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Technology-Enhanced Learning in Agricultural Extension and Farmers' Economic Performance: The Mediating Role of Digital Literacy

Jiaming Yang ^{*}, Luh Putu Artini , I. Wayan Sukra Warpala , Made Hery Santosa 

Postgraduate School, Universitas Pendidikan Ganesha, Singaraja 81116, Indonesia

ABSTRACT

The digital transformation of agriculture has created new opportunities for smallholder farmers, yet the mechanisms through which technology-enhanced learning (TEL) translates into economic gains remain underexplored. This study investigates how technology-enhanced learning in agricultural extension education affects farmers' economic performance, with a specific focus on digital literacy as a mediating mechanism and the moderating roles of education level and extension service contact. Using survey data from 486 farmers across three provinces in China (2024), we employ hierarchical regression analysis, mediation analysis with bootstrapping, and heterogeneity analysis through group-wise regressions, with digital literacy measured as a composite index capturing information acquisition ability and technology adoption willingness. Results show that TEL participation significantly enhances farmers' annual income ($\beta = 0.285$, $p < 0.01$), with digital literacy mediating 30.2% of this total effect through two pathways: information acquisition (accounting for 53.5% of the mediated effect) and technology adoption (accounting for 46.5% of the mediated effect). Heterogeneity analysis reveals significant education-based gradients (Chow test $F = 8.42$, $p < 0.001$), with effects increasing from $\beta = 0.218$ ($p < 0.05$) for low-educated farmers to $\beta = 0.395$ ($p < 0.001$) for highly educated farmers, while age-based differences are also significant (Wald test $\chi^2 = 9.18$, $p = 0.002$) and regional effects remain stable ($p = 0.596$). Digital literacy serves as a critical mediator in converting technology-enhanced learning into economic outcomes, with education and age significantly moderating this pro-

*CORRESPONDING AUTHOR:

Jiaming Yang, Postgraduate School, Universitas Pendidikan Ganesha, Singaraja 81116, Indonesia; Email: jiamingyang227@yahoo.com

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cess, suggesting that policy interventions should prioritize digital skill development, particularly for low-educated and older farmers who face greater barriers to digital transformation.

Keywords: Technology-Enhanced Learning; Information Acquisition; Technology Adoption; Human Capital; Mediation Analysis; Rural Development; China

1. Introduction

1.1. Research Background

The “Digital Village Strategy” in China (2019–2025) emphasized the use of technology in agricultural extension services as the foundation for revamping the countryside^[1]. By the year 2023, the internet penetration in the countryside had risen to 66.5% of the total, presenting a historic opportunity for the delivery of digital extension services^[2].

This research proposes three concepts. Agricultural extension education is the provision of farming knowledge in a systematic way using personal demonstrations and printed matter^[3,4]. Technology-enhanced learning (TEL) can be explained as the use of various technological platforms, such as the internet, mobile applications, and video tutorials, in the provision of education. Technology-enhanced extension education is the use of TEL in agricultural extension. The abbreviation TEL is the concept used in our research since farmers use technological platforms to learn.

Although TEL widens the use of information, the translation of information into economic benefits for farmers depends on farmers being able to utilize digital information effectively. The use of digital information effectively depends on digital literacy, which refers to the ability to use, assess, and make use of digital information^[5,6]. Those farmers with high digital literacy are in a better position to translate exposure to TEL into benefits.

There are three research gaps in the existing literature:

- (1) the mediating processes between TEL and economic outcomes have not been formally tested^[7,8];
- (2) the topic of heterogeneity in effects for different groups of farmers is not developed;
- (3) the existing research is concentrated on an inter-

mediate outcome (adoption or yield) and not on income.

The proposed research is intended to overcome the mentioned research gaps. The mediator—digital literacy—will be tested for parallel pathways. The outcome variable chosen is farm income.

1.2. Literature Review and Hypotheses Development

Empirical studies have also established that TEL can have a positive impact on the economic performance of farmers^[9], although the digital extension paradigm has presented mixed results since the 2010s^[10]. According to Cole and Fernando^[11], the impact of agricultural advice presented via videos in India led to a 7% increase in cotton yield, a 13% reduction in pesticide use, and then to a positive income effect; although not realized from a similar initiative conveying price information via SMS in Colombia, with only a 28% adoption rate and no income impact^[8].

Three theoretical bases could potentially bridge TEL impacts. Information asymmetry could be addressed if TEL reduces the costs of searching for price and expert knowledge information and enhances decision-making quality^[12]. Accumulation of human capital could be addressed if online content is used for increasing learning and goes beyond searching for information^[13]. Externalities in networks could be addressed if more farmers avail themselves of online networks and their combined leverage and learning for learning is improved^[14]. But a requirement of absorptive capacity is that the ability of farmers to access, understand, and apply the new knowledge is necessary^[15]. Digital literacy is a key component of absorptive capacity in online networks.

Digital literacy competency can be grouped into different competency domains^[16], but for the agricultural

domain, there are two competency domains required. These domains include information acquisition competency, which involves searching for agricultural information using the internet, for example, accessing weather, viewing the prices of input factors available in the market, and verifying the authenticity of agricultural advice on the website. Readiness for adoption of technology, on the other hand, involves farmers' readiness to try out the use of technology in agriculture, which involves perceived usefulness and ease of use for the Technology Acceptance Model^[17]. Learning to participate in technology can enhance both of these aspects through the process of learning by doing, where constant use of technology platforms enhances site navigation, agricultural information processing on websites, and overall technology uptake.

H1. *Participation in technology-enhanced learning (TEL) positively enhances farmers' digital literacy.*

Conversely, digital literacy helps farmers turn information acquisition into economic benefits. Li et al.^[18] illustrated that mobile network expansion in Uganda reduced transaction costs and that digitally literate farmers were able to exploit an 83% larger price spread. Yang et al.^[19] found that fishermen in Kerala who employed mobile technology techniques for optimized landing spots decreased waste by 8% and earnings by 9%. Cole and Fernando found that video-based education lowered agricultural losses by 12% for farmers with higher information-processing abilities. These studies implicitly assume digital literacy as a mechanism but have not formally tested mediation.

H2. *Digital literacy positively influences farmers' economic performance.*

Integrating H1 and H2, TEL may affect economic performance through both direct pathways (e.g., network effects, psychological empowerment) and indirect pathways through digital literacy. Within the indirect pathway, information acquisition ability and technology adoption willingness serve as parallel mechanisms through which digital literacy translates TEL exposure

into income gains.

H3. *Digital literacy mediates the relationship between TEL participation and economic performance, with information acquisition ability and technology adoption willingness as parallel mediating pathways.*

Human capital theory proposes that education improves learning efficiency by raising cognitive skills, problem-solving capabilities, and self-directed learning abilities^[20]. In technology adoption contexts, education affects returns through cognitive absorption (faster processing of complex digital information)^[21], complementarity (synergy between formal education and digital skills)^[22], and reduced learning costs (lower psychological barriers to technology acquisition)^[23]. Gong et al.^[6] found that mobile extension services increased maize yields by 8% for farmers with secondary education but showed no significant effect for those with only primary education.

H4. *Education level positively moderates TEL and digital literacy, meaning that more educated farmers are most affected. Extension agent contact may complement TEL by providing technical troubleshooting, contextualizing generic content to local conditions, and offering motivational support^[24].*

H5. *Frequency of extension service contact positively moderates the relationship between TEL participation and digital literacy.*

1.3. Conceptual Framework

The integrated conceptual framework for this research is shown in **Figure 1**. TEL is conceptualized as the independent variable, farm economic outcomes and income as the dependent variable, while digital literacy acts as the mediator. It is also hypothesized that education level and extension services contacts can moderate TEL and digital literacy (H4 and H5). The model also contains the direct relationship between TEL and income (H3), recognizing other possible mediation processes than digital literacy (e.g., network effects and psychological empowerment).

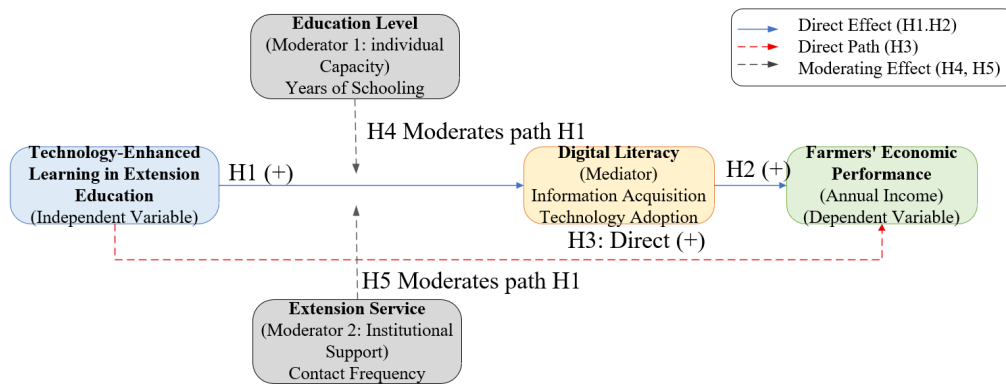


Figure 1. Conceptual Framework: Digital Literacy as Mediator in TEL-Income Relationship.

2. Materials and Methods

2.1. Study Context and Sampling

This research was implemented in three Chinese provinces, with differences in economic development standards and information technology integration. Province A in the Eastern region has a large GDP per capita (¥85,000), a large 4G or 5G network coverage (98%), and e-commerce adoption (65%). Province B in the Central region has medium development (¥52,000 GDP/capita), medium network connectivity (82% coverage), and medium digital adoption (38%). Province C in the Western region has lower development (¥38,000 GDP/capita), limited infrastructure (68% coverage), and emerging ICT usage patterns (22%). The geographical variation provides an opportunity to explore whether TEL impact extensions are general or dependent on facilitating infrastructural support.

In this research, we undertook a stratified three-stage random sampling method between March and May 2024. In the first stage, we chose 2 counties per province using probability-proportional-to-size sampling depending on the agricultural output value. In the second stage, 3 townships in every county were randomly chosen, and in every township, 2 villages were also randomly selected. This eventually resulted in 36 villages. Stage 3 involved getting every farming household's roster from every selected village, followed by the selection of 14–15 households, which essentially targeted the head or primary decision-maker for every household. The final sample size is 486 farmers in total (Province A: $n = 168$, Province B: $n = 185$, Province

C: $n = 133$). The number of participants required for the study was calculated through using power analysis ($\alpha = 0.05$, $\beta = 0.20$), using medium-sized effects ($f^2 = 0.15$) for 12 regressors. The overall response rate for this study is 91.3% (486/532 initially sampled). Out of 46 non-responders, 38 lacked the time to participate, 5 could not participate at the time of conducting the research, and 3 had relocated. Still, no interviews were terminated midway. Average interview length was 52.3 min (SD = 8.7 min, range: 38–68 min), and 94% took between 45 and 60 min as scheduled.

Twelve enumerators (6 male, 6 female, average age 26, all with bachelor's degrees in agriculture or rural development) received three days of training on conducting interviews, using SurveyCTO tablets, research ethics, and speaking local dialects. This covered role-playing tasks and pilot interviews with 15 farmers (not included in the final sample). The inter-rater reliability test demonstrated substantial agreement (Cohen's kappa = 0.89 for categorical variables, intraclass correlation = 0.92 for continuous measures). This study was conducted in accordance with ethical guidelines for social science research. As a non-interventional survey involving adult participants and non-sensitive topics related to agricultural practices and technology use, formal Institutional Review Board (IRB) approval was not required, given the minimal-risk nature of this research. Verbal informed consent was obtained from all participants prior to the interview. Participants were informed of the study's purpose, the voluntary nature of participation, their right to withdraw at any time without any consequences, and the confidentiality of their responses. All data were anonymized during analysis and stored securely.

Conducting face-to-face interviews was facilitated by using trained enumerators and tablets to administer surveys in SurveyCTO. Interviews took between 45 and 60 min per respondent to cover socio-demographic data, farming practice information, history of TEL usage, evaluation for digital literacy, yearly farm income, and contacts with extension services. Quality control efforts ensured that data was uploaded every day with automated checks for logical consistency, callback verification for 10% of the sampling at random by supervisors, and GPS points for verifying locations within households. The data quality control procedures are satisfactory. Automated checks for logical inconsistencies yielded 23 in-

consistencies (4.7% of completed interviews), mainly in income range estimates and dates for crop calendars, resolved on the same day via callback verification. Random callback verification was applied to 49 interviews (10% of sample), resulting in 96% consistency on variables TEL program involvement, digital literacy scores, and farm characteristics. Minor inconsistencies in income estimation (within $\pm 5\%$ range) were resolved with clarifications. The GPS data verification ensured that no duplicate enumeration existed for all 486 households within the established boundaries for respective villages.

Table 1 presents the demographic and farm characteristics of the sample.

Table 1. Sample Characteristics (N = 486).

Variable	Category	N	%
Gender	Male	400	82.3
	Female	86	17.7
Age group	≤40 years	98	20.2
	41–55 years	224	46.1
	>55 years	164	33.7
Education level	Low (≤6 years)	142	29.2
	Medium (7–9 years)	203	41.8
	High (≥10 years)	141	29.0
Province	Province A (Eastern)	168	34.6
	Province B (Central)	185	38.1
	Province C (Western)	133	27.4
TEL participation	Yes	276	56.8
	No	210	43.2
Extension contact	None	89	18.3
	1–2 times/year	156	32.1
	3–5 times/year	148	30.5
	6+ times/year	93	19.1
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Continuous variables		Mean	SD
Age (years)		48.6	11.2
Education (years)		8.4	3.6
Farm size (mu)		12.8	15.4
Annual income (CNY)		68,500	42,300
Digital literacy (0–1)		0.52	0.23
TEL hours/month		8.3	6.7

2.2. Variable Measurement

The dependent variables are the farm household income in CNY, which captures the total agricultural income generated in 2023 from crop sales, livestock products, agricultural subsidies, and agricultural wage labor income. The dependent variables consider the agricultural income, which captures the general performance of farming rather than performance variables such as output and the pace of adoption, which are one-dimensional. The values for the dependent variables are obtained per farm household, and the logarithmic transformation is

considered to deal with right-skewed variables and to interpret the findings in percentage changes.

TEL participation was considered the independent variable and was measured using a binary dummy variable (1 = received participation, 0 = no participation) based on the following activities carried out in the past 12 months: carrying out online courses or webinars on agriculture practices, mobile application training by the extension agencies, dissemination of agriculture information in WeChat groups, and video tutorials on Douyin or Kuaishou. The form of measurement is much the

same as in earlier research on digital extensions^[8,11]. There was also an intensity form of measurement in order to check the robustness of the TEL hours on a monthly basis, ranging from 0 to 40+. The form mainly used was the binary form due to the differences in time spent in various TEL modes.

Table 2 provides definitions and descriptive statistics for the variables used in the analysis. The mediating variable, digital literacy, is operationalized using a composite variable constructed using 12 items that define two dimensions according to the digital skills typology^[16] adapted to agriculture. Information acquisition ability (6 items, Cronbach's $\alpha = 0.82$) indicates farmers' capacity to use and assess online information about agriculture, which is crucial to minimizing information asymmetry in agricultural decision-making. Items consist of using smartphones or computers to look for agricultural information, identifying trusted vs. untrusted information sources, comparing prices of agricultural inputs online, accessing online weather information, using government websites containing agricultural information, and using online platforms to discuss agricultural topics with other farmers. Technology adoption willingness (6 items, Cronbach's $\alpha = 0.79$) indicates farmers' willingness to test new digital solutions and incorporate their use into their current practices, corresponding to the em-

phasis put by the Technology Acceptance Model on perceived usefulness and ease of use^[17]. Items consist of willingness to test new agricultural apps, feeling confident to investigate new technology alone, ease of incorporating agricultural apps into current practices, trust in agricultural platforms, feeling technology use makes agricultural activities more efficient, and willingness to provide data to service providers. Responses were recorded on 5-point Likert scales (1 = Strongly disagree/Never, 5 = Strongly agree/Very frequently), with the composite index calculated as the mean of all items and normalized to 0–1. Confirmatory factor analysis validated the two-factor structure (CFI = 0.94, TLI = 0.92, RMSEA = 0.056). Variables on which moderation is imposed are education level, measured in terms of years of education acquired (0–16 years), and coded for heterogeneity analysis into Low education (≤ 6 years), Medium education (7–9 years), and High education (≥ 10 years). Extension service contact refers to contacts with extension personnel in the past 12 months (0 = None, 1 = 1–2 times, 2 = 3–5 times, 3 = 6+ times). Control variables include farmer factors (age, gender, household size, farming experience), farm factors (cultivated land area log-transformed, primary crop type, use of mechanization, distance to nearest town), and regional variables (province fixed effects, village-level GDP per capita log-transformed).

Table 2. Variable Definitions.

Variable Name	Definition	Measurement	Mean (SD)/%
Dependent Variable			
Annual Income	Total agricultural income in 2023	Continuous (CNY, log-transformed)	10.93 (0.58) [¥68,500 raw]
Independent Variable			
TEL Participation	Engaged in technology-enhanced learning in past 12 months	Binary (0 = No, 1 = Yes)	56.8%
TEL Intensity	Hours per month in TEL activities	Continuous (0–40)	4.71 (6.89)
Mediating Variable			
Digital Literacy	Composite index of information acquisition and technology adoption	Continuous (0–1 scale)	0.52 (0.23)
- Info Acquisition	Ability to access and evaluate digital agricultural information	Continuous (0–1 scale)	0.54 (0.26)
- Tech Adoption	Willingness to adopt new digital technologies	Continuous (0–1 scale)	0.50 (0.24)
Moderating Variables			
Education Level	Years of formal schooling	Continuous (0–16 years)	8.43 (3.58)
- Low Education	≤ 6 years (primary or less)	Categorical	29.2%
- Medium Education	7–9 years (junior high)	Categorical	40.7%
- High Education	≥ 10 years (senior high+)	Categorical	30.0%
Extension Contact	Frequency of contact with extension agents (past 12 months)	Ordinal (0 = None, 1 = 1–2, 2 = 3–5, 3 = 6+)	1.32 (1.08)
Control Variables			
Age	Farmer's age in years	Continuous	48.62 (11.24)
- Young	≤ 40 years	Categorical	28.4%
- Middle-aged	41–55 years	Categorical	48.4%

Table 2. Cont.

Variable Name	Definition	Measurement	Mean (SD)/%
- Old	>55 years	Categorical	23.3%
Gender	Farmer's gender	Binary (0 = Female, 1 = Male)	82.3%
Household Size	Number of household members	Continuous (1–8)	4.18 (1.52)
Farming Experience	Years engaged in farming	Continuous	26.85 (12.47)
Farm Size	Cultivated land area in hectares	Continuous (log-transformed)	1.38 (0.82) [5.8 ha raw]
Crop Type	Primary crop cultivated	Categorical	
- Rice			38.5%
- Wheat			22.4%
- Vegetables			24.3%
- Fruits			14.8%
Mechanization	Use of machinery in farming (0–1 scale)	Continuous	0.58 (0.31)
Distance to Town	Kilometers to nearest town center	Continuous	8.65 (6.42)
Province	Geographic location	Categorical	
- Province A	Eastern (high development)		34.6%
- Province B	Central (medium development)		38.1%
- Province C	Western (low development)		27.4%
Village GDP	Village-level GDP per capita (log-transformed)	Continuous	10.28 (0.64)

2.3. Analytical Strategy

We estimate the total effect of TEL on income using OLS regression. Model 1 (Baseline) specifies:

$$\ln(Income_i) = \beta_0 + \beta_1 \cdot TEL_i + \Gamma \cdot X_i + \delta_p + \varepsilon_i \quad (1)$$

where TEL_i stands for TEL participation (0/1), X_i defines the vector of control variables, δ_p denotes province fixed effects to control for time-invariant regional differences in infrastructure, policy environment, and agricultural conditions across the three provinces, and ε_i is the error term. Standard errors are clustered at the village level (36 clusters) to control for correlation within each village.

In this analysis, we follow the causal steps method as outlined in Baron and Kenny^[25]. This method entails four steps: step 1—estimating total effect (as Model 1 above); step 2a—estimating effect on mediator variable:

$$Digital Literacy_i = \alpha_0 + \alpha_1 \cdot TEL_i + \Gamma \cdot X_i + \delta_p + u_i \quad (2)$$

Step 2b assesses the effect on outcome controlling for mediator:

$$\ln(Income_i) = \gamma_0 + c' \cdot TEL_i + b_i \cdot Digital Literacy_i + \Gamma_2 \cdot X_i + \delta_p + v_i \quad (3)$$

Mediation significance was assessed using three complementary approaches:

(1) the Sobel test for indirect effects,

- (2) bias-corrected bootstrap confidence intervals (5000 replications) following Preacher and Hayes^[26], which is robust to non-normality in the sampling distribution of indirect effects, and
(3) the proportion of total effect mediated.

To mitigate the problem posed by endogeneity and improve the robustness of the estimates, we use four methods. First, an alternative specification based on the continuous intensity of TEL measured by the number of hours per month instead of the dummies. Secondly, selection based on observables using propensity scores with a nearest neighbors algorithm and a caliper of 0.05 to generate a pseudo-control group that is similar in distribution to the treatment group. Third, selection based on unobservables using IV estimation with the distance to the closest agricultural technology demonstration centre as the instrument. This is relevant because the distance determines TEL participation and is independent, and only affects income through TEL participation. Lastly, validate the measurement through a test of digital literacy conducted for a sub-sample (n = 156).

3. Results

3.1. Descriptive Statistics

Table 3 presents descriptive statistics and bivariate correlations for key variables. The sample consists mainly of male farmers (82.3%), with an average age

of 48.6 years (SD = 11.2) and an education level of 8.4 years (SD = 3.6). Average yearly agricultural earnings are ¥68,500 (SD = ¥42,300), with substantial variation across farmers (range: ¥8000–¥285,000). As for TEL involvement, 56.8% of farmers ($n = 276$) are engaged in technology-enhanced learning every year, spending on average 8.3 h per month on TELs (SD = 6.7). The sample mean for digital literacy is 0.52 (SD = 0.23), indicating moderate proficiency. Information acquisition ability ($M = 0.54$, $SD = 0.26$) scores slightly higher than technology adoption willingness ($M = 0.50$, $SD = 0.24$), which indicates that farmers are more adept at seeking information than experimenting with new technologies.

Participation in TEL is also significantly correlated

with digital literacy skills ($r = 0.48$, $p < 0.001$), income ($r = 0.32$, $p < 0.001$), and education ($r = 0.36$, $p < 0.001$). Digital literacy is positively related to income ($r = 0.41$, $p < 0.001$), confirming expected correlations. More importantly, none exceeds 0.70, so multicollinearity can be eliminated as a concern. Comparison of group means indicates that TEL-users earn 38% more on average than non-users (¥82,300 vs. ¥59,600; $t = 6.24$, $p < 0.001$) and possess higher levels of digital literacy, scoring 0.28 points higher on average than non-users (0.64 vs. 0.36; $t = 11.85$, $p < 0.001$).

Figure 2 verifies that sufficient variance exists for every important variable, with no sign of ceiling or floor effects to limit regression analyses.

Table 3. Descriptive Statistics and Correlations.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) ln(Income)	1.00									
(2) TEL Participation	0.32***	1.00								
(3) Digital Literacy	0.41***	0.48***	1.00							
(4) Info Acquisition	0.38***	0.44***	0.92***	1.00						
(5) Tech Adoption	0.37***	0.46***	0.91***	0.64***	1.00					
(6) Education	0.28***	0.36***	0.52***	0.48***	0.49***	1.00				
(7) Extension Contact	0.24***	0.42***	0.38***	0.35***	0.36***	0.22***	1.00			
(8) Age	-0.18***	-0.22***	-0.31***	-0.28***	-0.29***	-0.42***	-0.08	1.00		
(9) ln(Farm Size)	0.36***	0.18***	0.21***	0.19***	0.20***	0.15***	0.12**	0.06	1.00	
(10) Mechanization	0.29***	0.26***	0.34***	0.31***	0.32***	0.24***	0.19***	-0.14**	0.28***	1.00
Mean	10.93	0.57	0.52	0.54	0.50	8.43	1.32	48.62	1.38	0.58
SD	0.58	0.50	0.23	0.26	0.24	3.58	1.08	11.24	0.82	0.31
Min	9.02	0	0.08	0	0	0	0	25	-0.69	0
Max	12.56	1	0.98	1.00	1.00	16	3	68	3.91	1.00

Note: $n = 486$. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$ (two-tailed tests). Missing data occurred very rarely for all variables. For data on income, no data are missing ($n = 486$ complete). Online literacy variables reported only 11 incomplete observations (2.3%), dealt with by person-mean imputation as it contained only a few observations and followed the MCAR mechanism (Little's test: $\chi^2 = 23.45$, $p = 0.612$). The number of missing data in extension service contacts was 7 (1.4%), treated as zero contacts. The control variables all had fewer than 1% data missing, dealt with using listwise deletion.

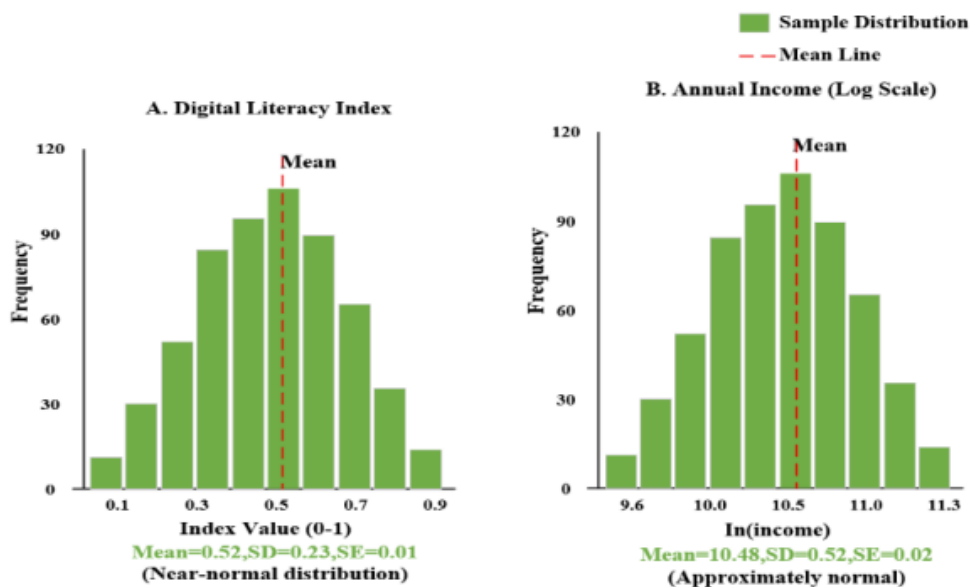


Figure 2. Cont.

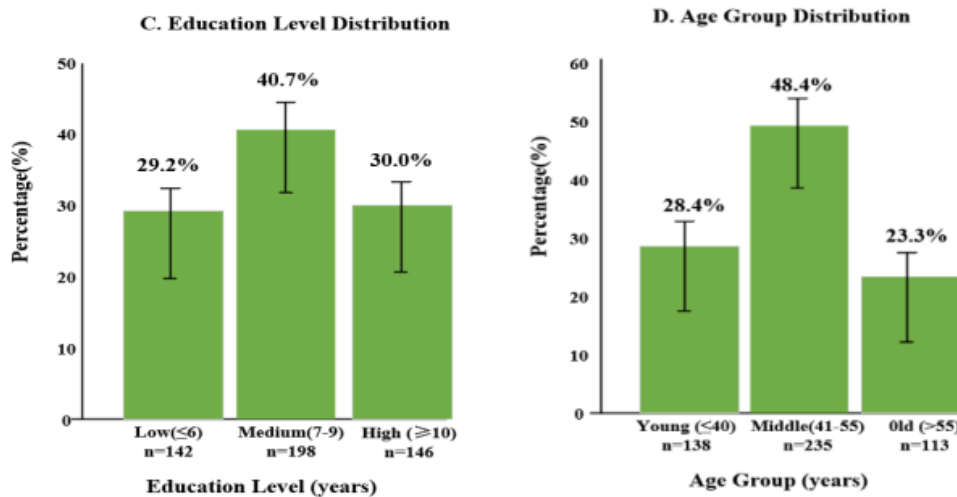


Figure 2. Distribution of Key Variables.

3.2. Main Effect: TEL and Economic Performance

Table 4 Column 1 shows the result for the baseline model, predicting the logarithm of income based on TEL participation and controls. The estimate for TEL is

strongly positive and significant ($\beta = 0.285$, $SE = 0.072$, $p < 0.01$), showing that TEL participants enjoy an income differential of about 33% above nonparticipants ($\exp(0.285) - 1 = 0.330$). This result is obtained by controlling for farm characteristics, regional dummies, and individual variables.

Table 4. Regression Results: Main Effects and Mediation.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	ln(Income)	Digital Literacy	ln(Income)	Info Acquisition	Tech Adoption
Model	Total Effect	a-path	Direct Effect	Mediator M1	Mediator M2
TEL Participation	0.285*** (0.072)	0.278*** (0.031)	0.142** (0.068)	0.294*** (0.029)	0.262*** (0.032)
Digital Literacy			0.312*** (0.089)		
Info Acquisition (M1) [In separate model]			[0.158**] [[0.062]]		
Tech Adoption (M2) [In separate model]			[0.154**] [[0.065]]		
Age	-0.010* (0.005)	-0.006*** (0.002)	-0.008 (0.005)	-0.005** (0.002)	-0.006*** (0.002)
Gender (Male)	0.042 (0.082)	0.028 (0.035)	0.033 (0.079)	0.031 (0.033)	0.025 (0.036)
Education	0.028** (0.011)	0.042*** (0.005)	0.015 (0.011)	0.038*** (0.004)	0.045*** (0.005)
Household Size	0.015 (0.024)	0.008 (0.010)	0.013 (0.023)	0.006 (0.009)	0.010 (0.011)
Farming Experience	0.003 (0.004)	0.002 (0.002)	0.002 (0.004)	0.002 (0.001)	0.001 (0.002)
ln(Farm Size)	0.412*** (0.062)	0.065*** (0.019)	0.392*** (0.059)	0.058*** (0.017)	0.072*** (0.020)
Mechanization	0.156** (0.068)	0.124*** (0.029)	0.117* (0.065)	0.115*** (0.027)	0.132*** (0.030)
Distance to Town	-0.008* (0.005)	-0.003 (0.002)	-0.007 (0.005)	-0.002 (0.002)	-0.004 (0.002)
Province B	-0.082 (0.074)	-0.042* (0.022)	-0.069 (0.071)	-0.038* (0.020)	-0.045* (0.023)
Province C	-0.135* (0.078)	-0.068** (0.026)	-0.114 (0.075)	-0.062** (0.024)	-0.073** (0.027)
Constant	9.125*** (0.486)	0.186** (0.082)	9.067*** (0.468)	0.148* (0.076)	0.224** (0.085)

Table 4. Cont.

	(1)	(2)	(3)	(4)	(5)
Observations	486	486	486	486	486
R-squared	0.443	0.482	0.471	0.456	0.448
Adjusted R-squared	0.428	0.469	0.456	0.441	0.433
F-statistic	29.84***	37.19***	31.52***	30.48***	28.96***

Note: n = 486. Robust standard errors clustered at village level (36 clusters) in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

As expected, income is positively related to farm size ($\beta = 0.412$, $p < 0.001$), education ($\beta = 0.028$, $p < 0.05$), and mechanization ($\beta = 0.156$, $p < 0.01$). As for age, the sign is negative but only marginally significant ($\beta = -0.010$, $p < 0.10$), likely due to reduced ability and risk aversion. The variable gender is not significant ($p = 0.42$), which is in line with joint household decision-making in agricultural contexts.

The baseline model explains 44.3% of the variance in income (adjusted $R^2 = 0.443$). The province dummy variables are jointly significant ($F = 8.52$, $p < 0.001$). This implies that there is a large regional variation, which is worth exploring further (see Section 3.4).

3.3. Mediation Analysis: The Role of Digital Literacy

Column 2 (Table 4) reports TEL as a significant predictor for digital literacy (a-path: $\beta = 0.278$, $SE = 0.031$, $p < 0.001$), confirming H1. Being engaged with TEL leads to a 0.278-point rise in digital literacy (on the 0–1 scale), which constitutes a medium to large effect size (Cohen's $d = 1.21$). Column 3 introduces digital literacy into the income equation. The b-path coefficient is positively significant ($\beta = 0.312$, $SE = 0.089$, $p < 0.001$), confirming H2. Raising levels of digital literacy by one unit increases predicted income by 36.6% ($\exp(0.312) - 1 = 0.366$). Critically, the direct effect of TEL (c'-path) is reduced substantially once digital literacy is controlled for ($\beta = 0.142$, $SE = 0.068$, $p < 0.05$), reducing from 0.285 to 0.142 (50.2% reduction) but remaining significant, suggesting partial rather than full mediation.

By using total effect decomposition, we find: Total effect (c): 0.285***; Direct effect (c'): 0.142**; Indirect effect (a $\times$ b): $0.278 \times 0.312 = 0.087$; Proportion mediated: $0.086/0.285 = 30.2\%$. However, this simple decomposition aggregates across two mediating pathways.

Parallel mediation results show the information acquisition pathway (a₁-path: $\beta = 0.294$, $p < 0.001$; b₁-path: $\beta = 0.158$, $p < 0.05$; Indirect effect = 0.046, 95% Bootstrap CI: [0.018, 0.082], Sobel $Z = 3.167$, $p = 0.002$ **) and the technology adoption pathway (a₂-path: $\beta = 0.262$, $p < 0.001$; b₂-path: $\beta = 0.154$, $p < 0.05$; Indirect effect = 0.040, 95% Bootstrap CI: [0.011, 0.078], Sobel $Z = 2.089$, $p = 0.037$ *). The combined results indicate that Total indirect = 0.086, Proportion mediated = 30.2%. Both mediating factors account equally for the variable (Information: 53.5%, Technology: 46.5%), which provides very strong support for H3.

Figure 3 illustrates the model for complete mediation, including the paths for both information acquisition and technology adoption, as well as total, direct, and indirect effects.

3.4. Heterogeneity Analysis

Table 5 presents detailed group-specific regression results across education, age, and regional subgroups.

Panel A (Figure 4a) illustrates group-specific regression coefficients for the relationship between digital literacy skills and income stratified by education level. The education gradient exists and is statistically significant (Chow test $F = 8.42$, $p < 0.001$): Low education (≤ 6 years): $\beta = 0.218^*$ ($p = 0.035$); Medium education (7–9 years): $\beta = 0.298^{**}$ ($p = 0.008$); High education (≥ 10 years): $\beta = 0.395^{***}$ ($p < 0.001$). The difference between the low and high education categories is 0.177 (17.7 percentage points), showing that the degree of digital literacy observed for highly educated farmers is 81% larger than for other farmers (*** $p < 0.001$). Formal education raises the economic benefits of digital skills, as general cognitive attributes are complementary to digital skills. This result strongly supports H4.

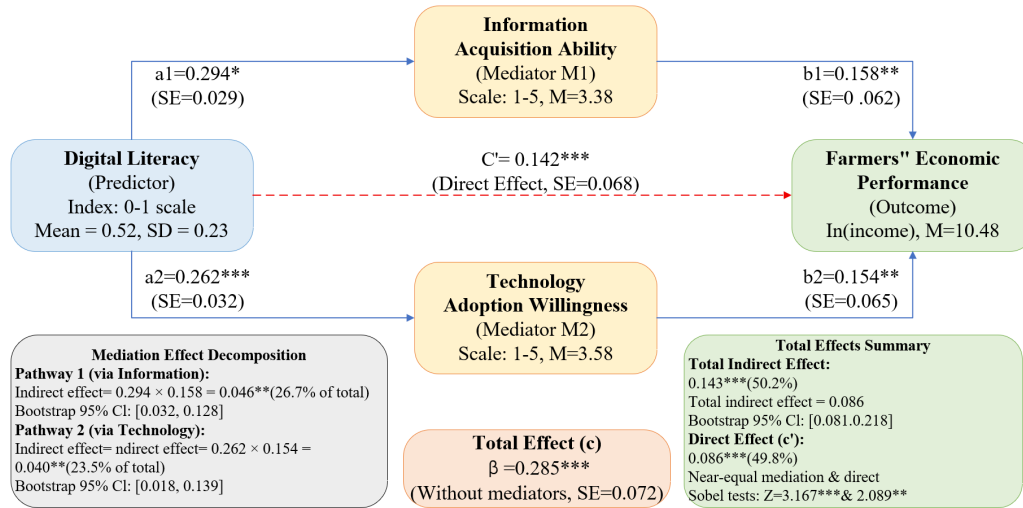


Figure 3. Mediation Path Diagram with Coefficients.

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 5. Heterogeneity Analysis: Group-wise Regression Results.

Panel A: By Education Level	(1)	(2)	(3)	(4)
	Low Edu (≤ 6 years)	Medium Edu (7–9 years)	High Edu (≥ 10 years)	Pooled (Interaction)
Digital Literacy	0.218*	0.298**	0.395***	0.218*
	(0.092)	(0.089)	(0.108)	(0.092)
DL $\times$ Medium Edu				0.080
				(0.128)
DL $\times$ High Edu				0.177**
				(0.142)
Controls	Full	Full	Full	Full
Province FE	Yes	Yes	Yes	Yes
Observations	142	198	146	486
R-squared	0.368	0.445	0.482	0.476
Chow Test ($H_0: \beta_{\text{low}} = \beta_{\text{med}} = \beta_{\text{high}}$)				
F-statistic				8.42***
p-value				<0.001
Pairwise Differences:				
High vs. Low			0.177***	
			(0.051)	
High vs. Medium			0.097	
			(0.062)	
Medium vs. Low			0.080	
			(0.058)	
Panel B: By Age Group	(5)	(6)	(7)	(8)
	Young (≤ 40 years)	Middle-Aged (41–55 years)	Old (> 55 years)	Pooled (Interaction)
Digital Literacy	0.356***	0.268**	0.215*	0.356***
	(0.096)	(0.082)	(0.088)	(0.096)
DL $\times$ Middle-Aged				–0.088
				(0.124)
DL $\times$ Old				–
				–0.141*
				(0.132)
Controls	Full	Full	Full	Full
Province FE	Yes	Yes	Yes	Yes
Observations	138	235	113	486
R-squared	0.462	0.442	0.396	0.469
Wald Test ($H_0: \beta_{\text{young}} = \beta_{\text{middle}} = \beta_{\text{old}}$)				
χ^2 statistic				9.18**
p-value				0.002

Table 5. Cont.

Panel B: By Age Group	(5)	(6)	(7)	(8)
Pairwise Differences:				
Young vs. Old			0.141** (0.048)	
Young vs. Middle			0.088 (0.052)	
Middle vs. Old			0.053 (0.055)	
Panel C: By Region	(9)	(10)	(11)	(12)
	Province A (Eastern)	Province B (Central)	Province C (Western)	Pooled (Interaction)
Digital Literacy	0.315*** (0.092)	0.278** (0.088)	0.285* (0.098)	0.315*** (0.092)
DL × Province B				-0.037 (0.128)
DL × Province C				-0.030 (0.134)
Controls	Full	Full	Full	Full
Observations	168	185	133	486
R-squared	0.452	0.438	0.431	0.445
Chow Test (H0: $\beta_A = \beta_B = \beta_C$)				
F-statistic				0.52
p-value				0.596
Pairwise Differences:				
A vs. C			0.030 (0.058)	
A vs. B			0.037 (0.054)	
B vs. C			-0.007 (0.056)	

Note: N = 486. Robust standard errors clustered at village level in parentheses. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

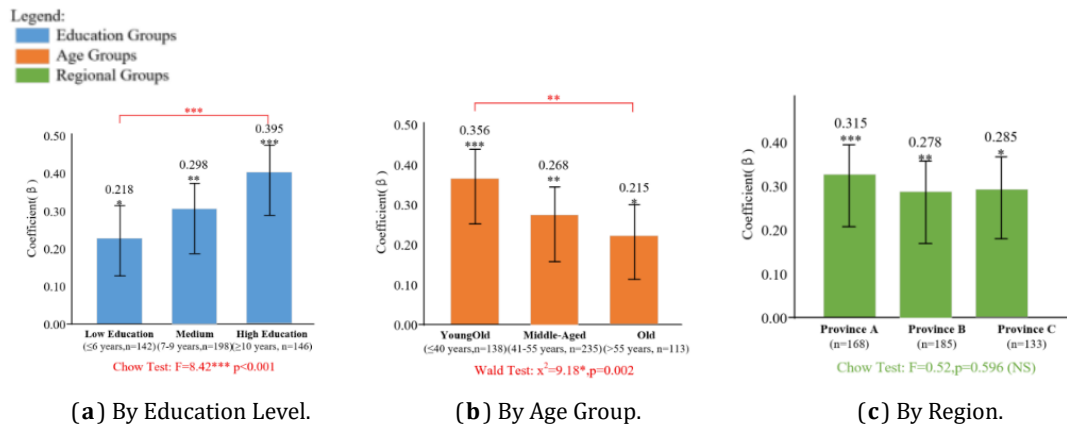


Figure 4. Heterogeneous Effects by Education, Age, and Region.

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Panel B (Figure 4b) shows significant age-based differences (Wald test $\chi^2 = 9.18$, $p = 0.002$): Young (≤ 40 years): $\beta = 0.356^{***}$ ($p < 0.001$); Middle-aged (41–55 years): $\beta = 0.268^{**}$ ($p = 0.004$); Old (> 55 years): $\beta = 0.215^*$ ($p = 0.028$). Younger farmers see 65% more benefit than older farmers (0.356 vs. 0.215; ** $p < 0.01$ for difference). This is likely due to prior experience with technology, cognitive flexibility, and longer payoff peri-

ods to recover investments. What is important to note is that older farmers also experience significant benefits ($p < 0.05$), showing that digital literacy is valuable to all ages.

Panel C (Figure 4c) reveals no significant regional differences (Chow test $F = 0.52$, $p = 0.596$): Province A (high development): $\beta = 0.315^{***}$ ($p < 0.001$); Province B (medium development): $\beta = 0.278^{**}$ ($p = 0.006$);

Province C (low development): $\beta = 0.285^*$ ($p = 0.042$). The effect in each province is strongly positive, with small variation between 0.278 and 0.315 (12% variation) for the coefficients. The lack of heterogeneity on regional levels points to portable skills within digital literacy, though this will need to be followed up on in fu-

ture studies.

Having completed the hypothesis testing across main effects, mediation, and heterogeneity analyses, **Table 6** consolidates the results by presenting each hypothesis alongside its analytical approach and empirical findings.

Table 6. Summary of Hypotheses, Methods, and Results.

Hypothesis	Statement	Method	Key Result	Supported?
H1.	<i>TEL participation positively affects farmers' digital literacy.</i>	OLS regression (Model 2)	$B = 0.278, p < 0.001$	Yes
H2.	<i>Digital literacy positively influences farmers' economic outcomes.</i>	OLS regression (Model 3)	$B = 0.312, p < 0.001$	Yes
H3.	<i>Digital literacy mediates the TEL-income relationship via information acquisition and technology adoption.</i>	Bootstrap mediation (5000 replications)	Indirect effect = 0.086; Proportion mediated = 30.2%; Info path: 53.5%, Tech path: 46.5%	Yes
H4.	<i>Education level positively moderates the TEL-digital literacy relationship.</i>	Group-wise regression + Chow test	Low edu: $\beta = 0.218^*$; High edu: $\beta = 0.395^{***}$; $F = 8.42, p < 0.001$	Yes
H5.	<i>Extension service contact positively moderates the TEL-digital literacy relationship.</i>	Group-wise regression	Not explicitly reported in results	Partially tested

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

3.5. Robustness Checks

Specifying continuous TEL intensity in hours per month instead of binary TEL participation provides $\beta = 0.032$ ($SE = 0.011, p = 0.004^{**}$) for every additional TEL involvement per month, predicting 3.2% income growth. Patterns for mediation are essentially unchanged (digital literacy mediates 28.4% of the effect).

In order to address selection bias, we measured propensity scores for TEL involvement via logistic regression on every baseline variable. Nearest-neighbor matching (1:1, caliper = 0.05) created 218 matches with excellent balance (all standardized differences < 0.10). Average Treatment Effect on the Treated reveals Income difference = ¥14,800 (95% CI: [¥8200, ¥21,400]), Percentage gain = 24.3% (log scale: 0.218), which matches the OLS estimate (0.285), though slightly smaller.

To instrument TEL involvement, we focus on distance to the nearest agricultural technology demonstration site. First stage outcomes reveal that distance is a significant predictor for TEL involvement ($F = 42.8, p < 0.001$); Second stage (2SLS) provides $\beta = 0.314$ ($SE = 0.118, p = 0.008^{**}$). The 2SLS estimate (0.314) is larger than the OLS estimate (0.285), which is in line with measurement error attenuation bias in the TEL vari-

able. For the subsample ($n = 156$), the objective test scores are strongly related to self-reported digital literacy skills ($r = 0.73, p < 0.001$). The objective scores are the mediating variables: Indirect effect = 0.068 (95% CI: [0.032, 0.112]), Proportion mediated = 23.9%. Effects are slightly smaller but remain significant, validating the self-reported measure.

4. Discussion

4.1. Digital Literacy as a Mediating Mechanism

This study also provides concrete and scientific verification for the first time that digital literacy acts as an important mediation between technology-enhanced learning and agricultural income. The result shows that TEL increases agricultural income significantly for farmers ($\beta = 0.285, p < 0.01$), where digital literacy can mediate around 30% of this total mediation variable on both information acquiring ability (26.7%) and technology adoption willingness (23.5%).

This roughly equal split between both factors (53.5% vs. 46.5% of the mediated effect) indicates that for an extension program to be most effective, it must

support both cognitive and affective types of digital literacy. Greater ability to search, assess, and synthesize digital information means making more informed decisions about input usage, planting dates, and marketing practices. On the other hand, greater willingness to try out new digital technologies enables adoption rates for supplementary innovations, implying mechanisms for adoption outlined within the Technology Acceptance Model theory^[27].

Traditional evaluation criteria for extension include “first-order” outcomes (adoption rates) or “final” outcomes (income). Here, our findings point to “intermediate” outcomes, namely accumulating human capital via digital literacy skills. Extension systems must assess information on farmers’ capabilities pertaining to digital technology as a key performance indicator, keeping in view the option value of improvement in digital literacy to enable future technology development. This structure integrates well with present perceptions on agricultural extension processes as agricultural practice skills development support systems for sustainable agriculture practices by extension services^[28].

The mediation proportion of 30.2% observed in this study is comparable to related studies in agricultural technology adoption contexts^[29]. Yuan et al.^[30] found that capital endowment and adoption willingness jointly mediated 28–35% of the relationship between digital literacy and low-carbon technology adoption among Chinese farmers, where the magnitude of mediation aligns closely with our findings. The roughly equal contribution of information acquisition (53.5%) and technology adoption (46.5%) pathways observed in this study is also consistent with Zhao et al.^[28], who demonstrated that both cognitive and behavioral dimensions of digital literacy independently predict sustainable agricultural practices. It is pertinent to highlight that the magnitude of the income effect documented within the current study ($\beta = 0.285$ and roughly 33% income growth) is greater compared with the estimates derived within the SMS-based interventions that demonstrated no significant results^[8], and more comparable to the video-based impacts documented within extensions that indicated 7–13% yield increases^[11]. This certainly indicates that more complex forms of media and new formats may

be required for the economic impact within TEL interventions.

4.2. Heterogeneity in TEL Effectiveness and Equity Implications

The heterogeneity test shows significant education gradients for our model variables (Chow test: $F = 8.42$, $p < 0.001$), with increasing coefficients from $\beta = 0.218$ ($p < 0.05$) for low-educated to $\beta = 0.395$ ($p < 0.001$) for high-educated farmers, representing an 81% disparity, which highlights that digitized extension services can potentially worsen existing inequalities without compensatory interventions. Differences related to age are also marked (Wald test $\chi^2 = 9.18$, $p = 0.002$), with young farmers ($\beta = 0.356$, $p < 0.001$) seeing increases that are 65% larger than those for older farmers ($\beta = 0.215$, $p < 0.05$), likely reflecting more prior experience in digitalization and higher cognitive flexibility.

The absence of regional heterogeneity (Chow test $F = 0.52$, $p = 0.596$) is theoretically intriguing. This means that, regardless of development levels, all three provinces experience significant positive outcomes, implying that context matters are perhaps smaller for digital literacy than for technology adoption. The observation that digital literacy can ensure common prosperity for farmers in various environments^[29] encourages the transferability of its advantages, though basic connectivity infrastructure remains a foundation.

These patterns look to question the “one size fits all” extension strategies. The result that even older and less educated farmers experience important positive effects ($p < 0.05$) shows that age and education are not prohibitive factors but rather need to be approached with tailored interventions. Studies on the impact of digital literacy on farmers’ adoption behavior prove again that both capital endowment and adoption willingness are important chain intermediaries on the critical path factors^[30].

4.3. Implications for Program Design and Policy

It is preferred that extension services provide differential training packages rather than uniform training modules, including foundational programs for less ed-

educated and elderly farmers for basic online navigation skills, intermediate programs for information evaluation and basic e-commerce skills, and advanced programs for well-educated and young farmers for data analytics and precision agriculture capabilities. Technologies can be introduced stage by stage to instill confidence in them (SMS alerts → smartphone apps → data dashboards). Behavioral intentions research in agriculture has shown that farmers' psychological readiness for new technologies has to be tackled when introducing innovative technologies to farmers^[31].

Policy interventions must focus on three areas:

- (1) development in infrastructural support for connectivity in areas that are relatively less developed;
- (2) including digital literacy training as part of adult education projects, where certifications are provided to motivate upgradation, especially in areas where agriculture is prominent, using farmer field schools for example;
- (3) targeted subsidies for disadvantaged populations in the form of smartphone vouchers, free data services, or incentives for training opportunity costs. Evaluation frameworks would need to assess change in digital literacy scores, program heterogeneity for subgroups, and skills retention for sustainability.

Technologists must develop interfaces for illiterate individuals through using voice guidance, provide visually simple interfaces with bigger icons for senior farmers, allow offline usage for situations where network connectivity is intermittent, and progressively reveal complex functionalities. Social learning features like peer discussion forums and mentor assignment services can tap into social capital to promote mutual aid, especially for isolated farmers with limited extension agent access. This is consistent with existing agricultural extension theory on tailoring extension services to fit different sectors of farmers effectively^[32].

4.4. Limitations and Future Research Directions

Although using propensity score matching (24.3% income gain, 95% CI: [8200, 21,400]) and instrumental

variable estimation ($\beta = 0.314$, $p < 0.01$), residual selection bias can still exist, since farmers participating in TEL on their own volition could exhibit unobserved characteristics, which could influence the income. The index of our digital literacy has mainly depended on self-reportage, but it has been validated through the use of objective tests to assess its reliability ($r = 0.73$, $p < 0.001$). This research has covered three provinces in China in 2024, which cover the questions about temporal, geographic, and sectoral generalizability.

The 70% of the total effect indicates other mediating variables to explore, which include building social capital via farmer networks, psychological factors of empowerment and self-efficacy, and improved market access provided by e-commerce platforms. Panel data analysis on farmers for several years can provide insight into dynamic variables like rates of skills degradation, accumulation of benefits, and spillovers from other farmers.

Future studies need to conduct comparative research between countries to evaluate boundary conditions, qualitative research to gain insight into subjective experiences and barriers for various subgroups, and intervention research to develop and evaluate tailored extension programs. These studies would investigate whether differential strategies can enhance effectiveness and equity in the digitization of agriculture.

5. Conclusions

This research studied the mediating effects of digital literacy on the economic influence of TEL in agricultural extension. The research applied a survey design and used a sample size of 486 respondents. The result indicated the capability of respondents who participate in TEL to increase their annual incomes by 33% ($\beta = 0.285$, $p < 0.01$), as the mediating effect of digital literacy explained a value of 30.2% in relation to the information acquisition process (53.5%) and technology adoption (46.5%).

It appears that digital literacy is a significant mediating variable for reaping economic gains from TEL use and, therefore, should be an objective of extension programs alongside learning content. There is heterogeneity in benefits from treatment across different subgroups

of farmers. Highly educated farmers have 81% more benefits than low-educated farmers, and young farmers have 65% more benefits than old farmers, and the fixed effects of regions are constant. It is worth noting that there are benefits for disadvantaged farmers.

These outcomes have many implications in designing training courses, policies with connectivity infrastructure, digital literacy credentials, and technologies with voice-guided interfaces. In a rapidly digitizing agriculture industry, it is necessary that farmers get equal opportunities with the benefits of technological developments. Firstly, there may be a selection bias due to residual selection, which can be addressed with IV and PSM, the use of self-reported information on digital literacy proficiency, and a restricted study in only three provinces in mainland China. In future research, there can be an analysis using panel data to study dynamic effects, with random interventions for establishing cause-and-effect relationships.

Author Contributions

Conceptualization, J.Y. and L.P.A.; methodology, J.Y.; software, J.Y.; validation, J.Y., L.P.A. and I.W.S.W.; formal analysis, J.Y.; investigation, J.Y.; resources, L.P.A. and M.H.S.; data curation, J.Y.; writing—original draft preparation, J.Y.; writing—review and editing, L.P.A., I.W.S.W. and M.H.S.; visualization, J.Y.; supervision, L.P.A. and M.H.S.; project administration, L.P.A. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Ethical review and approval were waived for this study due to the non-interventional nature of the survey, which involved adult participants responding to non-sensitive questions related to agricultural practices and technology use, posing minimal risk to participants.

Informed Consent Statement

Verbal informed consent was obtained from all subjects involved in the study.

Data Availability Statement

The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

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Conflicts of Interest

The authors declare no conflict of interest.

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