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IMPACT OF ICT USAGE LEVEL ON THE SMALL-SCALE CHILI PRODUCTIVITY IN INDONESIA

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ABSTRACT

Mobile and smartphone ownership at the agricultural household level is increasing, but a study of its impact on productivity is still limited. This study aims to analyze the impact of ICT usage levels on chili productivity among 151 smallholder farmers in Indonesia, highlighting five levels of ICT use: (1) no cell phone use; (2) basic mobile phones or smartphones for calls and SMS; (3) smartphones with WhatsApp; (4) smartphones with various social media apps; and (5) smartphones with diverse applications for broad purposes. Data was gathered through surveys and interviews conducted from November 2021 to March 2022 in the Cianjur, Sleman, and Malang districts of West Java, Yogyakarta, and East Java Provinces. Multivariate linear regression with Ordinary Least Squares (OLS) and a stepwise Akaike Information Criterion (AIC) model selection was used, alongside Heteroskedasticity and Autocorrelation Consistent (HAC) estimators to enhance robustness. The findings revealed that each level of ICT advancement results in an 8.9% in chili productivity. Moreover, farmers who rely on assistance from other parties (ICT dependency) can increase productivity by 17.1%. This finding adds to literacy related to transformational ICT in agriculture and provides implications for achieving economically viable chili production for smallholder farmers in Indonesia.

Key words: Agriculture digitalization, multivariate linear regression, productivity, smartphone

INTRODUCTION

In the economies of most developing countries, agriculture plays a crucial role with about two-thirds of the rural population residing in small farm households working on land plots smaller than 2 hectares. Unfortunately, smallholder farmers face significant challenges, including poverty, food insecurity, limited access to markets and services, and slowing agricultural productivity growth. In addition, the increasing global population projected to reach 9.3 billion by 2050 further exacerbates the demand for food consumption. In the light of this growing demand, smallholder agriculture must therefore find ways to increase food production (Krone et al. 2016; Levi et al. 2020; OECD/FAO 2021).

The development of information and communication technology (ICT), particularly in the digitalization of agriculture, is expected to address these challenges. Over the past decade, the use of

ICT, including mobile phones and smartphones, has been widespread in developing countries, and about one-third of people, including farmers, have access to the internet through smartphones (Aker and Fafchamps 2015; Brody and Pureswaran 2015; Chmielarz 2020; Hübler and Hartje 2016; Fabregas et al. 2019; 2020). The digitalization of agriculture provides smallholder farmers a wide range of opportunities to enhance productivity by utilizing ICT in production management, enabling them to control various aspects of agricultural activity (Deichmann et al. 2016; Garcia and Jerez 2020; Seenuankaew et al. 2018).

Although the potential benefits of ICT for smallholder farmers are evident, there are still issues. At the farmer level, an optimal production is a key discussion point as an aspect obtaining the optimal level of income through profit from farming (Fang et al. 2020). However, realizing this potential depends on the level of support for farmers in adopting ICT tools and technologies (Suroso et al. 2022). While the number of farmers owning mobile phones and smartphones with access to ICT has increased, there is limited evidence of its impact on improving productivity, especially in emerging and developing countries, composed of African, Asian, and Oceanic countries (Suroso et al. 2022).

Previous studies measured separately the impact of ICT, such as mobile or smartphones, on enhancing agricultural productivity. For example, studies explored the use of short message services (SMS) and phone calls on ordinary mobile phones (Quandt et al. 2020), utilizing smartphones with WhatsApp installed (Seminar and Sarwoprasodjo 2019), and leveraging smartphones with diverse applications (Emeana et al. 2020; Nugroho 2021). However, there exists a noticeable gap in the literature. Specifically, there is a lack of knowledge on whether differing levels (from basic to complex) of ICT usage contributed to enhanced productivity, specifically within the chili farming sector. Chili is vital to Indonesia's economy, serving as a staple in cuisine, sustaining farmer livelihoods, and contributing significantly to rural economies (Sundari et al. 2023). Understanding its productivity drivers, including ICT, is crucial for agricultural advancement and economic growth in the Indonesian study areas.

This research aimed to address the gap in the literature by exploring how smallholder farmers of chili in Indonesia can leverage digital agriculture using mobile or smartphones. The study sought to analyze the impact of ICT usage level and multivariate factors on increasing the productivity of chili.

METHODOLOGY

Research area, data collection, and ICT categories for respondents. This study did a survey of smallholder chili farmers (variety of curly red chili) using a structured interview schedule in three districts, namely Cianjur, Sleman, and Malang in West Java, Yogyakarta, and East Java Province, respectively. These regions were selected because of a high number of smallholder chili farmers with different capacities and distribution systems. The productivity in 2023 (harvest area in 2022) of curly red chili from Cianjur, Sleman, and Malang districts were 15-18 tons/ha (13,500 ha), 12-15 tons/ha (9,000 ha), and 16-19 tons/ha (16,500 ha), respectively (BPS 2024). These locations were also chosen because these farmers supply fresh chili to large cities.

Respondents were randomly selected through a sampling method following recommendations from experts, including agricultural scientists and extension officials, who provided the names of chili farmers in each area. Data was collected from 151 respondents consisting of 18, 109, and 24 people from the District of Cianjur, Sleman, and Malang, respectively and gathered from November 2021 to March 2022.

This study proposed five levels of ICT used by farmers based on the type of cell phone utilization, including (1) farmers who do not use cell phones at all, either basic mobile phones or smartphones; (2) farmers who use basic mobile phones or smartphones for phone calls and SMS purposes, (3) farmers who use smartphones using the Whatsapp application, but do not use many applications; (4) using smartphones with various applications for social media; and (5) using smartphones with various applications both for social media purposes or for other purposes broadly.

Econometric model employed for analysis. The study used the Multivariate Linear Regression (MLR) model (Aparicio and Villanua 2003) to assess the heterogeneous factors affecting the likelihood of increasing productivity of chili. The economic model augmented the studies of Aker (2010), Aker and Ksoll (2016), Aker and Fafchamps (2015), Aryal and Kassie (2017), Beuermann et al. (2012), Hou et al. (2019), Muto and Yamano (2009) and Shimamoto et al. (2015) which identified the impact of ICT such as mobile and smartphones. The research used an estimator of a model using Ordinary Least Square (OLS) and a step-by-step of Akaike information criterion (AIC) method. It provides a way to compare different models and determine which fit best to a given dataset. The lower AIC value indicates the model is better adapted. AIC considers the effectiveness of the model (the way the model explains data) and the complexity of the model (the number of parameters used) (Bozdogan 1987; Cavanaugh and Neath 2019).

Theoretically, those who are using ICT applications have the higher tendency to increase chili productivity than non-users (Subramanian 2021). It is also assumed that an i^{th} of agricultural households ($i = 1, 2, ..., N$) use ICT for a plot of land ($p = 1, 2, ..., P$). Based on theoretical and empirical research, the general model is shown in equation 1 while the specific variables for this are shown in equation 2.

$$Ln\ Y_{ip} = \alpha + \eta ICT_{ip} + X'_{ip}\beta + \mathcal{E}_{ip} \quad [1]$$

$$X'_{ip}\beta = \beta HH_i + \beta FARM_{ip} + \beta MSI_i + \beta VILL_i + \mathcal{E}_{ip} \quad [2]$$

$Ln\ Y_{ip}$ is a dependent variable representing the value of the natural logarithm of chili productivity. The ICT_{ip} as a main vector-explanatory variable cover the ICT usage, which is of five levels. X_{ip} is a multivariate vector of explanatory variables. These are household characteristics (HH_i), farming characteristics ($FARM_{ip}$), primary source of information (MSI_i), and geographical characteristics ($VILL_i$). The α, η, β are the estimated parameters; and $\mathcal{E}_{ip}$ is error term.

Following the primary survey, the data were initially analyzed using basic statistical methods. The quantitative data sets were then processed using the R Studio statistical tool. This model is consistent with the interpretation of parameters when unobserved heterogeneity is not associated with observed covariables and error terms. Many studies use this approach, using cross-sectional observation of multiple characteristics to capture the correlation between observed covariates and unobserved heterogeneity.

The Breusch Pagan test was used to check the assumption of homogeneity of the variance of the residuals, testing whether the distribution of residuals is inconsistent and results in unequal variation in the data points (Oman 1995). The Anderson-Darling test was also utilized to examine whether the data exhibit a normal distribution or a symmetrical distribution with the bell-shaped pattern commonly observed (Jäntschi and Bolboacă 2018). There may be a potential violation of the Gauss Markov assumption involving non-homogeneous variance or the presence of heteroscedasticity and autocorrelation. Assumption violations can be overcome (check the robustness and correct selection bias) by heteroskedasticity and autocorrelation consistent (HAC) estimators (Zeileis 2004).

Covariate variables identification. The model of productivity used 66 covariate variables which will be detailed subsequently. The level of ICT usage (ICT_{ip}) comprised of Type ICT usage in farming activity (Ordinal scale: 0 =no cell phone usage; 1=cell phone for only calling & texting; 2=smartphone with WA apps; 3=smartphone with various social media; 4=smartphone with full apps); Dummy for independent (ICT-self efficacy) or involvement of other people to help farmers (ICT dependency) using ICT in farming activities; Dummy of the usage of WhatsApp, Instagram, and Facebook apps.

Household characteristics (HH_i): A household's socio-economic and demographic characteristics consist of the main attributes of the head of the household, such as education, literacy status, age and gender, family size, farming experience, assets, loan status at a financial institution, household income derived from secondary agricultural farming and non-farming, and ownership status of cell phone.

Farming characteristics ($FARM_{ip}$): Farm plot features (farm plot size, tenancy status, soil fertility, plot slope) are included in the analysis. Furthermore, screen house, mulch, storage facility, weather condition, pest and disease control, fertilizer application, hydroponic system, harvest duration, best time for planting which is similar with the cropping time of the main vegetable, family labor number, non-family labor availability, cost of production, and livestock status are also included.

Main source of agricultural information (MSI_i) using dummy variable: The use of ICT also depends on the access to information. Farmers receive information through multiple sources including farmer-to-farmer communication, farmers group, agricultural-extension services/officer, agent/patron, social media, non-social media, training, and even traders.

An agent or patron for farmers can be a personal or communal (e.g. farmer groups, associations, and cooperatives) (Shang et al. 2021). Patrons may assist and help the farmers involved with ICT usage. The farmers may directly or indirectly use ICT helped by the farmer's agent or patron.

This research also considered the geographical characteristics ($VILL_i$) such as distance and journey time from field to local market, village population, location relative to the nearest capital center of district, road condition, and internet signal strength in the village.

The best model and robustness of multiple linear regression. The abundant variables were used to cover complex factors potentially affecting productivity. The initial set of 66 covariates has been reduced to 18 covariates of MLR model of chili productivity (Table 1). In contrast, 48 covariates were not selected in the final model due to the AIC method's application (Table 2). This reduction yielded the largest difference in AIC values, amounting to 106.214 between the initial and final models. This significant difference suggests that the final model optimally balances suitability and complexity, which is employed in this analysis.

Table 1. Selected independent variables using the AIC Method

Independent variable	Measurement unit or value	Mean	Parameter	Expected Sign
ICT usage				
ICT usage level	0 =no cell phone usage; 1=cell phone for only calling & texting; 2=smartphone with WA apps; 3=smartphone with various social media; 4=smartphone with full apps	2.17	β_1	+

Independent variable	Measurement unit or value	Mean	Parameter	Expected Sign
ICT self-efficacy (dummy)[a]	0=no; 1=yes	0.66	β_2	+
ICT dependency (dummy)[b]	0=no; 1=yes	0.23	β_3	+
Household characteristics				
Education of the oldest children as household member	Years	10.86	β_4	+
Farming experience: Farmer's wife	Years	15.22	β_5	+
Ln. Secondary agricultural household income	IDR per month (in million)	1.33	β_6	+
Loan status at a bank or other financial institution (dummy)	0=no; 1=yes	0.47	β_7	+
Farming characteristics				
Arable land used for primary vegetable farming	Ha	0.22	β_8	+/-
Soil fertility	0=no fertile; 1=quite fertile; 2=fertile; 3=very fertile	1.63	β_9	+
Harvest duration	Month	5.12	β_{10}	+
Screen house usage in field (dummy)	0=no; 1=yes	0.05	β_{11}	+
Non-family labor availability	1=lack; 2=adequate; 3=plentiful	1.75	β_{12}	+
Ln. Cost of production per ha	IDR per month (in million) per ha	12.91	β_{13}	+
Ownership of livestock in the household (dummy)	0=no; 1=yes	0.35	β_{14}	-
Main Source of agriculture information				
Agent/ patron (dummy)	0=no; 1=yes	0.38	β_{15}	+
Traders (dummy)	0=no; 1=yes	0.66	β_{16}	+/-
Geographical characteristics				
Journey time from the field to the nearest market	Hour	0.44	β_{17}	-
Paved road from the field to the nearest market	0=none; 1=partial; 2=all covered	1.57	β_{18}	+/-

[a] This pertains to farmer's belief in his own ability to effectively use ICT to achieve desired yields of chili. It reflects confidence in one's skills and knowledge related to ICT.

[b] This refers to the degree to which an individual of farmer relies on others for assistance, support, or guidance in using ICT.

Table 2. Unselected independent variables using the AIC Method

Independent variable	Measurement unit or value
ICT Usage	
ICT usage, whether through self-efficacy or with assistance from others (dummy)	0=no; 1=yes
Usage of WhatsApp (dummy)	0=no; 1=yes
Usage of Instagram apps (dummy)	0=no; 1=yes
Usage of Facebook apps (dummy)	0=no; 1=yes

Independent variable	Measurement unit or value
Household characteristics	
Marital status	2=Married; 1=Widowed/ divorced; 0=Not Married
Age of household head	Years
Education: the farmer	Years
Education: farmer's wife	Years
Farming experience: Farmer	Years
Farming experience: Farmer's wife	Years
Household (family) size (number of household member)	Persons
Ln. Agricultural assets	IDR
Ln. Non-agricultural household income	IDR per month (in million)
Ownership status of at least one cell phone within the household (dummy)	0=no; 1=yes
Number of individuals in the household who possess a cell phone	Persons
Status of cell phone utilization in the household for farming activities (dummy)	0=no; 1=yes
The price of the most expensive cell phone in the household	IDR
Livestock is a source of household income (dummy)	0=no; 1=yes
Household income from non-farming	0=no; 1=yes
Farming characteristics	
Arable land used for farming (plot area), totally	Ha
Land used for farming (plot area) vegetable generally	Ha
Type of crops cultivated	1=vegetable (vege); 2= vege & others; 3 = vege & food crops; 4=vege & fruit crops; 5=vege, fruit, others; 6= vege, fruit, food; 7 =all crops
Volume of harvest loss	percent
Land (plot) slope	3=flat; 2=quite flat; 1=quite steep; 0=steep
Tenure of plot	1=owned; 0=not owned
Hydroponic system in the main vegetable (dummy)	0=no; 1=yes
Weather (rainy) condition (dummy)	0= lack or excess; 1=sufficient
Integrated pest and disease control (dummy)	0=not integrated; 1=integrated
Fertilizer application	2=appropriate; 1=not appropriate; 0=none
Mulch application (dummy)	0=no; 1=yes
Intercropping (dummy)	0=no; 1=yes
Storage facility (dummy)	0=no; 1=yes
Family labor	Man-days per ha
Main Source of agriculture information	
Farmer to farmer	0=no; 1=yes
Agricultural extension officer	0=no; 1=yes

Independent variable	Measurement unit or value
Farmers group	0=no; 1=yes
Household member	0=no; 1=yes
Training	0=no; 1=yes
Social media	0=no; 1=yes
Non-social media	0=no; 1=yes
Television or radio	0=no; 1=yes
Geographical characteristics	
Distance from the field to the nearest market	Km
The level of population density in the village	3=crowded; 2=quiet crowd; 1=distant
Location to the nearest district center or urban	Km
Signal strength in the village	0=no signal; 1=low signal; 2=medium; 3=strong signal

Table 3 presents that data in the models as normally distributed and it reveals that heteroscedasticity did not exist in the models, as evidenced by a Breusch-Pagan test significance value exceeding 0.05. Even though heteroscedasticity does not occur in the productivity model, the HAC estimator is still applied to correct standard errors for all covariates, thereby obtaining the highest robustness of the regression model. Some standard errors of covariates were decreasing then causing t-value and significance were increasing, as well as otherwise.

Table 3. Hypothesis test of Gauss Markov assumption in multiple linear regression of chili

Hypothesis test	Productivity
Breusch-Pagan test	
BP-test	20.139
p-value	0.3152
Rejected H_0	No
Heteroscedasticity	No
Anderson-Darling normality test	
A-test	0.271
p-value	0.670
Rejected H_0	No
Normal distribution	Yes

RESULTS AND DISCUSSION

Summary statistics. This paper used the median rather than mean (average) to depict the household characteristics of the study area (Table 4). The typical age of farmers is approximately 48 years, with both farmers and their spouses having an average of 12 years of education. Farmers possess around 20 years of farming experience, while their spouses have an average of 13 years. Additionally, farming households generally own three cell phones.

Table 4. Summary of household characteristics of respondents (N=151)

Characteristics	Unit	Median	Mean	Standard Deviation	Variation Coefficient
Age of farmers	Year	48	48.31	9.16	19.0%

Characteristics	Unit	Median	Mean	Standard Deviation	Variation Coefficient
Education level of farmers	Year	12	11.12	2.84	25.6%
Education level of farmer's wife	Year	12	10.84	2.70	24.9%
Education level of the oldest child	Year	12	10.86	3.42	31.4%
Number of household members	Person	3	3.48	1.35	38.7%
Farming experience of farmers	Year	20	20.77	11.41	55.0%
Farming experience of farmer's wife	Year	13	15.22	9.06	59.6%
Number of cell phones in household	Unit	3	2.69	1.16	43.2%

Productivity of chili ranges from 0.67 to 30 tons per ha. The median and mean of productivity are 10.00 and 10.93 tons per ha, respectively with standard deviation of 4.92 tons per ha (Table 5). The variation in productivity is very large among chili farmers in the three locations in Indonesia. Nevertheless, there is no difference in productivity among the study areas: Cianjur, Sleman, and Malang as verified by the ANOVA of 0.69. This average of productivity in the study area has an excess of national-chili productivity of 8.69 tons per ha in Indonesia (BPS 2020). Most farmers (29.8%) obtained a productivity level of 8 – 12 tons per ha and only 7.3% and 11.9% of chili farmers achieved productivity less than or equal to 4 and above 16 tons per ha, respectively (Table 6).

Table 5. Summary of chili productivity (N=151)

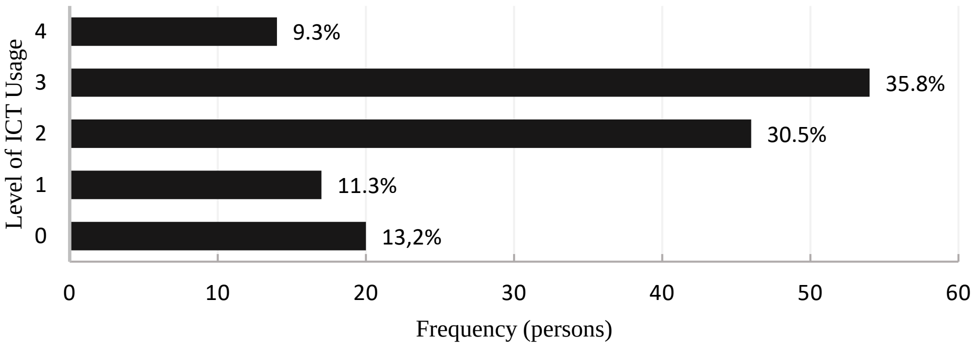
	Productivity (ton/ha)
Minimum	0.67
Median	10.00
Mean	10.93
Standard deviation	4.92
Maximum	30.00
ANOVA (p-value)	0.69
Difference among the study areas	None

Table 6. Range, frequency, and share of respondent toward chili productivity

Chili Productivity (ton/ha)	Frequency (persons)	Share (%)
Less than or equal to 4	11	7.3
4.01 - 8.00	39	25.8
8.01 - 12.00	45	29.8
12.01 - 16.00	38	25.2
More than 16	18	11.9
N (persons)	151	100.0

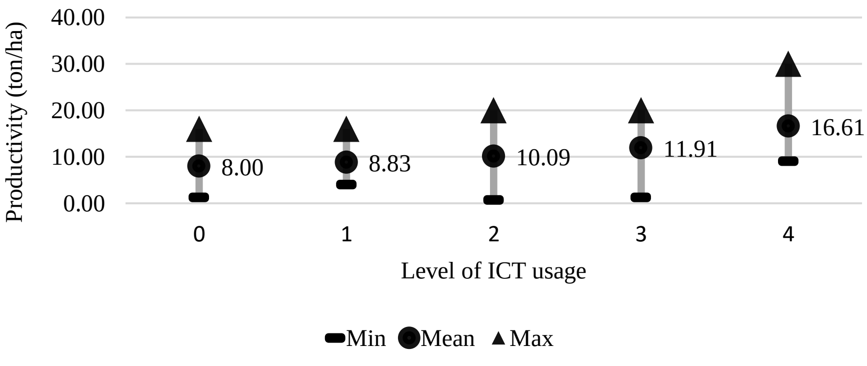
Chili farmers in this study are classified into five levels according to the type of mobile phone usage, from 0 (the lowest) to 4 (the highest). Most chili farmers (35.8%), fall into Level 3, use various social-media application through smartphone for farming activity (Fig. 1). The data revealed a positive correlation between the level of ICT adoption and the average productivity among farmers. As the level of ICT usage increased, so did productivity. For instance, farmers at Level 0, who do not use mobile phones, produce an average of 8.00 tons of chili per hectare. In contrast, those at Level 4, who utilize the most advanced ICT tools, achieve an average productivity of 16.61 tons per hectare, with some reaching a maximum productivity of 30.00 tons per hectare (Fig. 2).

Previous studies found that the adoption of cell phone usage can increase chili production (Mariyono and Sumarno 2015). This present study further demonstrated that measuring cell phone usage should move beyond simple binary (dummy) variables to a more nuanced approach that considers varying levels of ICT adoption.



Level of ICT usage:
(0) farmers who do not use basic mobile phones and smartphones at all
(1) farmers who use basic mobile phones or smartphones for calls and texts
(2) farmers who use smartphones only with the WhatsApp application
(3) farmers who use smartphones with various social-media application
(4) farmers who use smartphones with various applications both for social media and for various purposes

Figure 1. Number and share of chili farmers toward ICT used level



Level of ICT usage:
(0) farmers who do not use basic mobile phones and smartphones at all
(1) farmers who use basic mobile phones or smartphones for calls and texts
(2) farmers who use smartphones only with the WhatsApp application
(3) farmers who use smartphones with various social-media application
(4) farmers who use smartphones with various applications both for social media and for various purposes

Figure 2. Summary of chili productivity based on the level of ICT usage

Figure 3 shows more about the social media applications used by chili farmers. Social media can be used by farmers to communicate with fellow farmers and agricultural extension workers with the aim of increasing chili productivity, consistent with an earlier study (Seminar and Sarwoprasodjo 2019). However, this present study revealed that the social media used are WhatsApp, Facebook, YouTube, and Instagram. Most chili farmers used WhatsApp (79%) followed by Facebook (50%), YouTube (48%), and only a few chili farmers use Instagram (26%).

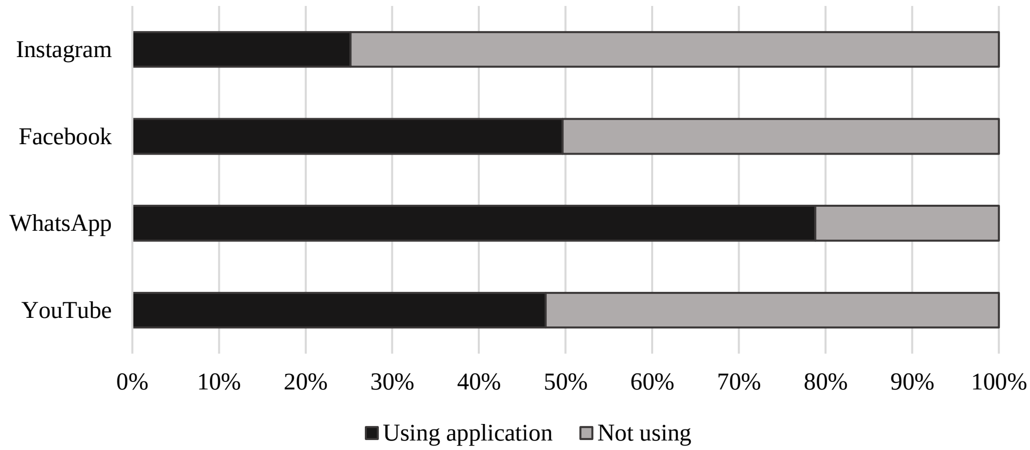


Figure 3. The applications used by farmers in chili farming (N=151 persons)

This study also determined that individuals or institutions are engaged with 35 chili farmers (23%) in farming activities (ICT-dependency) i.e. farmers who need help from others either not using ICT (6.62%) or using ICT (16.56%). However, most farmers (66.22%) used ICT independently in chili farming (ICT-self efficacy) as shown in Table 7.

Table 7. The engagement of individuals or institutions using ICT in farming activity.

Type of ICT use		Farmers (persons)	Share of Farmers (%)
Used ICT	**Helped (Dependent)**		
No	No	16	10.59
No	Yes	10	6.62
Yes	Yes	25	16.56
Yes	No	100	66.22
	N (persons)	151	100.00

Regression model of chili productivity. The results of the linear regression models for the natural logarithm of chili productivity are presented in Table 8, focusing on chili productivity as the dependent variable. The regression model for chili productivity demonstrated a relatively good fit with the observed data. A sum of 71.95% of variability of productivity can be explained significantly ($P < 0.01$) by 18 covariates while the rest is attributed to the others**.**

ICT use characteristics. This study found novelty that an increase of one level in the use of ICT (transition from lower level to higher level) had a significant positive effect (P < 0.05) on chili productivity (Table 8). For instance, suppose a farmer advances their ICT proficiency from level 2 (using a smartphone with the WhatsApp application) to level 3 (using a smartphone with various social media platforms), productivity is projected to rise by approximately 8.9%. These findings underscore the diverse ways in which ICT adoption can positively influence agricultural output, ultimately contributing to improved economic outcomes for smallholder farmers.

The empirical evidence highlights a significant positive correlation between the increasing adoption of ICT and the simultaneous increase in productivity of chili. While prior research has traditionally examined the ICT at individual levels (Emeana et al. 2020; Landmann et al. 2021; Nugroho 2021; Quandt et al. 2020; Seminar and Sarwoprasodjo 2019), this present study demonstrated that variations at each level impact significantly the enhancement of agricultural productivity.

The above results are consistent with the study conducted in China that demonstrated that the use of basic mobile phones alone can lead to increased productivity (Quandt et al. 2020). In parallel, studies carried out in Thailand, even the use of smartphones (without using certain applications) resulted in enhanced productivity levels (Landmann et al. 2021).

The study also revealed that farmers' independent utilization of ICT (ICT self-efficacy) is anticipated to enhance chili productivity by approximately 35.7% (Table 8). Earlier findings demonstrated that farmers possessing greater confidence in ICT operations were also inclined to explore a wider array of ICT tools and services, consequently driving up productivity levels (Singh and Jahanara 2023).

The study found the novelty that if farmers encounter challenges in using ICT independently, they can still boost chili productivity by up to 17.1% with assistance, support, or guidance from others (ICT dependency) (Table 8). Previous studies revealed that barriers to ICT adoption among farmers included high language difficulties, lack of skills, costs of gadgets, power supply interruptions, and inadequate service centers (Byamukama et al. 2022; Elijah et al. 2022).

Table 8. Results of regression analysis (ln model) for chili productivity corrected by HAC estimators

Independent Variables	Coeff.	Initial Standard Error			Standard Error Corrected		
		Std. Error	t-Value		Std. Error	t-Value	
Intercept	-6.029	0.848	-7.113	***	1.277	-4.721	***
ICT usage							
Level of ICT usage in farming activity (0 =no cell phone usage; 1=cell phone for only calling & texting; 2=smartphone with WA apps; 3=smartphone with various social media; 4=smartphone with full apps)	0.085	0.037	2.275	**	0.043	1.962	**
ICT self-efficacy (dummy)	0.305	0.133	2.291	**	0.152	2.004	**
ICT dependency (dummy)	0.158	0.121	1.307		0.138	1.142	
Household characteristics							
Education of the oldest children as household member (years)	0.019	0.008	2.239	**	0.008	2.428	**

Independent Variables	Coeff.	Initial Standard Error			Standard Error Corrected		
		Std. Error	t-Value		Std. Error	t-Value	
Farming experience: Farmer's wife (years)	0.009	0.003	2.585	**	0.003	2.953	***
Ln. Secondary agricultural household income (IDR per month, in million)	0.015	0.005	2.802	***	0.006	2.618	***
Loan status at a bank or other financial institution (dummy)	0.155	0.061	2.541	**	0.063	2.456	**
Farming characteristics							
Arable land used for primary vegetable farming (ha)	-1.12	0.168	-6.647	***	0.242	-4.637	***
Soil fertility (0=no fertile; 1=quite fertile; 2=fertile; 3=very fertile)	0.119	0.055	2.164	**	0.055	2.180	**
Harvest duration (month)	0.112	0.033	3.414	***	0.042	2.643	***
Screen house usage in field (dummy)	0.504	0.132	3.812	***	0.145	3.479	***
Non-family labor availability (1=lack; 2=adequate; 3=plentiful)	0.151	0.053	2.861	***	0.061	2.465	**
Ln. Cost of production (IDR per month per ha, in million)	0.386	0.048	7.971	***	0.075	5.129	***
Ownership of livestock in the household (dummy)	-0.146	0.061	-2.377	**	0.057	-2.535	**
Main Source of agriculture information							
Agent/ patron (dummy)	0.148	0.062	2.388	**	0.057	2.6	**
Traders (dummy)	-0.175	0.063	-2.763	***	0.055	-3.197	***
Geographical characteristics							
Duration time from the field to the nearest market (hour)	-0.081	0.017	-4.901	***	0.029	-2.782	***
Paved road from the field to the nearest market (0=none; 1=partial; 2=all covered)	-0.121	0.061	-1.996	**	0.072	-1.671	*
	Multiple R-square				0.720		
	Adjusted R-square				0.681		
	F-Stat				18.81 ***		

Household characteristics. This study identified that the chili productivity will be significantly higher due to the education of the oldest child in the household ($P<0.05$), longer farming experience of farmers' wives ($P<0.05$), household income derived from non-primary vegetable (secondary agriculture) sources ($P<0.01$), and loan status at a financial institution ($P<0.05$) (Table 8).

One significant finding is the positive impact of the farming experience of farmers' wives on chili productivity. This highlights the role of gender dynamics in farming and suggests that training in ICT, particularly for farmer's wives, can contribute to increased productivity. This finding is more specific than that of Mariyono and Sumarno (2015), as it explicitly identifies that the farming experience of the farmer, regardless of gender, contributes to the increased productivity of chili. In addition, it mentioned that a training in ICT, in terms of increasing the productivity of chili, should be given to the farmers as well as to young farmers (Mariyono 2019) while this present study recommends training also for the wives of farmers.

Chili is the primary focus of this research because it generates the highest income for agricultural households compared to other commodities. Secondary agricultural income, which encompasses other earnings from the agricultural sector, such as income from growing other crops, raising livestock, or selling agricultural by-products, also plays a crucial role. This research revealed that secondary agricultural income significantly increases chili productivity ($P<0.01$). A previous study also underscored the crucial role of secondary agricultural income in generating chili productivity (Maulana et al. 2023).

Farmers with loans from financial institutions had a 16.8% higher chance of increasing chili productivity, as loans boost financial capacity and enable greater investment in farming activities. This finding aligns with research from Pakistan (2023) and confirms that integrating digital technology via mobile and smartphones encourages farmers to invest more in chili cultivation, potentially enhancing productivity (Mariyono and Sumarno 2015). The increased use of financial loans and digital technology highlights farmers' motivation to adopt comprehensive, technology-driven chili farming practices.

Farming characteristics. Farmers leveraging financial institution services to enhance their financial capacity increase production costs (significant at $P<0.01$) by investing in agricultural tools and equipment, such as screen houses (significant at $P<0.05$) (Table 8). Farmers using screen houses can boost productivity by up to 65.5%, the highest impact among all variables. Screen houses enhance plants resistance to pests and diseases, prolong the harvest duration (significant at $P<0.01$) and finally enhance chili productivity, which aligned with results of previous studies (Nagaraju et al. 2022; Nithyashree and Vallabhaneni 2023; Raza et al. 2023).

This study identified a negative correlation between livestock ownership, particularly dairy cattle, and chili productivity levels ($P<0.01$). Livestock ownership impacts the efficiency and management of chili farming. This negative correlation is linked to the time allocation of farmers, as those who are also engaged in dairy farming must divide their time between milk production and chili farming. Consequently, chili productivity tends to be lower compared to farmers who do not engage in dairy farming activities.

Similar findings were reported in a previous research conducted in Thailand (Krasachat 2023). Livestock ownership, which impacts chili agricultural management, can also affect the allocation of non-family labor. Consequently, a lack of available non-family labor in agricultural areas can directly reduce productivity and vice versa ($P<0.05$), as observed in Thailand (Krasachat 2023).

There is a significant negative correlation between expanding arable land dedicated to primary vegetable cultivation and the productivity of these vegetables in the farming category ($P<0.01$) (Table 8). This adverse relationship can be attributed to several key limitations identified in the study. Firstly, the time allocation constraints of farmers play a crucial role in hindering productivity improvements as like in the previous study (Ma et al. 2020). Secondly, the scarcity of non-family labor in the study, as indicated in Table 1, further exacerbated the challenges faced in enhancing vegetable productivity (Amfo and Baba Ali 2021). Lastly, the financial capacity of farmers (indicated by average of cost of production per ha in Table 1) also emerges as a limiting factor. This restricts potential investments in resources that could boost productivity levels (Wang et al. 2019).

Information sources and geographical characteristics. It is evident that farmers in the research location significantly benefited from receiving information from agents or patrons, which positively impacted chili productivity ($P<0.05$) (Table 8). Conversely, information sourced from traders showed a notable negative correlation with chili productivity ($P<0.01$).

Agents or patrons work closely with farmers in both farming and selling activities. The benefits that farmers gain indirectly benefit the patrons as well. For instance, patrons using ICT to sell crops via e-commerce rely on farmers to maintain a steady supply for their consumers. Consequently, patrons provide farmers with information on increasing productivity and teach them how to use ICT to independently find information to enhance chili productivity. Positive interactions between patrons and farmers using ICT have been demonstrated also in Tanzania (Ndimbo et al. 2023).

On the other hand, traders tend to exploit farmers to maximize their profits, even though the information provided can sometimes reduce farmers' productivity. For example, farmers might receive advice on pesticide use without being informed about the negative side effects. Over time, this can lead to the death of many pest predators due to the application of certain pesticides, eventually causing a pest outbreak (Hennessy and Wolf 2018).

The duration time from the field to the nearest market has a negative effect on chili productivity ($P<0.01$). Key factors like transportation time and conditions during transit are essential in preserving the quality and freshness of the chilies, which in turn affects their market value and attractiveness to consumers. Furthermore, extended transportation times can result in post-harvest losses due to spoilage or damage, ultimately decreasing the overall productivity of the crop (Kantor and Whalley 2019).

The availability of paved roads may tend to a negative impact on agricultural productivity ($P<0.1$). The low agricultural productivity observed in villages closest to urban areas, as the geographical characteristic in this study, is a complex issue influenced by multiple factors (Holden and Fisher 2013; Josephson et al. 2014; Lipton 1980). Firstly, imperfections in land and labor markets, coupled with motivations for food self-sufficiency, contribute to an inverse relationship between farm size and productivity on smaller farms (Holden and Fisher 2013). The competition for labor between off-farm jobs and agricultural activities further compounds this challenge (Lipton 1980).

Limited land near cities motivates some farmers to migrate in search of work, aiming to increase household income. However, farmers requiring external labor face challenges in finding such workers, leading to a hindrance in focusing on increasing agricultural productivity and potentially reducing overall productivity.

These variables together account for a significant amount of the differences seen in independent variables at the village level. In addition, the combined influence of the field's distance to the nearest city and the socio-economic status of that city creates a U-shaped pattern. This pattern indicates that poverty rates in rural areas change depending on the characteristics of the nearby city. These factors highlight the intricate dynamics influencing the productivity challenges faced by villages closest to cities in agricultural contexts (Holden and Fisher 2013; Josephson et al. 2014; Lipton 1980).

CONCLUSION AND IMPLICATIONS

This research addressed a critical gap in the existing literature by delving into how smallholder farmers in Indonesia are engaged with transformational ICT (mobile and smartphones) in enhancing chili productivity. A significant impact of ICT usage levels on chili productivity was determined, with each incremental increase in ICT proficiency correlating with an 8.9% rise in productivity.

The study identified crucial multivariate factors, including household characteristics, farming, and geographical as well as information sources that contribute significantly to chili productivity. These factors enhance financial capacity, enabling farmers to make substantial investments in farming activities that directly translate into increased productivity. In terms of farming characteristics, investments in agricultural tools like screenhouses emerge as highly impactful. Information sources and geographical characteristics also play significant roles. Policymakers should prioritize gender-inclusive policies and training initiatives to empower women in adopting digital agriculture practices. Their involvement in ICT can significantly contribute to increased productivity.

Policymakers and stakeholders should design and implement selective ICT training programs based on farmers' existing skills and needs, represented by current level of ICT usage. Selective training can maximize the benefits of digital agriculture for farmers at different proficiency levels. Agricultural extension officers can play a pivotal role in delivering such training and providing ongoing support daily.

Investments in accessible ICT training programs, coupled with financial support for farmers, can enhance their technological capabilities and contribute to increased productivity. Furthermore, policies encouraging diversified farming practices, supported by adequate financial resources and loans, can lead to more comprehensive and technology-driven cultivation.

To enhance agricultural productivity in peri-urban areas, policy efforts should focus on improving road infrastructure, addressing land availability and tenure issues, enhancing access to agricultural inputs and technologies, and strengthening support systems for farmer organizations and cooperatives. Upgrading and maintaining efficient road networks can reduce transportation time and costs, facilitating market access. Secure land tenure arrangements and zoning regulations that prioritize agricultural use can protect farming areas from urban encroachment.

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