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Article

Increasing Household Income from Vegetable Farming through Mobile and Smartphones Apps

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Abstract: This study aims to determine the impact of the type of ICT usage on household income from main vegetables, agriculture (including main vegetables), and total income. This study is based on surveys and interviews with vegetable farmers using structured questionnaires conducted in three villages in Indonesia, including Cianjur, Sleman, and Malang in West Java, Yogyakarta, and East Java, respectively. The data were collected from 375 respondents selected in each region from November 2021 to March 2022. An econometric model called the multivariate linear regression (MLR) model is used to assess heterogeneous factors that influence the possibility of increasing the income of vegetable farmers. The study found that variables that use ICT as a primary variable, household, marketing, geographical characteristics, and immediate source information in agriculture have a significant impact on household income ($P < 0.01$) from primary vegetables, agriculture, and total income, with multiple R squares of 70.5, 72.0, 73.7% and F statistics of 28.48, 30.66, and 33.34, respectively. In summary, this novel study shows that the five categories of information technology used in farming and selling of harvest have a positive impact on household incomes.

Keywords: econometric model; household income; ICT; smartphone; vegetable farmer

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Introduction

Agricultural productivity growth is slowing worldwide due to reduced farm size, agricultural labour migration, and the increasing isolation of smallholders from the economic environment. In contrast, food consumption is growing demand due to the rising population (Levi et al. 2020).

As given above, the supply can be adjusted to the demand generated by applying information and communication technology (ICT) (Shimamoto et al. 2015). In other words, today, the world society is entering emerging digital technologies era for increasing productivity in the agricultural sector, namely agriculture digitalization (Deichmann et al. 2016; Majumdar et al. 2019; Fabregas et al. 2019; Sagarna Garcia et al. 2020).

Over the past decade, many people have been using information and communication technology (ICT), such as mobile phones, widely (Aker and Fafchamps 2015; Seenuankaew et al. 2018; Dutta et al. 2020) and have used smartphones recently (Chmielarz 2020). One-third of the population of developing countries, including smallholder farmers, uses smartphones to connect to the Internet (Fabregas et al. 2019).

The utilization of ICT, including mobile phones and smartphones, has emerged as a valuable tool for rural farmers. By harnessing these technological advancements, farmers can gather crucial information about crop production and market prices (Shimamoto et al. 2015). This ability to access real-time data addresses challenges associated with market inefficiency and information asymmetry, ultimately empowering farmers to overcome obstacles that may lead to excess profits being claimed

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by traders. Therefore, farmers have the opportunity to increase their income and improve their overall economic well-being (Sheng 2020).

Some studies have shown that households can increase incomes by (1) generating sources of off-farm income and marketing strategies, (2) obtaining subsidies and appropriate policies, (3) selecting other commodities, (4) using mechanization, and (5) linking enterprises to farmers to provide agricultural markets (Jankelova et al. 2017; Ma et al. 2018). In addition, Ma (2018) studied farmers and their families' views that using smartphones can generate off-farm workers to obtain additional income.

However, studies focusing specifically on the type of ICT farmers use for income generation are scarce because of the transition from mobile phones to smartphone apps. Furthermore, the household income derived from the main commodity such as vegetables and other agricultures has received limited attention in the literature. Previous studies may probably generate this study. This study aims to determine the impact of ICT usage type on household income derived from main vegetables, agriculture (including main vegetables), and total income.

Method

Study Area, Data Collection, and Respondent

This study is based on a survey and interview of the vegetable farmers using a structured questionnaire carried out in one village in every three districts in Indonesia, such as Cianjur, Sleman, and Malang in West Java, Yogyakarta, and East Java Province, respectively. These regions were chosen because there were many small commercial vegetable farmers with different capacities and distribution systems. These locations were also selected because of their availability of fresh vegetables for large cities.

Respondents were selected by purposive sampling through focus group discussion (FGD) involving experts such as agricultural scientists and agricultural extension officers in each location. A maximal variation of ICT usage in selecting respondents was noticed for achieving a range of differentiation in the field.

Data are gathered from 375 chosen respondents in their respective parts between November 2021 to March 2022. Our respondent was male or female in each household as head or spouse. This study encompasses research on smallholder farmers in vegetable commodity farming and selling stages. The initial information provided by 34 farmers was validated and verified to adjust the best questionnaire for collecting comprehensive data. Additionally, it addressed several ambiguous issues farmers brought up during the first data collection.

Econometric Model Employed for Analysis and Robustness

Recently, some farmers have been smart enough to use the Android/IOS system on their smartphones by downloading and installing various applications. They can also use social media such as Whatsapp applications (WA) to exchange information and distribute information between individuals outside and outside the community, enabling them to support agricultural activities. Based on previous studies, this study divided the farmers become to six possible categories on the type of cell phone usage, such as (1) farmers who do not use mobile phones or smartphones at all, (2) farmers who use ordinary mobile phones for phone calls and text messages (basic handphone), (3) farmers using smartphones, but only for phone calls and text messages, (4) farmers using smartphones with the Whatsapp application but few other applications., (5) farmers using smartphones with various applications for social media, and (6) farmers using smartphones with various applications both for social media and for other purposes widely (Krone et al. 2016; Seenuankaew et al. 2018; Majumdar et al. 2019; Seminar et al. 2019; Dutta et al. 2020).

The validity test was firstly conducted by examining whether ICT categories expanded mainly had the most significant impact on household income from the main vegetable in log natural (Y_{ipv}/ as one vegetable commodity indicated by the most important proportion of total household income). Multiple dummy regression model of the ICT category was proved using the OLS method as

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Equation 1 following Majumdar & Singh (Majumdar et al. 2019). Five dummies are considered for measuring the categories of ICT usage by farmers (based on six types of cell phones described above) to avoid the dummy trap.

$$Y_i = \alpha + \beta_1 D1_i + \beta_2 D2_i + \beta_3 D3_i + \beta_4 D4_i + \beta_5 D5_i + \varepsilon_i \quad (1)$$

The farmers who do not use mobile phones and smartphones at all would obtain the mean household income from the main vegetable in log natural (α). While the farmers using the type of ICT in a particular category would obtain a household income of α *and specific* β. $D1$ represents farmers who use ordinary mobile phones for phone calls and text messages, while $D5$ represents farmers who use smartphones with various applications. ε_i is *a* disturbance term.

After the categories of ICT_i had been determined as a primary variable, then this study used the econometric model called Multivariate Linear Regression (MLR) model to assess the heterogeneous factors affecting the likelihood of increasing household income of vegetable smallholders. The econometric model of this research augments the study conducted by (Aker and Ksoll 2015; Aker and Fafchamps 2015; Shimamoto et al. 2015), which identifies the impact of information and communication technology such as mobile and smartphones. The research used the estimator of the model through Ordinary Least Squares (OLS). It used stepwise regression Akaike's Information Criterion (AIC) method for selecting one of the best models from a data set (Cavanaugh et al. 2019).

Theoretically, using ICT Applications is more likely to increase the income of vegetable smallholders compared to non-users. It was assumed that an i^{th} farm household ($i = 1, 2, ..., N$) has cropped in its farm ($p = 1, 2, ..., P$) using ICT for farming (f) and for selling (s) activity and in the recent village ($v = 1, 2, \ldots, V$). Based on the theoretical and empirical study, the model is generally shown in Equation 2 and is further developed in Equation 3.

$$Y_{ipv} = \alpha + \eta ICT_i + X'_{ip}\beta + Z_v + \varepsilon_{ipv} \quad (2)$$

$ICT_i = T^*_i\ (1, 2, 3, \ldots, N)$, If $T^*_i \neq 0$ and $T_i = 0$, otherwise

$$Y_{ipv} = \alpha + \eta_f ICTf_i + \eta_s ICTs_i + \beta_1 HH_i + \beta_2 FARM_{ip} + \beta_3 SELL_{ip} + \beta_4 MSI_i + Z_v + \varepsilon_{ipv} \quad (3)$$

Y_{ipv} is a dependent variable representing the value of household income in log natural (Ln EUR) in terms of income from main vegetables, income from agriculture including main vegetables, and total household income. X_{ip} is the vector-explanatory variable as multivariate in this model, and Z_v is the village fixed effect. There is ICT_i as a main variable in this research covering the usage of ICT. It uses an ordinal scale (T_i) 0 for those who do not use it and otherwise (T^*i) who use ICT. Theoretically, the farmers using ICT ($ICTi$) are more likely to increase Y_{ipz} than non-users. The parameters to be estimated are α, η, and β. The error term is ε_{ipv} reflecting unobserved characteristics affecting the dependent variable.

An increase in income at the household level is influenced by multiple factors. The vector-explanatory variable (X'_{ipz}) and its effects on the dependent variable in Equation 2 are developed in Equation 3 by comprising the various characteristics of household (HH_i), farming ($FARM_{ip}$), marketing ($SELL_{ip}$), main source information (MSI_i), and fixed village characteristics (Z_v).

Following the primary survey, the data were analysed by simple statistics using XL-Stat of MS Excel. Quantitative data sets were then processed using the statistical tools of R- Studio. This model is consistent for interpreting parameters if the unobserved heterogeneities are uncorrelated with observed covariates and the error term. Many studies have applied this approach to capture correlations between observed covariates and heterogeneity using cross-sectional observations with multiple characteristics.

The tests used to verify the model's validity were the Breusch-Pagan, Breusch-Godfrey, and Anderson-Darling tests. Assumption violations can be overcome (check the robustness and correct selection bias) by heteroskedasticity and autocorrelation consistent (HAC) estimators (Zeileis 2004) and Instrumental Variable (IV) (Bascle 2008). In addition, the variable inflation factor (VIF) was also used.

Cross-section data would include characteristics potentially affecting the endogen variable, such as ICT categories (ICT_i), to explain instrumental variables for correcting selection bias and robustness

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achievement. Finally Multinominal logit model in Equation 4, ICT might be determined by the phone characteristic ($PHONE_i$) such as phone household possession, the type of primary phone, number of household members owning the phone, and signal strength, mobile or smartphone price, household holding the phone for agribusiness activity (for farming and for selling only). In addition, it might be determined by the farmer's capacity and perception of ICT ($SKILL_i$).

$$ICT_i = \alpha + \beta_1 PHONEi + \beta_2 SKILLi + \varepsilon_i \quad (4)$$

$ICT_i = T^*_i\ (1, 2, 3, 4, 5)$, If $T^*_i \neq 0$ and $T_i = 0$, otherwise

Covariate Variables Identification

The model used 72 covariate variables for Equation 3, which will be explained in the following. Household characteristics (HH_i) are education, literacy, age, gender, family size, experience, spouse status, and assets.

Farming characteristics ($FARM_{ip}$): Primary crop type, land size, rent status, soil fertility, and slope included in the analysis. Furthermore, storage facility, weather conditions, quality seed, pest and disease control, fertilizer application, labor, and livestock status are also included.

Marketing characteristics ($SELL_{ip}$): Access to markets, probability of selling at a farm-gate market, and to whom the farmers sell the harvest are essential variables. This study includes engaging with ICT for selling harvest. Furthermore, this study will observe how the farmers sell the harvest to the trader, whether in the village or directly in the market since the previous harvest, and whether the farmers follow price information.

The main source of information (MSI_i) using dummy variable: ICT use depends on access to information. Farmers receive information from various sources, including communications between farmers, agricultural-extension services/officers, social media, farmer's groups, training, and even traders.

This research also observes the village fixed effect (Z_v), such as distance to a local market, journey time to a local market, village population, location to the nearest center, road condition, and signal strength in the village. The fixed village level is included because households live in the same village. Therefore, village fixed effects may control non-parametrical estimation for any invariant observable and unobservable characteristics at the village level.

The Likert scale, ranged 0 to 5, is used to measure farmers' capacity and perception of ICT ($SKILL_i$) with the meaning of the lowest to highest score. The analysis of the interviews was based on the principles of qualitative content analysis and was mainly used to interpret the quantitative results (Krone et al. 2016). The characteristic of $SKILL_i$ comprises 18 attributes in terms of knowledge and ability to use ICT (ICT Literacy); three attributes of farmer's skill to sell by using ICT and bargaining toward trader; and fourteen attributes of farmer's perception about ICT and its usage.

Results and Discussion

Based on Equation 1, the multiple dummy regression model for the ICT - six categories have been built by using HAC estimators to correct standard errors in Table 1. Two dummies as basic variables, either for farming or selling, were insignificant such as mobile phones (D1) and smartphones (D2), respectively, for calling and texting. Those dummies were firstly combined into one dummy to be D1 as a corrected variable of cell phones, for only calling and texting. So, the five categories of ICT utilization among farmers are considered the main variable to determine vegetable-smallholder income in the following regression.

This study found technological developments adopted by farmers in terms of the use of ICT. When Majumdar and Singh (Majumdar et al. 2019) found that new ICT was only limited to ordinary mobile phones and internet use, farmers currently use smartphones. Even this research is one step ahead of the research in Indonesia conducted by Seminar & Sarwoprasodjo (Seminar et al. 2019) on the use of the Whatsapp application. Some farmers even use smartphones with various applications that can be downloaded, both social media and non-social media applications, such as applications that can increase their knowledge and skills in increasing agricultural productivity and e-commerce applications for selling agricultural products.

Table 1. Determination of log natural income of the main vegetable due to dummies of ICT category by using HAC estimators to correct standard error.

Dummy	Types of ICT used by farmers	for Farming ($ICTf_i$)			for Selling ($ICTs_i$)		
		Coeff.	t-value		Coeff.	t-value	
	Basic Variables						
Intercept	No cell phone usage	4.381	45.811	***	4.468	56.834	***
D1	Mobile phone for phone calls and text messages	0.157	0.959		0.232	1.317	
D2	Smartphones, but only for phone calls and text messages	0.273	1.66	*	0.144	1.086	
D3	Smartphone with WA apps	0.929	8.337	***	0.928	10.016	***
D4	Smartphone with various social media	1.487	13.799	***	1.525	15.789	***
D5	Smartphone with full apps	1.961	14.762	***	1.915	16.692	***
	Corrected Variables						
Intercept	No cell phone usage	4.381	45.85	***	4.468	56.895	***
D1	Cell phone for only calling & texting	0.215	1.601		0.172	1.454	
D2	Smartphone with WA apps	0.929	8.344	***	0.928	10.027	***
D3	Smartphone with various social media	1.487	13.811	***	1.525	15.806	***
D4	Smartphone with full apps	1.961	14.775	***	1.915	16.71	***
	Multiple R-square	0.505			0.554		
	F-Stat	94.373	***		114.973	***	

***, **, * are significant at 1%, 5%, and 10%, respectively. Source: own processing.

The following graph will display the proportion of farmers using ICT based on the type of use (Figure 1). Most farmers in this research location have used smartphones with social media applications for farming activities (67.8%) and selling (62.9%). In this study, farmers were divided into two categories in using social media: farmers who only used Whatsapp apps and those who used various social media applications on their smartphones.

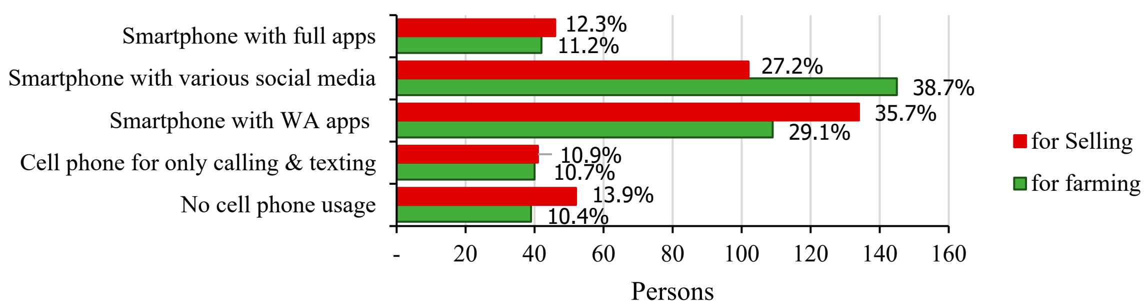

Figure 1. Type of ICT usage by farmers for farming and selling activity. Source: own processing.

This study divided household income into three types: from main vegetable, from agriculture including main vegetable, and total household income representing the value of household income per month following previous studies (Ma et al. 2018).

This study found (Table 2) that vegetable households in Indonesia earned an average income from main vegetables, agriculture, and a total income of EUR 329.4, 424.6, and 430.4 per month, respectively. In addition, the minimum income is EUR 16.4, 16.4, and 34.4 per month, respectively.

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Meanwhile, the maximum income is EUR 2 130.2, 2 178.2, and 2 562.0 per month. The range is very large, possibly due to differences in the use of ICT types and other factors such as dissimilar capabilities of farmers or types of agriculture (Krone et al. 2016).

Most vegetable smallholders in Indonesia had an income of EUR 159.9 – 287.9 per month from main vegetables, 287.9 – 479.8 per month from agriculture, and 319.9 – 511.8 per month from total income (Table 2). The range does not distinguish which farmers use a particular type of ICT. Whereas in Table 1, the average income of vegetable farming households can be seen based on the type of ICT usage by following Equation 1 and by adding the basic calculation (intercept), then inverse exponentially shown in Table 3.

Household income was getting bigger, marked by the higher level of the type of ICT usage, aligned with previous research (Aker and Ksoll 2015; Ma et al. 2018), from no cell phone usage to smartphones with full apps (Table 3).

Households earn the average main vegetable income if farmers do not use a phone at all for farming and selling in the amount of EUR 79.9 and 87.2 per month, respectively. Otherwise, households earn it if farmers use smartphones supported by full apps for farming and for selling EUR 567.9 and 591.7 per month, respectively.

Table 2. Simple descriptive statistics of household income (N=375 persons).

Income (EUR)	Main vegetable		Agriculture		Total income	
	Range	Freq.	Range	Freq.	Range	Freq.
	< 95.96	48	< 159.93	54	< 191.91	57
	95.96 - 159.93	66	159.93 - 287.87	89	191.91 - 319.86	80
	159.94 - 287.87	107	287.88 - 479.79	120	319.87 - 511.77	121
	287.88 - 479.79	82	479.79 - 735.67	63	511.78 - 767.66	64
	> 479.70	72	> 735.67	49	> 767.66	53
Minimum	16.36		16.36		38.38	
Mean	329.40		424.61		480.36	
SD	298.67		319.83		346.48	
Maximum	2,130.25		2,178.22		2,562.05	

Source: own processing.

Table 3. Household income of the main vegetable based on the type of ICT usage by farmers for farming and selling activity.

Scale	Type of ICT usage	Household income (EUR) by using ICT			
		for Farming ($ICTf_i$)		for Selling ($ICTs_i$)	
		Freq	Mean	Freq	Mean
0	No cell phone usage	39	79.92	52	87.18
1	Cell phone for only calling & texting	40	99.09	41	103.54
2	Smartphone with WA apps	109	202.35	134	220.52
3	Smartphone with various social media	145	353.54	102	400.61
4	Smartphone with full apps	42	567.93	46	591.70
	Total household farmers	375		375	

Source: own processing.

Our findings detail the stages farmers use ICT to increase their income. Ma et al. (2018) have conducted a study and found that the use of smartphones has boosted farmers' income by 14%, while this study found in Indonesia that it can increase doubles if farmers who previously used cell phones for only calling and texting adopt smartphones with WA apps both for farming and selling or even their income can be more than 500% if they eagerly adopt a smartphone with full apps.

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Impact of ICT and Other Covariates on Household Income

This study collects many variables that can affect income from previous studies. This study found that the variable using ICT usage as the main variable, the characteristics of household, marketing, and geographical characteristics, as well as the main source information of agriculture significantly ($P < 0.01$), affects farmers' income, both farmers' income from main vegetable, agriculture, and total income with multiple R-square 70.5, 72.0, 73.7% and F statistics of 28.48, 30.66, and 33.34, respectively as shown in Table 4. In addition, all variables that affect household income do not have multicollinearity with a VIF value of less than 10.

Our finding showed that type of ICT usage comprises farming and selling activity. Both significantly ($P < 0.01$) affect household income derived from main vegetables, agricultures, and total income shown in Table 4. Farmers can gain their incremental income from main agriculture (ceteris paribus) for EUR 8.2 from the farming activity and EUR 8.9 from selling activity if farmers can increase each level of using ICT.

Table 4. Linear multivariate regression of vegetable-farmers income in log natural by using HAC estimators to correct standard error.

Variable	VIF	Household income from								
		Main vegetable			Agricultures			Total income		
Household income base (intercept) (Ln. EUR)		3.365	***	(10.94)	3.803	***	(13.19)	3.991	***	(15.53)
ICT usage										
Type of ICT usage by farmers (Scale 0-4, based on Table 3):										
• for farming activities	4.64	0.249	***	(5.94)	0.201	***	(6.36)	0.182	***	(5.59)
• for selling activities	4.42	0.269	***	(6.58)	0.241	***	(7.07)	0.208	***	(6.32)
Household characteristics										
Age of household head (years)	1.92	-0.006		(-1.57)	-0.005		(-1.35)	-0.003		(-0.91)
Education of male adult as household head (years)	1.45	-0.013	*	(-1.79)	-0.014	***	(-2.62)	-0.013	**	(-2.44)
Farming experience of female adult as spouse of household head (years)	1.61	0.008	**	(2.56)	0.006	**	(2.13)	0.002		(0.68)
Asset for farm production (Ln. EUR)	1.44	0.028	*	(1.93)	0.026	**	(2.17)	0.034	***	(3.12)
Number of household member owning phone (persons)	1.45	-0.041	*	(-1.78)	-0.026		(-1.29)	-0.014		(-0.78)
Household owning phone used for farming only (unit)	1.81	0.025		(0.24)	-0.026		(-0.27)	-0.029		(-0.37)
The highest price of a cellphone owned by a household member (Ln. EUR)	1.80	-0.021		(-0.61)	0.001		(0.04)	0.027		(1.00)
Livestock is a source of household income (dummy)	1.12	0.089		(1.52)	0.122	**	(2.45)	0.085	*	(1.92)
Income from non-agriculture (dummy)	1.21	-0.064		(-1.18)	-0.046		(-1.00)	0.256	***	(6.01)
Farming characteristics										
Type of the main vegetable (Ordinal scale, lowest value: vegetables commonly grown by farmers, otherwise the highest value)	1.28	0.009	**	(2.31)	0.008	***	(2.98)	0.008	***	(3.15)
Total arable land for farming (ha)	1.77	0.064		(1.07)	0.131	**	(2.53)	0.128	**	(2.41)
Land used for farming the main vegetable (ha)	1.59	0.18		(1.15)	0.100		(0.93)	0.089		(0.83)
Best time for planting, similar with the cropping time of the main vegetable (in month)	1.09	0.081		(1.55)	0.082	*	(1.91)	0.049		(1.24)

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Intercropping (dummy)	1.27	-0.238	***	(-4.18)	-0.069		(-1.31)	-0.066		(-1.35)
Hydroponic system in the main vegetable (dummy)	1.10	0.346	**	(2.42)	0.258	**	(2.34)	0.099		(0.98)
Land (plot) slope (percent)	1.18	0.072		(1.62)	0.063		(1.53)	0.058		(1.51)
Weather (rainy) condition (dummy, 0 = lack or excess; 1 = sufficient)	1.14	-0.117	*	(-1.84)	-0.111	**	(-2.25)	-0.091	**	(-1.98)
Family labor man-days per ha (man-days)	1.27	0.001		(1.28)	0.001	**	(2.01)	0.001		(1.59)
The main vegetable harvest period (days)	1.45	0.078	***	(4.83)	0.062	***	(3.97)	0.058	***	(4.29)
Marketing characteristics										
Sell harvest to whom/ primary marketing channel (ordinal, lowest value: longest chain; highest value: shortest distribution chain)	1.42	0.045	**	(2.31)	0.021		(1.36)	0.014		(0.98)
Ability to sell harvest using various applications of non-social media (Likert scale, 0=never; 5=always)	1.77	0.033	**	(1.97)	0.042	***	(2.85)	0.046	***	(3.33)
Ability to sell harvest toward more than one trader (Likert scale, 0=never; 5=always)	1.25	0.017		(0.88)	0.039	**	(2.2)	0.018		(1.19)
Main source information of agriculture										
Household member (dummy)	1.16	-0.077		(-1.15)	-0.075		(-1.32)	-0.085	*	(-1.68)
Agricultural extension officer (dummy)	1.33	0.231	***	(3.49)	0.171	***	(2.78)	0.152	***	(2.77)
Training (dummy)	1.31	0.088		(1.50)	0.085		(1.58)	0.05		(1.04)
Geographical characteristics										
Journey time from field to local market (minutes)	1.10	-0.017	**	(-2.00)	0.004		(0.38)	-0.002		(-0.28)
The level of population density in the village (1=seldom; 2=dense; 3=moderate)	1.13	0.115	**	(2.31)	0.116	***	(2.79)	0.053		(1.44)
AIC		-539.400			-424.530			-424.530		
Multiple R-square		0.705			0.720			0.737		
F-Stat		28.48***			30.66***			33.34***		

***, **, * are significant at 1%, 5%, and 10%, respectively; the t-value is enclosed in parentheses. Source: own processing.

Some variables in household characteristics significantly affect household income from main vegetables, namely the education of a male adult as household head; farming experience of a female adult as a household head's spouse; household assets for farm production; and the number of household members owning phones. Meanwhile, the farming experience of a female adult as the household head's spouse is the most significant. However, the education of a male adult as household head; household assets for farm production; income from non-agriculture, and livestock as a source of household income can significantly generate total household income.

This study found that educating an adult male as the head of the household harms agricultural household income and total income. Meanwhile, the farming experience of adult women as spouses of household heads is the opposite. Lately, some of the younger generations have been interested in farming vegetables. They are more educated than other farmers but have little experience farming vegetables. In contrast, as a spouse of household heads with longer experience, female adults have found ways to earn higher incomes for their households.

The number of household members (people) who have a phone and the presence of a phone in the household used only for farming (units) does not significantly affect income from agriculture and total income but significantly affects income from main vegetables. The fact is in line with previous studies, which revealed that farmers were more likely to use ICT as a search tool and mobile phone ownership was not directly correlated with changes in main income (Aker and Fafchamps 2015; Shimamoto et al. 2015; Magesa et al. 2020).

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This study found several variables from farming characteristics that significantly affected household income. The type of the main vegetable has a more pronounced effect on total household income. In contrast, types of vegetables that are rarely grown at the farm level can have an impact on increasing income, such as wan soy (coriander leaves), lettuce head, mizuna (Japanese mustard), Japanese green pepper, baby beans, edamame, honey pumpkin, zucchini, kabocha (Japanese pumpkin), and baby cucumber. These are indicated to have a higher price than the types of vegetables generally grown by farmers, so they have the potential to provide higher household income (Mariyono et al. 2020).

Total arable land used for various farming (ha) significantly (P < 0.01) affects income from agriculture and total income. However, land used for farming the main vegetable is insignificant for any household income. Farmers who use the intercropping system have lower incomes. They implement this system to avoid the risk of crop failure due to limited funds (Salam et al. 2020). In addition, some farmers had higher assets by implementing a hydroponic system in the main vegetable and other agriculture to achieve higher income.

Rainy weather conditions significantly affect (P < 0.05) in reverse. Most farmers usually plant in conditions of sufficient rainfall. Vegetable productivity will be optimal, then there will be a big harvest in the aggregate, but prices will fall so that household income will decrease. In addition, farmers' income increases significantly (P < 0.01 for each income) if they plant crops with a longer harvest duration, such as chili peppers which can last up to 12 months (Sahara et al. 2015).

Three marketing characteristics affect household income significantly, such as selling harvest to a marketing channel, farmers' ability to sell harvest using various applications of non-social media (e-commerce), and farmers' ability to sell the harvest to more than one trader. The farmers will increase household income from the main vegetable if they sell through a shorter distribution chain. For example, a farmer selling their harvest to consumers through e-commerce will earn a much higher household income than farmers who sell their crops through intermediaries in the village, in line with a previous study (Courtois et al. 2015; et al. 2015). Farmers also get a higher income if they are used to selling harvests using various applications of non-social media (e-commerce) and selling harvests toward more than one trader, in line with a previous study.

Farming households that receive information about agriculture from agricultural extension officers will have the opportunity to increase their income significantly (P < 0.01) from main vegetables, agriculture, and total household income. However, household members and training cannot help farmers to improve their skills and indirectly increase income from agriculture.

This research confirms that farmers with close access to markets characterized by a relatively short journey from the field to the local assembly market will earn less household income from main agriculture. Access to local assembly markets provides greater opportunities for farmers to sell their crops to intermediaries in the village. The result aligned with a previous study (Courtois et al. 2015). The location to the nearest district center or urban also indicates the same thing. It is different regarding the level of population density in the village. Moderate population density provides opportunities for farmers to increase their income from agriculture.

Factors Affecting the Use of ICT as an Instrumental Variable

This study distinguishes ICT for farming and selling to find out more about using each ICT for household income. The use of ICT is endogenous in the household income regression above, so applying the instrumental variable (IV) method to correct self-selection bias is necessary. IV Regression on ICT usage for farming and selling activities is shown in Table 5.

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Table 5. IV regression results of ICT usage for farming activities by using HAC estimators to correct standard error.

Variable	Estimate (t value)	
	For farming	For selling
Phone characteristics		
Using cell phones to support selling activities (dummy)		0.522 (2.265) *
Using cell phones equipped with applications to support farming/ selling activities (dummy)	0.305 (2.306) *	0.567 (3.552) ***
One's engagement in ICT usage for farming/ selling activities (Likert scale, 0=farmers do not use ICT at all, 1=do not use ICT but with someone's help, 2=use it with help, 3=use it independently)	0.189 (3.417) ***	0.053 (0.748)
Type of cell phone owned to support farming/ selling activities (0=no phone; 1=ordinary mobile phone; 2=mobile phone connected internet; 3=laptop connected internet; 4=smartphone)	0.153 (3.922) ***	0.074 (2.001) *
Obtaining agricultural information from non-social media applications (dummy)	0.387 (4.227) ***	0.279 (2.867) **
Obtaining agricultural information from social media applications (dummy)	0.437 (2.383) *	
Farmers' skill and perception		
This era, cell phones cannot be separated from the internet (dummy)	0.053 (0.411)	
Activating internet via wi-fi or data plan (dummy)		0.039 (0.318)
Selling crops using social media applications (Likert scale, 0=never; 5=always)		0.129 (3.484) ***
Selling crops using non-social media applications (Likert scale, 0=never; 5=always)		0.185 (7.301) ***
Modifying or editing files, data, images, photos, or videos on the phone (dummy)		0.227 (2.499) *
Adding layout or graphics design using a cell phone (dummy)	0.204 (1.996) *	
Operating a cell phone or smartphone (Likert scale, 0=very difficult; 5=very easy)	0.023 (0.556)	
Cell phones can improve communication with output traders (Likert scale, 0=very unreliable; 5=very reliable)		0.047 (1.319)
Mobile phone prices (Likert scale, 0=very cheap; 5=very expensive)		-0.034 (-1.042)
Multiple R-square	0.682	0.748
F-Stat	78.02***	89.56***

***, **, * are significant at 1%, 5%, and 10%, respectively; the t-value is enclosed in parentheses. Source: own processing.

There are 10 of the 42 variables selected using Akaike's Information Criterion (AIC) method using R Studio. Among them, seven variables significantly affect the type of ICT usage for farming, with a multiple R-square of 0.6819 and a very significant F-stat of 78.02 ($P < 0.01$), as shown in Table 5. Furthermore, there are 12 of 52 variables selected using the AIC method. Among them, seven variables significantly influence the type of ICT usage for selling activities, with a multiple R-square of 0.6819 and an F-stat of 78.02 ($P < 0.01$), as shown in Table 5.

One's involvement with farmers in using ICT for farming activities significantly determines the type of ICT use. Farmers who are assisted in using ICT, moreover, can use it independently, tend to use ICT with a higher type, namely smartphones with applications such as WA, social media, or even various non-social media applications. In addition, ownership of ICT types such as internet-connected smartphones strengthens the use of higher types of ICT. In contrast to selling activities, one's engagement towards the farmer in ICT usage is insignificant. At the same time, ownership of

ICT types is less significant. Furthermore, farmers' skills in selling their harvest using social media applications or non-social media applications positively affect the type of ICT use ($P < 0.01$).

Conclusion

From the results, we have drawn the following conclusion. It is concluded that the farmers can be divided into five categories in terms of the type of ICT utilization, such as (1) farmers who do not use mobile phones and smartphones at all, (2) farmers using cell phones for only calling & texting, (3) farmers using Whatsapp application in smartphone, (4) farmers using various social media in the smartphone, and (5) farmers using complete applications for smartphones for social media and other widely used purposes. The five categories of ICT utilization among farmers have enormous potential in the main variable to determine vegetable-smallholder income.

These categories are also crucial for the government to make policies to increase income in agricultural households. The government can organize training on the use of ICT for farmers. Training is carried out selectively based on the skill of farmers. For example, farmers who use their smartphones only for calling and texting can increase their skills by using smartphones with the WhatsApp application and other applications to increase yield productivity or sell prices. In this way, farmers can increase their household income from vegetables or other commodities. In addition, agricultural extension officers are also essential to be involved in the training or as the main source of information for farmers and are also crucial as parties involved in assisting farmers use ICT.

Finally, this novel study shows that the five categories of ICT utilization for farming and selling positively impact household income derived from the main vegetables, agriculture, and total income. Nonetheless, there are different covariates other than five categories of ICT to increase household income from main vegetable, agriculture, or total income. It depends on which farmer will focus on income growth. If the proportion of main vegetables is very dominant to total income, then the household income derived from the main vegetable model should be used, but conversely, if the proportion of income from off-farm is relatively large, then the household income derived from the total income model should be used.

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