial groups in digital countryside construction.

The structure of the remainder of this paper is as follows. Section 2 presents a literature review on digital competence, wages of employed farmers, credit accessibility, and talent drain. Based on relevant theories, research hypotheses have been proposed. Section 3 elaborates on the research methodology, including data collection processes, variable measurement, and estimation strategies. Section 4 of this paper showcases the empirical findings derived from the study. Section 5 delves into a comparative analysis, examining the congruence, deviations, or supplementary nature of these discoveries in relation to the extant research corpus. Ultimately, Section 6 concludes the research endeavor by summarizing the key insights and outlining their implications for policy formulation and future research avenues.

2. Prior Literature Review and Hypothesis

2.1. Digital Capabilities and the Growth of Employed Peasants' Wage

In 1976, the term "empowerment" was first used in Barbara Solomon's book "Black Empowerment: Social Work in Oppressed Communities", where empowerment was defined as a process that aids marginalized groups in enhancing their sense of worth and dignity, ultimately aiming to improve living conditions for both current and future generations. Solomon [18] regarded empowerment theory as a supplement to existing theories, emphasizing that empowerment is not a privilege for the few but a fundamental force for survival. Through social policies, individuals can be empowered with the belief to control their lives and gradually regain their footing. From a management perspective, methods for achieving empowerment include education, leadership, organization, provision, guidance, and implementation [19], all of which are correlated with performance [20]. Joseph [21] critically analyzed empowerment theory using the Theoretical Evaluation Scale (TES), demonstrating its suitability as an ideal framework for mixed-methods research paradigms as a theoretical model. During China's economic transformation and development, while achieving economic prosperity and remarkable accomplishments, it has also led to the emergence of vulnerable groups, particularly laid-off workers, landless farmers, and rural left-behind populations due to social changes. These groups struggle to sustain their lives through their own means, forming impoverished segments of society. In this context, introducing empowerment theory can reignite the life aspirations of vulnerable groups. Yue Xiaowenxu et al. [22] proposed a new endogenous development mechanism for rural China centered on self-empowerment of capable individuals, organizational empowerment, community empowerment, and empowerment of collective members. Therefore, based on empowerment theory, farmer entrepreneurs' digital capabilities should serve as a catalyst for their own effectiveness in transforming existing production and operation status, altering adverse social positions, and restoring societal functional deficiencies.

This paper regards farmer entrepreneurs as capable actors who, through learning and utilizing digital tools empower themselves with control and coping skills in daily life and production. This empowerment does not solely stem from the mere possession of digital tools; rather, it encompasses a multi-faceted and sequential process [23]. The digital capabilities of farmer entrepreneurs are influenced by multiple factors, with existing research mainly focusing on the quality of digital infrastructure, public policies (such as broadband subsidies), the educational level of rural residents, and their digital skill levels [24–26]. Researchers have concluded that digital capability is a multidimensional concept, involving proficiency in utilizing software applications or operating digital instruments and cognitive complexities, emotional factors, and interpersonal abilities [27,28], which can be measured through micro-survey databases or questionnaire data.

A standard system of measurement indicators for digital capabilities has not yet been established. The existing research primarily constructs digital capability indices from three dimensions: digital access, digital usage, and digital transformation [29]. In small and medium-sized enterprises, digital capabilities positively impact employees' digital performance [30]. In farmer enterprises, digital capabilities not only enhance farmers' household resilience by encouraging entrepreneurship and deepening their involvement in financial markets [31] but also promote herders' income growth by elevating human capital levels, facilitating the adoption of production technologies, strengthening bargaining power, and reducing information search costs [5]. Farmers' wage income is a crucial component of their overall income growth, influenced by their personal qualities and intimately tied to their economic environment [32]. Building upon previous research [33,34] and integrating the realities of farmers' entrepreneurial practices, this paper categorizes farmers' entrepreneurs' digital capabilities into three tiers: digital basic capabilities, digital application capabilities, and digital innovation capabilities [35,36]. In addition, it proposes the following research hypotheses:

H1. *Digital capabilities positively contribute to the wage growth of employed peasants.*

H1a. *Digital foundational capabilities positively contribute to the wage growth of employed peasants.*

H1b. *Digital application capabilities positively contribute to the wage growth of employed peasants.*

H1c. *Digital innovative capabilities positively contribute to the wage growth of employed peasants.*

2.2. The Mediating Role of Credit Availability (CA)

The fundamental reason for farmers' difficulty obtaining formal credit lies in information asymmetry, and particularly, the lack of effective collateral accepted by banks [37]. Coupled with the characteristics of farmers' financing needs, such as large amounts, long terms, and low interest rates [38], this further exacerbates the challenge. To address this issue, prior research has unearthed that the engagement of large-scale farmers within agricultural and industrial supply chain networks can effectively mitigate transaction expenses stemming from informational disparities and contractual imperfections inherent in their interactions and formal financial institutions, thereby enhancing their credit availability [39]. Additionally, the confirmation of rural land rights has significantly increased the credit availability of high-income farmers [40]. Meanwhile, various factors influence farmers' credit availability, including the household head's age, gender, education level, farming experience, farm size, and social networks [41,42]. Digital technology plays a pivotal role among these influencing factors. It reduces transaction costs, enhances operational capabilities, and mitigates the impact of under investment [43], but it also increases credit availability, promotes income growth, and narrows income gaps, thereby alleviating poverty [44].

As digital technology continues to infiltrate traditional rural life, data footprints generated by mobile devices can effectively alleviate information asymmetry, elevate individual risk preferences, strengthen social trust and interaction, and significantly increase the probability of household credit availability [45]. The emergence of digital inclusive finance has notably impacted the credit availability of farmers with borrowing needs, labor capabilities, and learning abilities [46]. Digital capabilities can enhance farmers' agricultural entrepreneurial capabilities by increasing production credit [47], providing favorable conditions for farmers' entrepreneurship [48]. Therefore, this paper proposes the following research hypothesis:

H2. *Credit availability mediates the relationship between digital capabilities positively and the wage growth of employed peasants.*

2.3. The Mediating Role of Talent Loss (TL)

The migration of rural populations to cities has led to a trend of population contraction in rural settlements [49], objectively plunging rural China into the predicaments of "hollowing out", "aging", and "empty-nest syndrome". Faced with the coexistence of multiple hollowing-out phenomena, including industrial hollowing, cultural hollowing, and social fragmentation, the Chinese government has made strategic adjustments and path innovations [50]. Factors influencing brain drain encompass overt factors such as work environment, compensation, and career platforms [51], and psychological factors akin to regional identity, among which psychological factors are the most significant [52]. By integrating local elites, labor, and funds, the Chinese government guides migrant workers to seek employment locally, restoring the family's elderly care and education functions, thereby addressing significant social issues stemming from rural decline and imbalances in urban-rural development [53]. In the process of modernization, rural and urban areas enjoy equal rights to development. Driven by both urbanization and marketization, the revitalization of rural areas and villages is imminent [54].

In rural areas where agriculture is the dominant industry, returnees tend to engage in agricultural work [55]. The emergence of rural e-commerce has facilitated the coordinated development of regional economies. Smartphones, as crucial tools for digital technology access, influence flexible employment through information acquisition and social activities [56]. Digital infrastructure promotes employment structural transformation by fostering internet development, digital inclusive finance, and entrepreneurial growth channels [57]. Digital technology enables flexible workers with low security and income to access more stable and higher-quality employment opportunities, fostering a high concentration of digital technology within formal employment [58]. Digital empowerment increases the proportion of highly skilled labor, in turn, this leads to an optimization of the employment skillset configuration within the labor force, enhancing its overall competence and efficiency [59]. Corporate digital transformation positively impacts the scale of labor employment and salary levels [60], enhancing the salaries of both management and ordinary employees [61]. It is evident that the higher the digital capability of rural entrepreneurs, the higher the employment skill requirements for labor. Given the continuous mobility of the rural population, rural entrepreneurs may attract highly skilled talent by increasing the wages of employed farmers. Therefore, this paper proposes the following research hypothesis:

H3. *The degree of talent loss mediates the relationship between digital capabilities and the wage growth of employed peasants.*

2.4. The Theoretical Model

Based on the empowerment theory, this paper regards farmer entrepreneurs as capable subjects and actors who can develop digital capabilities through digital tools, thereby transforming existing production and business methods, reversing unfavorable social status, and restoring social functions. The availability of formal credit and the extent of talent loss are crucial factors for farmer entrepreneurs to expand their business scale, enhance the market competitiveness of their products, and determine whether they can provide higher wages and benefits to employed peasants. On this basis, from the perspectives of credit availability and talent loss, this paper delves into the intricate mechanisms and pathways that underpin the relationship between digital capabilities and the sustainable augmentation of employed peasants' wage growth. Please refer to Figure 1 for specific contents.

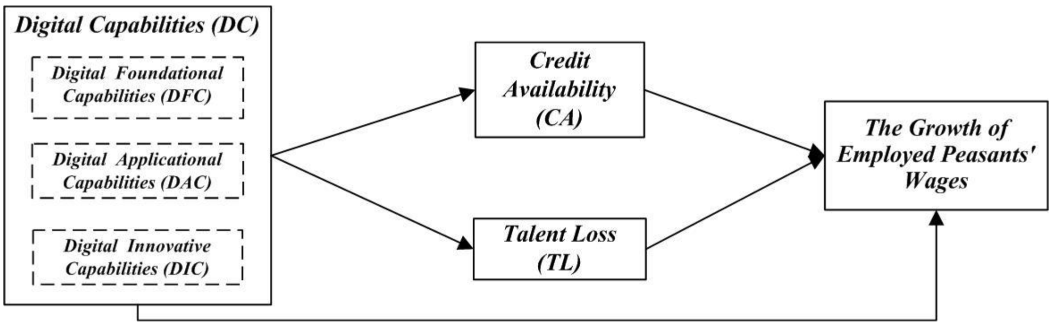

Figure 1. The relationship mechanism between DC and the growth of employed peasants' wages.

3. Materials and Methods

3.1. Sample and Data Collection

Sichuan Province, a pivotal exporter of migrant labor, possesses an extensive pool of empirical exemplars. Capitalizing on the momentum of fostering rural industrial rejuvenation leaders in Sichuan in 2022, this study embarked on a questionnaire survey spanning from early March to late May 2023. Our investigative objectives transcend the conventional focus on migrant workers repatriating for entrepreneurial endeavors, embracing a broader spectrum that encompasses returning entrepreneurs, university graduates, military veterans, and technical specialists—a collective termed "famer entrepreneurs". For a more detailed sampling method of the questionnaire, please refer to the published research of our research team [35].

The survey was structured into two distinct phases: an initial phase utilizing paper questionnaires, followed by a subsequent phase employing electronic questionnaires. The electronic version mirrored the content of the paper counterpart, ensuring consistency. During the first phase, participants received clarifications on pertinent matters and precautions pertaining to questionnaire completion. The majority of questionnaires were completed independently, while personalized, one-on-one interviews were arranged on-site for those encountering difficulties. Proceeding to the second phase, each paper questionnaire underwent meticulous individual verification for logical inconsistencies, inaccuracies, omissions, and other potential issues. To address these, follow-up interviews were conducted either via telephone or by sending revised electronic questionnaires for completion and additional information gathering. Detailed information is provided in Table 1.

Table 1. Questionnaire survey schedule.

Time	Phase	Event	Number of Questionnaires
March 2023–May 2023	Phase I	Distribute paper questionnaires	418
May 2023–June 2023	Phase II	Supplement electronic questionnaires	232

A total of 650 questionnaires were disseminated, with subsequent screening to exclude invalid responses featuring incomplete data, uncorrectable logical inconsistencies, and uniform responses across key metrics. This process yielded 490 valid samples, translating to an effective response rate of 75.38%. The sample composition is predominantly male, with females comprising a relatively modest 20% of the total. Age-wise, the majority falls within the 31–40 and 41–50 age brackets, constituting 31.22% and 45.92%, respectively. For a comprehensive breakdown, please refer to Table 2.

Table 2. Distribution of samples.

Category	Classification	Sample Count (n = 490)	Percentage (%)
Gender	Male	392	80.00
	Female	98	20.00
Age	18~25	8	1.63
	26~30	34	6.94
	31~40	153	31.22
	41~50	225	45.92
	Above 50	70	14.29
Education	Below Primary School	8	1.63
	Junior High School	27	5.51
	High School/Vocational School	169	34.49
	Junior College	198	40.41
	Bachelor's Degree or Above	88	17.96
Entrepreneurship Duration	0–3 year	45	9.18
	3–5 year	66	13.47
	5–7 year	107	21.84
	7–9 year	96	19.59
	9 years and above	176	35.92

3.2. Variable Measurement

3.2.1. Dependent Variable

The dependent variable is the wages of hired peasants. To reduce the influence of regional economic development level, rural labor force quantity, and other relevant factors on the core dependent variable, this paper takes the degree of conformity of agricultural entrepreneurs' self-evaluation of "peasants' wages are not lower than those of peer enterprises" as the core dependent variable and adopts the Likert 5-point scoring method for valuation. The higher wage of peasants hired by farmer entrepreneurs means that the entrepreneurial project is in the development or maturity stage, and requires more labor support; additionally, it indicates that the supply and demand situation in the labor market is shifting towards the supply side. Agricultural entrepreneurs must offer higher wages and benefits to attract more peasants to work.

3.2.2. Independent Variable

The independent variable is digital capabilities (DC), which includes three dimensions: digital foundational capabilities, digital applicational capabilities, and digital innovative capabilities, with 12 measurement items in total. For the specific item content and the results of reliability and validity tests of the questionnaire, please refer to the published research of our research team [35].

3.2.3. Mechanism Variables

Credit availability (CA) and talent loss (TL) are the two mechanism variables. (1) CA: Based on the dummy variable of "whether credit is obtained" [62], this paper uses the Likert 5-point scale to measure farmer entrepreneurs' evaluation of the extent to which "it is now easy to borrow from banks to support entrepreneurship" is true. As the score increases, so does the availability of credit, indicating a positive correlation. (2) TL: This paper still uses the Likert 5-point scale to measure farmer entrepreneurs' evaluation of the extent to which "there are difficulties in recruitment or serious TL" is true. The higher the score is, the more severe the TL is.

3.2.4. Control Variable

This paper controls two variables that may affect the wage growth of employed farmers [63]: (1) Characteristics of entrepreneurial projects: family farms, investment scale, and product quality. (2) Regarding the external environment, dummy variables are utilized for specific locations, thereby mitigating the potential impact of geographical factors, technological progress, and policy uncertainty. The definitions of the main variables and the descriptive statistics are shown in Table 3.

Table 3. Definition and descriptive statistics of major variables.

Type	Variable	Description	Mean	Standard Deviation
Dependent Variable	Wages (W)	Peasants' wages are not lower than those in peer enterprises: 1 = Completely disagree, 2 = Somewhat disagree, 3 = Cannot say, 4 = Somewhat agree, 5 = Strongly agree.	3.918	0.941
Independent Variable	Digital Capabilities (DC)	Calculated by the entropy method.	0.513	0.258
	Digital Foundational Competence (DFC)	Calculated by the entropy method.	0.064	0.019
	Digital Applicational Capabilities (DAC)	Calculated by the entropy method.	0.125	0.058
	Digital Innovative Capabilities (DIC)	Calculated by the entropy method.	0.324	0.206
Mechanism Variables	Credit Availability (CA)	It is easy to obtain bank loans to support entrepreneurship: 1 = Completely disagree, 2 = Somewhat disagree, 3 = Cannot say, 4 = Somewhat agree, 5 = Strongly agree.	3.306	1.245
	Talent Loss (TL)	There are difficulties in recruitment or serious talent loss: 1 = Completely disagree, 2 = Somewhat disagree, 3 = Cannot say, 4 = Somewhat agree, 5 = Strongly agree.	3.301	1.233

Table 3. *Cont.*

Type	Variable	Description	Mean	Standard Deviation
Control Variables	Family Farm (FF)	Family Farm Owner: 0 = No, 1 = Yes	0.478	0.500
	Investment Scale (IS)	Logarithm of the cumulative investment amount with base 10.	2.467	0.591
	Product Quality (PQ)	Compared to similar products, the quality of the products operated by this entrepreneurial project: 1 = Poor, 2 = Slightly Poor, 3 = Average, 4 = Good, 5 = Excellent.	3.861	0.966
	Regional Dummy Variable (RDV)	Whether it belongs to the Chengdu Plain Economic Zone: 0 = No; 1 = Yes	0.386	0.487
	Technological Progress (TP)	The rapid development of production technology provides significant opportunities for entrepreneurial projects: 1 = Completely Disagree, 2 = Somewhat Disagree, 3 = Neutral, 4 = Somewhat Agree, 5 = Strongly Agree.	3.745	1.016
	Policy Uncertainty (PU)	In the past year, there have been significant adjustments to economic policies and regulatory systems related to the entrepreneurial project: 1 = Completely Disagree, 2 = Somewhat Disagree, 3 = Neutral, 4 = Somewhat Agree, 5 = Strongly Agree.	3.733	1.091

3.3. Approach and Identification Techniques

3.3.1. Benchmark Model Construction

To test the direct impact of DC of farmer entrepreneurs on the continuous growth of employed peasants' wages, the model is constructed as follows:

$$W_i = \alpha + \beta X_i + \gamma \mathrm{Control}_i + \varepsilon_i \tag{1}$$

In this model, W_i represents the numerical value of the wage paid by farmer entrepreneur *i* to employed peasants relative to the peer level, X represents the DC or DFC or DAC or DIC of farmer entrepreneur *i*, $\mathrm{Control}_i$ represents relevant control variables, ε_i is the random error term, and α is the constant term. β is the estimated coefficient of the core explanatory variable. If this coefficient is significantly greater than 0, it indicates that the improvement of farmer entrepreneurs' DC is conducive to the continuous growth of employed peasants' wages; otherwise, it has a negative impact.

3.3.2. Mediation Analysis Model

To further explore the influence mechanism of farmer entrepreneurs' DC on the continuous wage growth of employed peasants, this study employs a methodology akin to Jiang Ting's approach [64]. The precise configuration of the model is outlined below:

$$M_i = \omega_0 + \omega_1 X_i + \omega_2 \mathrm{Control}_i + \varepsilon_i \tag{2}$$

wherein M_i represents the mediating variables, including credit CA and TL; ω_0 is constant terms, and ω_1 represents the estimated coefficients.

4. Results

4.1. Fundamental Regression Analysis

Prior to executing the foundational regression analysis framework, we conducted the Breusch–Pagan (BP) and White tests at a 95% confidence threshold to ascertain the presence of heteroscedasticity, subsequently applying robust standard errors for adjustment. The peak variance inflation factor (VIF) observed for an individual explanatory variable was 1.42, while the model's mean VIF stood at 1.17, both comfortably below the threshold of 5, attesting to the absence of multicollinearity among the variables chosen in this study. Furthermore, the Ramsey RESET test and Link test outcomes upheld the null hypothesis (H0), signifying no omitted nonlinear terms within the model, thereby justifying the adoption of a linear model.

See Table 4 for details. DC, DFC, DAC, and DIC all positively affect the wages of employed peasants at a 1% confidence level. Moreover, the effect of DFC is higher than that of DAC, and the effect of DAC is higher than that of DIC. The possible explanations are as follows. First, with the continuous advancement of digital rural construction, farmer entrepreneurs can obtain digital technology support at extremely low costs, making it easy to enhance their DFC. By connecting to larger markets through the internet, they can expand production scales while increasing the wages of employed peasants to attract more labor force. Second, the continuous integration of new formats and scenarios in smart agriculture provides a platform for peasants to participate in the multifunctional market operation of agriculture and rural entrepreneurship, significantly promoting local rural employment and increasing peasants' wages. The above results indicate that Hypotheses H1, H1a, H1b, and H1c are verified.

Table 4. Key regression outcomes: digital capabilities facilitating sustained wage growth among employed peasants.

Variable	Wage			
	Model 1	**Model 2**	**Model 3**	**Model 4**
DC	0.9355 *** (0.1732)			
DFC		10.7829 *** (2.5202)		
DAC			3.9377 *** (0.7747)	
DIC				1.0556 *** (0.2174)
FF	0.0722 (0.0557)	0.0401 (0.0562)	0.0708 (0.0559)	0.0618 (0.0556)
IS	−0.0538 (0.0992)	−0.0193 (0.0991)	−0.0476 (0.1005)	−0.0587 (0.0999)
PQ	−0.0411 (0.0466)	−0.0772 (0.0477)	−0.0313 (0.0471)	−0.0419 (0.0470)
RDV	0.2519 * (0.1442)	0.2761 ** (0.1378)	0.2109 (0.1433)	0.2703 * (0.1446)
TP	0.0133 (0.1210)	0.0157 (0.1235)	−0.0068 (0.1191)	0.0235 (0.1226)
PU	−0.1475 * (0.0843)	−0.1361 (0.0856)	−0.1557 * (0.0842)	−0.1372 (0.0849)
Constant	2.8794 *** (0.4098)	2.6978 *** (0.4371)	2.8126 *** (0.4210)	3.0344 *** (0.4079)
R^2	0.1095 ***	0.0936 ***	0.1035 ***	0.0981 ***
Number	490	490	490	490

Note: The values in parentheses are standard errors, and ***, **, and * indicate that the regression results pass the significance test at the 1%, 5%, and 10% confidence levels, respectively. The same applies to the following tables.

4.2. Robustness Test

4.2.1. Three Aspects of Robustness Test

To fortify the reliability of the regression analysis outcomes, validation was undertaken from three distinct angles: altering the examination approach, substituting the computational method utilized for the key dependent variables, and exchanging the independent variables. The results are shown in Table 5. First, the test method was altered by treating the explained variable, originally a continuous numerical value, as an ordered discrete value and estimating it using the ordered Probit model. Under the ordered Probit model, Model (1) produced a coefficient linking digital capabilities (DC) to employed peasants' wages that was in alignment with the baseline model and achieved statistical significance at the 5% confidence threshold, thereby demonstrating the model's robustness. Second, the calculation method was replaced with the core dependent variables. Using the entropy weight TOSIS method, the DC values were recalculated. Model (2) produced a DC coefficient that was generally consistent in direction with the benchmark model and passed the 1% significance test, demonstrating the model's robustness. Third, the independent variable was substituted by replacing the farmer entrepreneurs' self-assessed hired peasants' wages with the logarithm of the average monthly wage of farmers (base 10). Model (3) exhibited a coefficient for digital capabilities (DC) that concurred with the standard regression model and was statistically significant at the 5% confidence level, thereby reinforcing the model's robustness. In summary, the constructed OLS regression model passed the tests in all three aspects, confirming its robustness. This underscores the benchmark regression model employed in this paper as maintaining a consistent and steadfast interpretation of the evaluation outcomes, thereby ensuring their reliability.

Table 5. The robustness test results.

Variable	Model (1)	Model (2)	Model (3)
	Wage	**Wage**	**Logarithm of Monthly Average Wage**
DC	0.5266 ** (0.2222)	0.4711 *** (0.1815)	0.1546 ** (0.0621)
Control	Yes	Yes	Yes
Constant		1.7295 *** (0.3135)	3.1690 *** (0.1063)
Threshold	Omit		
Pseudo R^2	0.0793 ***		
R^2		0.1875 ***	0.0602 ***
Number	490	490	490

Note: *** and ** indicate statistical significance at the 1% and 5% level.

4.2.2. Addressing Endogeneity Issues

To more accurately evaluate the net effect of DC on the sustained wage growth of employed farmers, a propensity score matching method was applied to process the samples [65], aiming to address the issue of "sample selection bias". Taking the median value of DC among farmer entrepreneurs as the threshold, the entire sample was divided into a treatment group and a control group. Those with values greater than the median were assigned to the treatment group (coded as 1), while those with values less than the median were assigned to the control group (coded as 0). The specific results are shown in Table 6. It can be observed that the average treatment effects (ATTs) from the three methods, namely, K-nearest neighbor matching (n = 4), radius matching, and kernel matching, were all significant at the 1% confidence level. Furthermore, the average of these three ATTs was 0.1546, lower than the pre-matching value of 0.3429, indicating that without controlling for sample selection bias, the role of farmer entrepreneurs' digital capabilities in the wage growth of employed peasants would be overestimated. A balance test was conducted on the variables to ensure the accuracy of the results. After matching, the absolute values of the standard deviations were significantly reduced, which met the relevant standards of the propensity score matching method for weakening the systematic differences of variables. Therefore, the selection bias of the samples was eliminated. It can be seen that the positive values of the average treatment effects (ATTs) are consistent with the direction of the benchmark model coefficients, suggesting that the results of the benchmark model in this paper are relatively stable.

Table 6. Propensity scores matching results of the impact of DC on the wage growth of employed peasants.

Variable	Matching Method	Treatment Group	Control Group	ATT	Standard Error	T-Value
	Before Matching	**4.0898**	**3.7469**	**0.3429 *****	**0.0837**	**4.10**
Wages	K-Nearest Neighbor Matching (n = 4)	4.0769	3.9017	0.1752 *	0.1000	1.75
	Radius Matching	4.0769	3.9200	0.1569 *	0.0975	1.61
	Kernel Matching	4.0769	3.9451	0.1318 *	0.0932	1.41

Note: *** and * indicate statistical significance at the 1% and 10% level.

4.3. Mechanism Analysis

4.3.1. Path Test of CA

The results obtained from the mediation test model are shown in Model (1) in Table 7, indicating that DC significantly enhances CA for farmer entrepreneurs at the 5% significance level. Specifically, the DC of farmer entrepreneurs first bridges the digital divide, promotes entrepreneurial activities by alleviating financing constraints and improving CA, and positively impacts farmer household income [66]. Second, enhancing CA positively affects adopting agricultural technologies [67], helping farmer producers increase their yields and incomes, thereby reducing poverty, improving food security, and promoting inclusive development [68]. Third, providing credit to credit-constrained farmers can achieve better welfare outcomes [69]. Consequently, it is conducive to increasing the wage income of employed farmers, verifying H2.

Table 7. The results of the mechanism test on the impact of DC on the growth of employed peasants' wages.

Variable	Model (1)	Model (2)
	CA	**TL**
DC	0.5705 **	0.4317 *
	(0.2483)	(0.2482)
Control	Yes	Yes
Constant	1.8320 ***	2.7186 ***
	(0.3855)	(0.3914)
R^2	0.1451 ***	0.0458 ***
Number	490	490

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

4.3.2. Path Test of TL

As shown in Model (2) in Table 7, a positive correlation exists between entrepreneurs' DC and their perceived severity of TL at the 10% significance level. As farmer entrepreneurs' DC escalates, their standards for employee quality correspondingly intensify, thereby exacerbating their perception of TL. Farmer entrepreneurs can only attract talents who would otherwise work outside the local area to work nearby by increasing wages and benefits. High-quality talents are always crucial for farmer entrepreneurs to achieve sustainable development. For instance, appointing college graduates as village officials aims to transfer high-quality talents from big cities to rural areas. These talents can contribute to the increase in transfer income, property income, and wage income in rural areas, and they have a more substantial effect on boosting the income of disadvantaged groups in rural areas, thereby promoting common prosperity in rural regions [70]. Therefore, H3 is verified.

4.4. Differentiated Analysis of Variations

4.4.1. Differential Analysis of Agricultural Entrepreneurs' Related Characteristics

The heterogeneity analysis of the different impacts of agricultural entrepreneurs' age, education level, and family-dependency ratio on the wage growth of employed peasants is presented in Table 8. First, according to the United Nations World Health Organization (WHO), youth are defined as individuals under 44 years old, while those over 45 are considered middle-aged and elderly [71]. Based on this criterion, this paper categorizes farmers into two groups, young entrepreneurs (aged 18–40) and middle-aged entrepreneurs (over 40), for regression analysis. Models 1 and 2 demonstrate a statistically significant and positive influence of DC on the wage augmentation of farmers employed by youthful entrepreneurs, reaching a 1% level of statistical significance. However, its effect on the wage growth of peasants employed by middle-aged entrepreneurs is insignificant. The possible reason is that youthful entrepreneurs exhibit an elevated level of eagerness and cognitive prowess in acquiring digital technology skills and have stronger receptivity to new knowledge, thereby achieving continuous income growth and increasing wages for employed peasants. Influenced by historical factors, the traditional mindset of middle-aged individuals in rural China is deeply entrenched, making it difficult for them to comprehend and accept new knowledge, which limits the significance of digital competence in boosting the wages of employed peasants.

Table 8. Outcomes of disparate analysis on farmer entrepreneurs' relevant characteristics.

Variable	Young	Middle-Aged	Below High School	Above High School	Low Family Dependency Ratio	High Family Dependency Ratio
	(1) Wage	**(2) Wage**	**(3) Wage**	**(4) Wage**	**(5) Wage**	**(6) Wage**
DC	0.9773 ***	0.0326	0.1470	0.6236 **	0.5143 *	0.4015 *
	(0.2552)	(0.2264)	(0.2507)	(0.2424)	(0.2991)	(0.2092)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.1928 ***	1.3899 ***	2.1753 ***	1.4635 ***	1.9601 ***	1.6340 ***
	(0.4604)	(0.4319)	(0.5147)	(0.3982)	(0.6225)	(0.3338)
R^2	0.1987 ***	0.2093 ***	0.1321 **	0.2496 ***	0.1690 ***	0.2234 ***
Number	195	295	204	286	166	324

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

Secondly, as the primary decision-makers driving the development of entrepreneurial projects, agricultural entrepreneurs' education level is crucial to the success of these projects. This paper adopts high school education as the dividing line [70] and conducts a grouped regression analysis of agricultural entrepreneurs. As shown in Models 3 and 4, DC significantly and positively affects the wage growth of peasants employed by entrepreneurs with education levels above high school at the 5% statistical level. However, its effect on those employed by entrepreneurs with education levels below high school is not significant. This can be attributed to the fact that more educated agricultural entrepreneurs can integrate modern management concepts with information technology equipment, innovate entrepreneurial business models, enhance operational management efficiency, and, ultimately, generate better entrepreneurial performance, thereby lifting the wages of employed peasants.

Lastly, China's population structure is undergoing rapid transformation. On the one hand, the birth rate is declining rapidly, while on the other hand, the average life expectancy of Chinese residents is increasing, accelerating the aging process of the age structure and resulting in an increased family-dependency ratio. A higher family-dependency ratio for agricultural entrepreneurs translates into heavier family responsibilities, implicitly creating a crowding-out effect on entrepreneurial time. For regression analysis, this paper classifies agricultural entrepreneurs into two groups based on their family-dependency ratio: low (below 0.5) and high (above 0.5). Models 5 and 6 reveal that DC significantly and positively affects the wage growth of peasants employed by entrepreneurs with a low family-dependency ratio at the 10% statistical level, with a coefficient greater than that of entrepreneurs with a high family-dependency ratio. This indicates that a higher family-dependency ratio exerts a more substantial crowding-out effect on entrepreneurial time, adversely impacting entrepreneurship and the wage growth of employed peasants. A robust social security system can alleviate the dependency burden in such scenarios.

4.4.2. Heterogeneity Analysis of Policy Uncertainty

Policy uncertainty refers to the difficulty for farmer entrepreneurs to accurately predict whether the government will alter existing economic policies [72]. In today's volatile and ever-changing world, farmer entrepreneurs face a significant rise in economic PU. This paper divides the sample into two groups based on a threshold value of 3 for PU: a group with high PU (value > 3) and a group with low PU (value $\leq$ 3). The analysis compares whether PU exerts heterogeneous effects on the wage growth of employed peasants. As shown in Table 9, PU affects employed peasants' wage growth. When PU is low, DC significantly and positively impacts wage growth at the 5% statistical level, with a higher coefficient and significance than in the high PU group. At different levels, when PU is low, DIC significantly and positively affects wage growth at the 10% statistical level. In contrast, when PU is high, both DFC and DAC significantly and positively impact wage growth at the 5% statistical level, which may be attributed to high PU exposing target groups participating in benefit distribution to different rules, leading to speculative behavior and structural short-term actions in pursuit of benefits. In turn, this makes it difficult for farmer entrepreneurs to predict market changes, creating entrepreneurial risks that ultimately affect the wage growth of employed peasants.

Table 9. Heterogeneity analysis results of policy uncertainty.

Variable	Low PU				High pu			
	(1) Wages	**(2) Wages**	**(3) Wages**	**(4) Wages**	**(5) Wages**	**(6) Wages**	**(7) Wages**	**(8) Wages**
DC	0.5913 **				0.3754 *			
	(0.2922)				(0.2044)			
DFC		4.2732				6.6868 **		
		(4.3496)				(2.7586)		
DAC			2.0206				2.0087 **	
			(1.2600)				(0.9159)	
DIC				0.7137 *				0.3511
				(0.3721)				(0.2505)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.7029 ***	2.5401 ***	2.6151 ***	2.7570 ***	2.1646 ***	1.9116 ***	2.1312 ***	2.1956 ***
	(0.4850)	(0.5026)	(0.4838)	(0.4882)	(0.3580)	(0.3788)	(0.3634)	(0.3581)
R^2	0.0844 **	0.0726 **	0.0791 **	0.0825 **	0.1683 ***	0.1772 ***	0.1726 ***	0.1642 ***
Number	183	183	183	183	307	307	307	307

Note: ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level.

5. Interpretation and Implications

This study delves into the pragmatic implications of issues surrounding the relationship between digital competence and wage growth among employed farmers. Employing survey outcomes garnered from 490 agricultural entrepreneurs spanning 21 municipalities (or prefectures) within Sichuan Province, it uses methods such as the entropy weight method, the OLS linear model, the mediation model, and propensity score matching to specifically address the mechanisms and pathways through which DC promotes wage growth among employed farmers. The results signify that DC exerts a direct and affirmative influence on wage advancement, while also exerting an indirect effect through the mediation of either CA or TL mechanisms. The present investigation uncovers the facilitating mechanisms of digital technology integration within rural entrepreneurial collectives and procedures, thereby broadening the horizons of empowerment theory-based research endeavors. Furthermore, it provides quantitative evidence and empirical insights for achieving sustained wage growth among employed peasants. The subsequent sections provide a nuanced examination and clarification of the concordance, disparities, and mutual reinforcement between our research findings and the extant scholarly works.

(1) DC positively affects wage growth among employed peasants. The testing of H1, H1a, H1b, and H1c indicates that Research Objective 1 has been achieved. The significant positive impact of peasant entrepreneurs' digital capability on the wage growth of employed peasants is consistent with the prior findings of Wang et al. (2024), who identified that corporate digital capability positively influences employees' digital performance [30]. This discovery implies that peasant entrepreneurs' digital capability is crucial in promoting local employment of rural labor and increasing their income. Consequently, the government should strengthen the cultivation of peasant entrepreneurs' digital capability, focusing on the needs of agricultural digitization, which can be achieved by integrating mobile application usage, live streaming sales, rural e-commerce, and smart agriculture into training programs tailored to local talents' comprehension, learning ability, and free time. By combining online and offline training, as well as short-term and long-term approaches, the government can simplify theoretical training and enhance practical, interactive, and engaging content, which will enable continuous improvement in peasant entrepreneurs' digital capabilities.

(2) CA and TL mediate the relationship between DC and wage growth among employed peasants. The results of testing H2 and H3 indicate that Research Objective 2 has been achieved. DC plays a vital role in influencing CA [43], and access to formal credit facilitates the successful development of entrepreneurial activities [47], subsequently impacting the wages of employed peasants. TL is a real dilemma in China's rural development [50]. The emergence of rural e-commerce promotes regional coordinated development [56], and digital technology enables employees to engage in more stable and higher-quality jobs [58], ultimately positively affecting wage growth among employed peasants. This finding underscores the importance of enhancing DC and CA in addressing rural TL, offering valuable lessons for policymakers. Policy makers ought to enhance comprehensive strategic planning, expedite the development of rural digital infrastructure, and tackle challenges including inadequate broadband coverage, network instability, and elevated tariffs in select rural regions, thereby fostering a conducive business ecosystem. This will enable farmers' entrepreneurs to access financial loans, job opportunities, and other information through the internet, simultaneously fostering continuous improvement in DC.

(3) The DC enhancement of young, highly educated farmers' entrepreneurs with low family-dependency ratios has a more pronounced effect on wage growth among employed peasants. Additionally, lower PU correlates with a larger and more significant coefficient of DC impact on wage growth. Through a heterogeneous analysis of peasant entrepreneurs' groups and policy uncertainty, Research Objective 3 has been achieved. These findings suggest that farmers' entrepreneurs must possess a certain human capital to adapt to the digital era's changes and maintain a competitive edge in the market. Excessive caregiving burdens can negatively impact entrepreneurial development. Comprehensive social security systems provided by policymakers can alleviate caregivers' pressures. A stable policy environment means the government adheres to its commitments in long-term interactions with farmers' entrepreneurs, enhancing policy compliance, government credibility, and authority, which reduces speculative and structured short-term behaviors in pursuit of benefits, mitigating entrepreneurial risks.

6. Conclusions

6.1. Study Conclusions

Understanding the impact of farmer entrepreneurs' digital capabilities on the wages of employed peasants contributes to China's goal of achieving common prosperity. Theoretically, this study empirically demonstrates the critical driving factors behind the wage growth of employed peasants, thereby expanding the empowerment theory within the context of digital rural development. Our study demonstrates that an increase in farmer entrepreneurs' DC fosters a significant advancement in the wage growth of employed peasants. This result remains valid after a series of robustness tests, namely, H1 holds. In terms of effect, DFC > DAC > DIC, namely, H1a, H1b, H1c holds. Furthermore, this study addresses the research gap mentioned in previous chapters. It proposes a theoretical framework for understanding how enhancing farmer entrepreneurs' digital capabilities can promote wage growth among employed peasants. DC can positively affect the wage increase of employed peasants through CA and TL, namely, H2, H3 holds. This theoretical framework provides avenues for future researchers to expand their research models.

Practically, this study contributes to entrepreneurs and policymakers in related fields by emphasizing the impact of cultivating farmer entrepreneurs' digital capabilities and credit availability on the wage growth of employed peasants. The differentiated analysis revealed that the wage augmentation among employed peasants is notably more pronounced under the leadership of young farmer entrepreneurs, in comparison to their middle-aged counterparts, and the wage growth of employed peasants under entrepreneurs with higher education is more significant than that under entrepreneurs with lower education. Entrepreneurs with a lower family-dependency ratio have a greater effect on the wage growth of employed peasants than those with a higher family-dependency ratio. These research findings can encourage peasant entrepreneurs to recognize that starting businesses earlier, improving educational attainment, and controlling the family-dependency ratio can all positively influence entrepreneurship, thereby providing possibilities for peasant entrepreneurs to enhance the quality of their businesses. The lower the uncertainty in the policy environment, the greater the effect of DC on the wage growth of employed peasants, reminding policymakers of the importance of maintaining policy stability.

6.2. Limitations and Future Research Directions

Given the author's inherent limitations in energy and cognition, coupled with the external constraints posed by research funding, human resources, and operational conditions, there remains ample scope for further exploration on the theme of DC and wage growth among employed peasants. Future endeavors can aim to enrich and refine the following aspects:

Firstly, research content could be broadened. Future studies might endeavor to conduct an in-depth exploration of the nuances of DC levels and their contributing factors or determinants among farmer entrepreneurs, encompassing variations in industries, business models, agricultural product types, geographical terrains, and entrepreneurial stages. Such a granular analysis would offer profound insights into the localized mechanisms underpinning DC.

Secondly, transitioning from cross-sectional data to longitudinal panel data is crucial to enhance the study's robustness. The current findings tend to emphasize short-term effects, overlooking potential lags between DC and sustainable entrepreneurial income growth. With adequate resources and opportune timings, conducting at least two rounds of data collection and analysis would provide a more holistic view of the influence exerted by digital technology on sustained income or long-run earnings.

Thirdly, expanding the sample survey's geographical scope would yield richer data. The current focus on Sichuan Province limits the generalizability of findings to other regions. Enlarging the sample to encompass provinces like Anhui, which are also significant labor exporters, would facilitate comparative analyses, ultimately yielding more comprehensive and reliable conclusions.

Lastly, the absence of a standardized DC measurement framework poses challenges for inter-study comparisons. While the 5-point Likert scale is prevalent, it may not fully encapsulate the intricacies of the analyzed phenomena. Thus, there is a need for more detailed investigations into specific facets of DC.

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