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Offline and hungry: the effect of internet use on the food insecurity of Indonesian agricultural households

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Abstract

Food insecurity is essential since its prevalence may hinder an individual or an economy from developing. The issue still lacks attention in Indonesia, as reflected in the lagging efforts to reduce food insecurity. Meanwhile, several previous studies have found that increasing internet access may decrease food insecurity. Using a sample of 140,892 agricultural households from the National Socioeconomic Survey data, this study uses quantitative measures to evaluate the effects of internet use on the food insecurity of Indonesian agricultural households. The present study uses raw and Rasch scores to measure food insecurity, based on the Food Insecurity Experience Scale question items. To estimate the effect of internet use on food insecurity, this study uses the two-stage least square estimation with topography as the instrumental variable, which is important due to the existence of an endogeneity problem. The present research also evaluates the possible mediating effect between internet use and food insecurity through households' per capita income. Findings reveal that internet use negatively affects agricultural households' food insecurity. This study also demonstrates that internet use can lower food insecurity in agricultural households through the mediating effects of income. From these results, policy implications are as follows; prioritization of internet infrastructure in remote areas, dissemination of information to enhance the production of agricultural households, and efforts to increase internet use among agricultural households.

Keywords: Food insecurity, Indonesia, Internet, Two-stages least square

Introduction

Food is an essential aspect of human life. A condition when humans do not have sufficient access to safe and nutritious food to achieve average growth, development, and health is referred to as food insecurity (Food and Agriculture Organization (FAO) 2020). The condition may hinder an individual or a household's ability to develop in terms of education, health, and employment, limiting access to a decent income and ultimately leading to extreme poverty (FAO 2020). The FAO defined four aspects of food security; food availability, food accessibility, food utilization, and food stability. Respectively, these aspects are defined as the availability of sufficient food in quantity and quality through production or imports (including food assistance), the availability of access to adequate food resources for every individual, the ability to utilize food to obtain the nutrients needed for daily life, and the ability for each individual to access sufficient food at all times. If these conditions are not met, it can lead to food insecurity.

In Indonesia, the issue of household food insecurity still needs attention. The latest World Food Programme (2022) annual report stated that 4.85% of households throughout the country experience moderate to severe food insecurity, with a higher prevalence in women and girls at 13.48%. Data from the Central Statistics Agency of Indonesia (Badan Pusat Statistik, BPS) also show that the prevalence of insufficient food consumption in Indonesia reached 8.34% in 2020. This figure has increased compared to the previous year's 7.63%. Indonesia's hunger index, assessed through the Global Hunger Index (GHI), has decreased since 2006. However, the country ranked 70th out of 107 countries in 2020. Although the hunger index in Indonesia has a declining trend, its level is still higher than that of other Southeast Asian countries such as Thailand, Vietnam, Malaysia, and the Philippines. Thus, it is evident that Indonesia's attempts to decrease food insecurity are still lagging.

Previous studies have found that internet access decisively influences household welfare (Ma et al. 2019; Leng et al. 2020; Siaw et al. 2020), particularly food security (Jere and Maharaj 2017). Bowman et al. (2014) mention that technology, information, and communication, including cellular telephones, radio, TV, computers, and satellite systems, have positively contributed to achieving global food security. According to Adeniji (2010), internet technology can be a two-way communication tool. It is used to exchange product information between the government and farmers; and communicate between farmers and other farmers, leading to a potential reduction in food insecurity. Information and communication technology are also known to increase food security through access to information. Namubiru et al. (2018) show that households in Uganda that use technology, information, and communication to access agricultural and market information can improve their food security status.

Empirical studies focusing on the effect of internet access or use on food insecurity typically found a negative effect (Anser et al. 2021; Twumasi et al. 2021; Xue et al. 2021). The present literature still lacks discussions on Indonesia, as it concentrates on general welfare, particularly internet use's effect on household income (Ariansyah 2018; Rahayu and Riyanto 2020; Gurning and Khaliqi 2021). Therefore, there is a need for a study focusing on the impact of internet use on food insecurity in Indonesian agricultural households.

The present research differs from the previous ones regarding food insecurity measurement. The Food Insecurity Experience Scale (FIES) is a new global standard to compare the severity of food insecurity between countries (FAO, 2013). This study will measure food insecurity using a direct approach, in contrast to the measurements in the prior studies, which used indirect approaches, such as expenditure on calorie intake, food consumption, and food diversity (Adeyanju et al. 2023; Twumasi et al. 2021; Xue et al. 2021). The indirect approach to measuring food insecurity cannot be used to compare food insecurity between countries due to an indefinite method for classifying foods. Moreover, the indirect techniques have a high possibility of measurement errors, take a long time to measure since consumption patterns must be recorded in detail, and produce biased results due to inaccuracies in determining food items, groupings, portion sizes, and intake frequency (Fawole & Ozkan 2017). According to FAO, using FIES as a food insecurity measurement method has several advantages. It directly inquires individuals or households about food insecurity experiences, ease of use, and lowers costs compared to other methods. It can also describe the severity of food insecurity and provides basic information for policymakers.

From a methodological point of view, potential endogeneity problems may arise in examining the impact of internet use on food insecurity in agricultural households. Agricultural household decisions using the internet may be "self-selected" so that they are not randomly distributed (Twumasi et al. 2021; Xue et al. 2021). Households that desire to increase agricultural productivity will use the internet to obtain information on increasing household productivity and income. On the other hand, households may decide not to use the internet and choose a different method. Unobservable factors influence internet use decisions and are likely to affect food security, such as social networks, skills, or motivation (Xue et al. 2021). According to Crown (2014), these problems may cause selection bias and produce endogeneity problems. Therefore, this study will use the instrumental variable (IV) approach to ensure the results are robust to endogeneity.

The present study examines internet use's effect on food security. Furthermore, it will also determine whether income acts as a mediator for the role of internet use on food security. The research is expected to contribute to providing empirical evidence about food security for agricultural households. Addressing the measurement error and endogeneity issues, the present study will undertake the abovementioned measures, such as using FIES to measure food insecurity and employing the two-stage least square estimation with instrumental variables to estimate the effect of internet use on food insecurity.

Data and methodology

Variable measurement and data source description

The data used in this study is mainly sourced from the 2021 National Socio-Economic Survey (Statistics Indonesia 2021a). The present study also uses topographic data in a village area obtained from the 2021 Village Potential Data Collection (Statistics Indonesia 2021b). This study included 140,892 agricultural households as samples from those datasets.

The study uses the Food Insecurity Experience Scale (FIES) to measure food insecurity. FIES includes worry experiences from mild to severe over a while. This scale is constructed from questions about food insecurity experienced by households from Susenas 2021 questionnaire. The first question describes concerns about not having enough food. The second question concerns changes in the quality of healthy and nutritious food. The third question is about decreasing the type and diversity of food. The fourth question is about lowering the frequency of eating. The fifth question is about reducing food portions. The sixth question is about running out of food. The seventh question is about being hungry but unable to eat. Finally, the eighth question concerns not eating at all within a day. Responses to the FIES questions consisted of yes or no answers. Then, two approaches will be used to measure food insecurity; the raw and the Rasch scores. The Raw scores are obtained by adding the "yes" entries from the 8 FIES assessment questions. The higher the raw score, the higher the food insecurity experienced by the household. Meanwhile, the Rasch score is obtained using the Item Response Theory (IRT) method of the Rasch model. The measurement of these variables is adopted from the studies of Anwar & Nasrudin (2021) and Ronalia (2021), which is shown by Eq. (1).

$$Rasch_i = \sum \mathrm{W}_n\left(\theta_n, \delta_j\right).X_{nj} \tag{1}$$

In the equation, θ is a parameter that represents severity associated with the experience captured by different questions in the FIES assessment, subscript j means the number of FIES assessment questions, while δ is a parameter representing food insecurity experienced by household n. X_{nj} is a random variable representing the response of household n to question number j. The higher the Rasch score, the higher the food insecurity experienced by the household.

The primary explanatory variable in the current study is internet use. The internet use variable in this study is based on the National Socioeconomic Survey questionnaire question, "In the last 3 months, do you use the internet (including Facebook, Twitter, Youtube, Instagram, Whatsapp, etc.)?" with two possible responses, yes or no. The responses are then coded to a dichotomous variable equal to 1 if the household uses the internet and 0 if it does not. Households that use the internet, even though they cannot open and close (log in and log out) the internet, are categorized as internet-using households. It also classifies households that are not only using the internet to obtain information but also to communicate using social media as internet-using households. The internet-using households may connect through mobile or Wi-Fi from smartphones, computers, or laptops.

The topography variable used in this study as an instrumental variable is obtained from Podes 2021 and measured based on the village's most significant topography characteristics. It is later classified as a binary variable with a value of 1 if households live in non-plain topography (hilly or mountainous areas) and 0 if they live in plain topography areas. Plain topography areas are flat parts or sides of the land that stretches over most of the village area, while non-plain topography areas are attributed if most of the village areas consist of slopes, peaks, or valleys. The slope or peak means that most of the village area is part of the mountain or high, located between the peak and the valley. Slopes include ridges and peaks (the very top of the mountain). Valley is defined as a low area between two mountains or an area with a lower position than the surrounding area. Table 1 provides the definitions and sources of the variables used in this study.

Two-stages least square model

Research on the impact of internet use on household food insecurity may have a potential endogeneity problem. In some households, using the internet is a "self-selected" process, so it is not randomly distributed (Twumasi et al. 2021; Xue et al. 2021). A household's decision to use the internet can be made consciously. Hence the internet use variable is not exogenous. Many factors influence observable and non-observable factors, such as social networks, abilities, and motivation to use the internet, which may also correlate with outcome variables (Xue et al. 2021). These individual-specific

Table 1 Definition and source of variables

Variables	Description	Source
Raw score	Raw score of household food insecurity	Statistics Indonesia 2021a
Rasch score	Rasch score of household food insecurity	Statistics Indonesia 2021a
Internet use	Whether household utilizes internet (0 = no, 1 = yes)	Statistics Indonesia 2021a
Gender	Whether household head is a male (0 = no, 1 = yes)	Statistics Indonesia 2021a
Age	Household head age	Statistics Indonesia 2021a
Education	Whether the household head finished elementary school (0 = no, 1 = yes)	Statistics Indonesia 2021a
Elders	Whether the household has a member above 60 years (0 = no, 1 = yes)	Statistics Indonesia 2021a
Credit	Whether the household has credit (0 = no, 1 = yes)	Statistics Indonesia 2021a
Cooperation	Whether the household has member cooperation (0 = no, 1 = yes)	Statistics Indonesia 2021a
Household size	Total family size	Statistics Indonesia 2021a
Urban	Whether the household resides in the city (0 = no, 1 = yes)	Statistics Indonesia 2021a
Land ownership	Whether the household owns land (0 = no, 1 = yes)	Statistics Indonesia 2021a
Dummy Java	Whether the household resides in Java (0 = no, 1 = yes)	Statistics Indonesia 2021a
Dummy sumatera	Whether the household resides in Sumatera (0 = no, 1 = yes)	Statistics Indonesia 2021a
Dummy Kalimantan	Whether the household resides in Kalimantan (0 = no, 1 = yes)	Statistics Indonesia 2021a
Dummy Sulawesi	Whether the household resides in Sulawesi (0 = no, 1 = yes)	Statistics Indonesia 2021a
Dummy Bali and Nusa Tenggara	Whether the household resides in Bali and Nusa Tenggara (0 = no, 1 = yes)	Statistics Indonesia 2021a
Dummy Maluku and Papua	Whether the household resides in Maluku or Papua (0 = no, 1 = yes)	Statistics Indonesia 2021a
Topography	Whether topography is plain or hill (0 = plain, 1 = hill)	Statistics Indonesia 2021b

unobservable factors can lead to selection bias and endogeneity problems (Crown 2014). Another source of endogeneity problems in research on internet use and food insecurity using FIES is measurement error since it is based on subjective answers from the respondent's memory.

Besides the measurement error, another problem to consider in formulating the model is the endogeneity problem. The endogeneity problem resulted in the assumption of no covariance for one variable in the model, and the error term was violated. This condition can result in biased (overestimated or underestimated) and inconsistent parameter estimates. When the assumption of $E(x|u) = 0$ is violated, the ordinary least square (OLS) estimation will produce an inconsistent estimate and cannot provide a causal interpretation (Cameron and Trivedi 2009). In the case of selection bias, endogeneity may harm the results by providing overestimates of the coefficients. One way to overcome this problem is to use the two-stage least square (2-SLS) model. This model requires an instrumental variable (IV), which is explicitly excluded from the second stage of the model and included in the first stage, and therefore correlated with some outcomes only through their effect on other variables (Angrist, 1996). A strong and valid IV has to significantly influence the outcome of the independent variable, while it does not correlate with the dependent variable.

Addressing the potential endogeneity, this study uses the 2-SLS model to identify the impact of internet use on food insecurity among agricultural households. Using 2-SLS is expected to overcome the endogeneity bias caused by individual-specific unobservable factors (Hong and Chang 2020). In the present research, the first stage of the 2-SLS model is estimated using a linear probability equation. The second stage of the model uses an equation that explains observed variation in household food insecurity using a vector of explanatory variables and the predicted value of internet use from the first stage. Referring to Hong and Chang (2020), the first stage is carried out to determine the internet use of agricultural households in Eq. (2).

$$internet_i = \alpha_0 + \alpha_1 Z_i + \alpha_2 X_i + \varepsilon_i \tag{2}$$

Agricultural households that use the internet (as the treatment group) may also have different characteristics from those that do not use the internet (as the control group). Therefore, several household characteristics were controlled to examine internet use's impact on food security. Furthermore, the second stage regression will estimate the effect of internet use on household food security using Eq. (3) as follows:

$$Y_i = \beta_o + \beta_1 \widehat{internet}_i + \beta_2 X_i + e_i \tag{3}$$

In Eqs. (2) and (3), i indicates the i-th agricultural household, Y_i indicates the outcome variable, namely the food insecurity of the i-th household, $internet_i$ is the internet use status coded 1 if the household i has an internet user and 0 has no internet user. $\widehat{internet}_i$ is the predicted value from the estimation result in the first stage, X_i is the control variable for internet use status and food security variable. X_i consists of the household head's gender, age, and education, the presence of elderly members, access to credit, cooperative membership, household size and location, and land ownership. ε_i and e_i denote random error terms. Z_i represents topography as the IV. The IV used must have a significant effect on internet use ($cov(Z, internet) \neq 0$), but IV also does not correlate with unobserved factors or errors that affect agricultural household food insecurity ($cov(Z, \varepsilon) = 0$). α and β indicate the parameters to be estimated. The parameters will be interpreted as the increase in the dependent variable's value per one growth unit in the independent variable's value.

The selection of topography as IV also refers to the research of Deng et al. (2019) and Olken (2009) that proved households in hilly or mountainous areas had a lower chance of using the internet than those in plain areas. In other words, topography had a negative effect on internet use. Several assumptions are emphasized in the selection of IV. The IV must be independent or exogenous. Topography is a natural formation, so the variable is estimated to be exogenous. However, this assumption cannot be tested as it is difficult to test using observational data. The relevance condition describes IV that influences endogenous variables. In this case, topography has a strong influence in determining household decisions to use the internet. Households in the mountains or non-plain areas will have less chance of internet use than households living on the plains. Deng et al. (2019) argued that this is related to the lack of infrastructure in mountainous or hilly areas (not plains), making it difficult for households to access internet signals. In addition, Olken's (2009) study on television and radio signals shows that the presence of mountains will affect the strength of the electromagnetic signal that will be received because mountains or areas that are not flat can prevent signals from being received by users compared to plain areas where signals can be received easily. Thus, the presence of an area that is not flat (slopes, peaks, or valleys) is negatively related to the probability of households using the internet.

The strength of the relationship between the instrumental variable and the treatment variable can be done by testing the weak instrument. The last is the assumption of exclusion restriction, namely, the instrument variable affects the outcome variable only through the treatment variable. This study's topography variables can affect household food insecurity only through internet use. In testing these assumptions, observational data is challenging, so this study uses weak instrument tests using The Kleibergen-Paap rk Wald F statistic and Tetrachoric correlation between topography and internet use variables. Topography variables such as IV may not be optimal in overcoming the endogeneity problem. Still, due to the limited data available, using topography as IV is the best alternative.

Furthermore, in the analysis of the transmission of the impact of internet use on food insecurity, income can be said to be a mediator variable if internet use has a significant effect on income and if income is included in Eq. (2), the coefficient of internet use (β_1) will decrease or become insignificant. The test of the validity of the mediator variable refers to the research of Acheampong (2021), which used the topography of the village (kelurahan/desa) as the instrument.

Result

Descriptive analysis

Prior to conducting an empirical analysis to assess the impact of internet use on food security in agricultural households, a preliminary data exploration was undertaken to obtain a comprehensive understanding of household characteristics. The classification of food insecurity refers to Maitra and Rao (2017). The classification of food insecurity

Table 2 Agricultural Households by Island and Food Insecurity Severity. *Source*: Processed Statistics Indonesia (2021a)

Island	Food Insecurity Status (Percentage)			
	high food security	**marginal food security**	**moderate food insecurity**	**severe food insecurity**
Java	95.26	3.18	0.98	0.58
Sumatera	92.20	5.40	1.44	0.96
Kalimantan	92.33	5.29	1.30	1.08
Sulawesi	90.52	6.31	1.89	1.28
Bali and Nusa Tenggara	79.87	14.05	4.49	1.59
Maluku and Papua	84.19	9.33	3.08	3.39
Total	90.57	6.27	1.86	1.30

status comprises 4 distinct categories: high food security ($0 \leq$ raw score < 3), marginal food security ($3 \leq$ raw score < 5), moderate food insecurity ($5 \leq$ raw score < 7), and severe food insecurity ($7 \leq$ raw score ≤ 8). The fluctuation in the food insecurity status of agricultural households by island is shown in Table 2. Severe food insecurity, the most frequent cases, occurs in the eastern region of Indonesia, namely Maluku, and Papua. Java exhibits the highest proportion of food-secure households in comparison to other islands. The disparities in food insecurity among regions can be attributed to factors such as low agricultural production efficiency and inadequate infrastructure (Samim et al. 2021).

Table 3 presents a summary of statistics for the variables utilized in this study. The average raw score is 0.6253, while a Rasch score is 0.0681. Higher raw and Rasch scores indicate that the household is experiencing increasingly severe food insecurity. From the sample of 140,892 agricultural households, about 66.45% of internet-using agricultural households and 89.74% of the heads of the households are male. The average age of the head of agricultural households ranges from 49 to 50 years old, indicating that the agricultural sector is less appealing to younger generations of people. Urban areas accommodate approximately 16.58% of these households, while the majority reside in rural areas. Access to credit is available to 17.76% of agricultural households, and 58.77% of households are members of cooperatives. The average household size ranges from 3 to 4 individuals. Notably, among the sampled agricultural households, the education level of the heads of households is predominantly limited to a maximum diploma equivalent to elementary school, accounting for 64.99% of cases.

Table 3 Summary statistics. *Source*: Processed Statistics Indonesia (2021a, b)

	count	mean	Sd	min	max
Outcome variable					
Raw Score	140,892	0.6253	1.3948	0	8
Rasch Score	140,892	0.0681	0.7007	− 0.3302	2.5089
Explanatory variable					
Internet use	140,892	0.6645	0.4722	0	1
Gender	140,892	0.8974	0.3035	0	1
Age	140,892	49.0480	12.9541	11	97
Education	140,892	0.3501	0.4770	0	1
Elders	140,892	0.2913	0.4544	0	1
Credit	140,892	0.1776	0.3822	0	1
Cooperation	140,892	0.5877	0.4923	0	1
Household size	140,892	3.8414	1.7259	1	22
Urban	140,892	0.1658	0.3719	0	1
Land ownership	140,892	0.8234	0.3813	0	1
Java	140,892	0.2205	0.4146	0	1
Sumatera	140,892	0.3178	0.4656	0	1
Kalimantan	140,892	0.0984	0.2978	0	1
Sulawesi	140,892	0.1517	0.3587	0	1
Bali and Nusa Tenggara	140,892	0.0857	0.2799	0	1
Maluku and Papua	140,892	0.1260	0.3318	0	1
Topography	140,892	0.4861	0.4998	0	1

Table 4 Internet users (internet = 1) and non-internet users (internet = 0) mean differences. *Source:* Processed Susenas & Podes 2021

Variable	Internet = 0		Internet = 1		*Mean differences*
	Mean	Std. Dev	Mean	Std. Dev	
Outcome variable					
Raw score	0.8024	1.6061	0.5359	1.2655	− 0.2665***
Rasch score	0.1524	0.7652	0.0256	0.6617	− 0.1268***
Explanatory variable					
Gender	0.8474	0.3596	0.9226	0.2672	0.0752***
Age	51.2848	14.5677	47.9186	11.8990	− 3.3662***
Education	0.2346	0.4237	0.4084	0.4915	0.1738***
Elders	0.3723	0.4834	0.2504	0.4333	− 0.1219***
Credit	0.0868	0.2816	0.2235	0.4166	0.1366***
Cooperation	0.3691	0.4826	0.6980	0.4591	0.3289***
Household size	3.9666	1.9317	4.0668	1.3740	0.1002***
Urban	0.1073	0.3094	0.1953	0.3965	0.0881***
Land ownership	0.7946	0.4040	0.8380	0.3685	0.0434***
Java	0.1939	0.3954	0.2339	0.4233	0.1079***
Sumatera	0.2461	0.4308	0.3540	0.4782	0.0373***
Kalimantan	0.0736	0.2612	0.1109	0.3140	0.0418***
Sulawesi	0.1239	0.3295	0.1657	0.3718	− 0.0185***
Bali and Nusa Tenggara	0.0980	0.2973	0.0795	0.2705	− 0.2083***
Maluku and Papua	0.2644	0.4410	0.0561	0.2301	0.1194***
Topography	0.4067	0.4912	0.5262	0.4993	− 0.2665***
Observations	47,270		93,622		140,892

(**p* < 0,001, ** *p* < 0.05, *** *p* < 0.01)

The averages of the variables used in this study, both internet and non-internet users, are shown in Table 4. When comparing the two subsamples, it is evident that the Rasch scores for non-internet users are higher and more statistically significant compared to those of internet users. This suggests that households not using the internet experience higher levels of food insecurity compared to internet-using agricultural households. Further findings also show that internet-using households are more educated, and the household head's age is older than in non-internet-using households. Most internet-using households also live in urban areas. Besides, the proportion of internet-using agricultural households that have access to credit and are members of cooperatives is more significant than that of non-internet-using households. There is also a more significant proportion of non-internet-using households in mountainous, slope, or hilly areas compared to other areas. This condition is an early indication that topography is negatively related to the chances of households using the internet.

Two-stages least square estimation results

Before conducting analysis using the IV model, Durbin-Wu-Hausman (DWH) test was conducted to determine whether the independent variable was exogenous or endogenous. The p-value generated from the DWH test for both the raw and the Rasch scores is smaller than the smallest significance level used (0.01). It rejects the null hypothesis that internet use is an exogenous variable (see Additional file 1: Appendix Table S1).

Table 5 Determinant of internet use and its Impact on agricultural household food insecurity. *Source*: Processed Susenas & Podes 2021

	(1) Internet	(2) Internet	(3) Raw Score	(4) Raw Score	(5) Rasch Score	(6) Rasch Score
Internet use			− 2.167***	− 1.714***	− 1.247***	− 1.201***
			(0.082)	(0.180)	(0.044)	(0.098)
Topography	− 0.107***	− 0.047***				
	(0.002)	(0.002)				
Gender		− 0.007*		− 0.256***		− 0.132***
		(0.004)		(0.015)		(0.008)
Age		− 0.002***		− 0.006***		− 0.004***
		(0.000)		(0.001)		(0.000)
Education		0.095***		0.004		0.022**
		(0.002)		(0.019)		(0.010)
Elders		− 0.083***		− 0.131***		− 0.095***
		(0.003)		(0.019)		(0.010)
Credit		0.057***		0.108***		0.076***
		(0.003)		(0.014)		(0.008)
Cooperation		0.177***		0.154***		0.137***
		(0.002)		(0.033)		(0.018)
Household size		0.083***		0.196***		0.126***
		(0.001)		(0.015)		(0.008)
Urban		0.070***		0.132***		0.083***
		(0.003)		(0.017)		(0.009)
Land ownership		0.034***		− 0.108***		− 0.040***
		(0.003)		(0.014)		(0.007)
Constant	0.719***	0.395***	2.065***	1.433***	0.897***	0.611***
	(0.002)	(0.007)	(0.056)	(0.074)	(0.029)	(0.040)
Island dummy	No	Yes	No	Yes	No	Yes
Observations	140,892	140,892	140,892	140,892	140,892	140,892

Robust standard errors in parentheses; *$p < 0{,}001$, ** $p < 0.05$, *** $p < 0.01$

Therefore, it can be concluded that the internet use variable is endogenous, so the IV model is more appropriate than the OLS method.

The next stage is to test the feasibility of the instrumental variable. The instrument variable used in this study is topography adapted from Olken (2009) and Deng et al. (2019). The mountainous, slope, or hilly topography of an area depicts the obstacles that are expected to be closely related to the availability of internet facilities so that it is related to household decisions in using the internet (Deng et al. 2019). Topography testing as a feasible instrument variable was carried out in various ways. In Table 5, columns (1) and (2) display the results of the first stage in the IV model, indicating a significant negative relationship between topography and internet use.

Furthermore, The Kleibergen-Paap rk Wald F statistic for both raw and Rasch scores are more significant than the entire Stock-Yogo weak ID test critical value of 16.38 (Stock and Yogo, 2005). Thus, the null hypothesis that IV is a weak instrument can be rejected. Referring to Maitra & Rao (2017), a Tetrachoric correlation was carried out between topography and internet usage to ensure that topography has a relationship with internet use. The results show that the 2-side exact p = 0.00 is smaller than all the significance levels used, which rejects the null hypothesis that the internet and topography are independent (see Additional file 1: Appendix Table S2).

The results in Table 5 show that the relationship between the instrumental variable and household decision to use the internet is negative and significant. This condition shows that the mountainous slope or hilly topography can reduce agricultural households' internet use probability. With a 99% confidence level, agricultural households living in non-hilly and mountainous areas are 0.107 points less likely to use the internet than those living in lowland areas assuming other variables are constant. These results align with the study of Deng et al. (2019), which states that hills and mountains negatively impact agricultural households' decisions to use the internet. Agricultural households in hills and mountains use the internet less frequently than those in flat topography. This tendency is related to inadequate internet-supporting infrastructure in mountain or hills areas (Deng et al. 2019). Furthermore, uneven topography can lead to suboptimal internet signal strength, which may discourage households from using the internet. The effect of education of the head of the household on internet use is positive and significant. This result shows that the higher the education of the head of the agricultural household, the greater the likelihood of using the internet compared to the household head with lower education. In other words, the higher the education of the head of the household, the higher the chances of the household using the internet. In this case, benefiting from internet use requires expertise and knowledge gained from education (Twumasi et al. 2021). Higher education can increase skills and a better understanding of utilizing the internet so that the possibility of using the internet also increases (Yang et al. 2021).

According to Yang et al. (2021), there are differences in internet use between urban and rural residential locations of households. Households living in rural areas use the internet less. Table 5, column (2) shows that agricultural households in urban areas are more likely to use the internet than those in rural areas. This result relates to the lack of infrastructure supporting internet access in rural areas (Yang et al. 2021). Access to financial facilities such as credit and cooperative membership also positively and significantly influences internet use. In other words, internet users tend to have more access to credit and cooperatives than non-internet users, which also follows the study conducted by Yang et al. (2021). The effect of gender of the household head on internet use is negative, meaning that female household heads are more likely to use the internet than male household heads. Other household characteristics, such as the number of household members, are also positively related to internet use, following the study of Hong & Chang (2020), which explains that the larger the number of household members, the greater the opportunity to use the internet. The internet can be used to obtain information and communicate with other household members (Hong & Chang 2020). Furthermore, households with land ownership tend to use the internet compared to those that do not own land.

The second stage results of the IV model estimation illustrate the influence of internet use on agricultural household food insecurity. In Table 5, columns (3) through (6) show the comparison of the estimation results using the IV model with or without control variables. This food insecurity indicator is measured using the raw and Rasch scores. Both measurements show that internet use can reduce agricultural households' food insecurity.

The results from Table 5, specifically columns (4) and (6), demonstrate a significant negative impact of internet use on food insecurity in agricultural households at a 1% level of significance. When households have access to the internet, it leads to a reduction of approximately 1.714 units in the raw score and 1.201 units in the Rasch score. The role of internet use in mitigating food insecurity in agricultural households is substantial, with a relative reduction of 2.741 compared to the average raw score of all observations, and a relative reduction of 17.636 in food insecurity according to the Rasch score relative to the average Rasch score of all observations.

The empirical evidence of previous studies that internet use can reduce food insecurity in agricultural households was further strengthened in this study. According to Twumasi et al. (2021), their study revealed that internet use has the potential to alleviate food insecurity in agricultural households in Ghana. Specifically, the research indicates that the internet can lower the access score related to food insecurity by 0.061 points (Twumasi et al. 2021). Similar findings were observed by Xue (2021) in a study focused on rural households in China, where internet use was found to positively influence household consumption of protein, fat, and daily energy nutrients. Internet users have several advantages compared to non-internet users, such as information about employment, marketing, and selling agricultural sector products or other benefits that lead to additional income, ultimately increasing food security (Twumasi et al. 2021). Besides Twumasi et al. (2021), the results of the present study also align with Namubiru's (2018) study. Namubiru's study revealed that utilizing ICT tools such as cellular phones, radios, and computers to access agricultural information and market data can significantly enhance food security in Uganda, with a notable increase of 33.4% in the likelihood of households being food secure. The internet plays a crucial role in facilitating communication among agricultural households and improving access to information regarding inputs, new techniques, and technologies.

In the digital era, the internet serves as a widespread platform for social interactions among individuals from diverse backgrounds, races, genders, and ages, facilitated by various applications such as Facebook, WhatsApp, WeChat, and others (Siaw et al. 2020). As reported by the Indonesia Internet Service Provider Association (APJII) in 2018, the primary motivations for internet usage include communication through messages (24.7%), engagement with social media (18.9%), and information search, particularly work-related information (11.5%). Utama and Waruwu (2019) found that internet users in Indonesia spend more than 2 h per day online. The internet is predominantly utilized to access sources of knowledge, such as media, for communication, information acquisition, data exchange, and online transactions. Notably, only a small fraction of Indonesian internet users engage in negative activities online, such as accessing adult content, engaging in violence, participating in online gambling, or committing cybercrimes (Utama and Waruwu 2019). Therefore, the use of the internet offers significant positive benefits for households. Also, the internet can ease access to information such as weather forecasts, prices for agricultural products, increase agricultural products, and reduce damage to agricultural products.

Households with a female head are more food insecure than male-headed households. Male household heads can reduce food insecurity's raw and Rasch scores by 0.256 and 0.132 units, respectively. This result is in line with Agidew & Singh (2018). Male household heads have a higher opportunity to earn income to better provide for household members' food needs (Twumasi et al. 2021). Traditionally, in some countries, men tend to be able to find higher-paying jobs than women (Ma et al. 2019).

Households with access to credit are expected to experience greater food insecurity compared to those without, indicating that indebted households may face an increased risk of food insecurity. These findings do not align with those of Twumasi et al. (2021). In this case, credit plays a beneficial role for households by enhancing agricultural production, maximizing profits, generating employment opportunities, and ultimately improving household incomes and food security. However, it has the opposite effect in the Indonesian context. The ease of access to credit can raise the likelihood of agricultural households experiencing food insecurity, as the obtained credit may be utilized for unproductive activities, rendering households unable to repay it. This outcome may also be attributed to high-interest rates and the inability to utilize the credit for its intended purpose. (Agidew and Singh 2018).

The size of the household, as another characteristic, can contribute to increased food insecurity among agricultural households. This suggests that as the number of household members increases, assuming other variables remain constant, food insecurity is more likely to occur. This finding can be attributed to a decrease in the ability to afford quality food due to higher expenses and the greater number of household members (Twumasi et al. 2021). Similarly, residing in urban areas can result in higher raw and Rasch food insecurity scores, with an increase of 0.132 units and 0.083 units, respectively. In contrast, a larger proportion of agricultural households are located in rural areas, indicating greater food access. According to Felker-Kantor & Wood (2012), the population in urban areas is also denser, and the soil conditions are less fertile, making urban areas 1.6 times more prone to food insecurity than rural areas.

On the contrary, land ownership may affect food insecurity negatively. Land ownership is often associated, in general, with a high degree of welfare. In particular, an agricultural household with land ownership may have better means of agricultural production, hence strengthening its food security.

The mediatory effect of income between internet use and food insecurity

This study also attempts to describe how internet use affects household food insecurity through the mediatory effect of household income. The analysis of the mediatory impact is carried out in 2 stages. First, the household income variable must be correlated with internet use. The first stage will be estimated using the LPM method (Hong and Chang 2020). Second, inserting the income variable into Eq. (2) as an additional explanatory variable should reduce the coefficient of internet use or even make the coefficient statistically insignificant (Acheampong, 2021). Due to the limited available data, the income variable will be proxied using household consumption expenditures. In the Indonesian case, income is generally underestimated because households tend to provide lower-income data than the actual consumption value.

Column (1) of Table 6 shows the result of the first stage estimation. Internet usage has a positive and significant effect on the per capita income of agricultural households. These results align with internet use's impact on reducing food insecurity in agricultural households through increasing household income. In Table 6, columns (3) and (5)

Table 6 Mediatory effect analysis using household income. *Source*: Processed Susenas & Podes 2021

	(1) Ln (Income per capita)	(2) Raw score	(3) Raw score	(4) Rasch score	(5) Rasch score
Internet use	0.260***	− 1.714***	− 1.671***	− 1.201***	− 1.186***
	(0.058)	(0.180)	(0.185)	(0.098)	(0.101)
Ln (income per capita)			− 0.164***		− 0.059***
			(0.025)		(0.014)
Constant	13.520***	1.433***	3.652***	0.611***	1.414***
	(0.024)	(0.074)	(0.281)	(0.040)	(0.152)
Household Head Characteristics	Yes	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes	Yes
Island dummy	Yes	Yes	Yes	Yes	Yes
K-P-F Statistic					
Observations	140,892	140,892	140,892	140,892	140,892

Robust standard errors in parentheses; *$p<0{,}001$, ** $p<0.05$, *** $p<0.01$

Table 7 Estimation Results of Internet Use on Food Insecurity Using 2-SLS and ETR. *Source*: Processed Susenas & Podes 2021

	Raw Score			*Rasch Score*		
	2-SLS	ETR	OLS	2-SLS	ETR	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Internet use	− 1.714***	− 0.176***	− 0.223***	− 1.201***	− 0.089***	− 0.114***
	(0.180)	(0.019)	(0.010)	(0.098)	(0.012)	(0.005)
Household head characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Island dummy	Yes	Yes	Yes	Yes	Yes	Yes
observations	140,892	140,892	140,892	140,892	140,892	140,892
Wald test (rho = 0)						
Chi2(1)		5,660.11			7,290.42	
Prob > chi2		0.00	0.00		0.00	0.00

Robust standard errors in parentheses; *$p<0{,}001$, ** $p<0.05$, *** $p<0.01$

show that the coefficient of internet use decreases after the income per capita variable is inserted into the model. Therefore, it can be inferred that income can explain the transmission of internet usage in reducing food insecurity in Indonesian agricultural households. The full results showing all the independent variables are in the Additional file 1: Appendix (Table S3 and S4).

Robustness test

A robustness test is employed in this section. Deng et al. (2019) argued that strategies could be used for robustness tests using an alternative econometric model. This study will use endogenous treatment regression (ETR) for the robustness test, which refers to Twumasi et al. (2021). The ETR model can directly estimate treatment variables' impact on outcome variables (Ma et al. 2019; Twumasi et al. 2021). The ETR estimation method is an alternative method in tackling the endogeneity problem in the form of selection bias by simultaneously estimating the equation using the probit model in the first stage. The ETR method will be employed using 2 stages. The first stage was to determine internet use by agricultural households as a dichotomy model.

Furthermore, household characteristics and other factors influencing internet use will be identified. The second stage will estimate the impact of internet use on household food insecurity. Later, the results from the ETR model will be compared with the primary econometric model used in the present study.

Table 7 shows that the 2-SLS and ETR approaches produce similar estimation results. Both results show that internet use has an impact on reducing food insecurity in agricultural households for both raw and Rasch scores. Despite considerable differences between the coefficients' magnitude, the ETR model confirms the negative effect of internet use on food insecurity.

Conclusion and policy implication

Based on the descriptive analysis, this study discovered evidence indicating variations in the level of food insecurity among internet-using and non-internet-using agricultural households in Indonesia. Using the IV model to overcome the endogeneity problem, the topography of the non-plain area is found to impact agricultural households' decisions to use the internet negatively. Furthermore, the present study's findings complement the existing ones in developing countries, which suggests a negative correlation between internet use and food insecurity in agricultural households. Therefore, it can be inferred that internet use has the potential to alleviate food insecurity in such households. Internet use may increase access to agricultural information, increase income, and reduce food insecurity. Other variables that can effectively reduce food insecurity in agricultural households encompass the gender and age of the household head, the presence of elderly members, and land ownership. Meanwhile, credit access, cooperative membership, household size, and location are other variables that increase food insecurity.

This study also provided evidence indicating that male household heads have a more significant influence in reducing household food insecurity compared to female household heads. The male household heads have discretion in finding work for greater income than the female ones. Further analysis reveals that the impact of internet use in reducing food insecurity is transmitted through the per capita income variable. The utilization of the internet has a positive effect on income by providing marketing and product sales information as well as more efficient production techniques to generate better incomes which in turn can reduce food insecurity.

The present study possesses several policy implications for enhancing food security. First, it discovered evidence that agricultural households in the mountainous topography use the internet less frequently than those in flat topography. Consequently, the government should focus more on investments related to internet infrastructure in remote hilly and mountainous areas, namely by supporting the provision of Base Transceiver Stations (BTS). It is essential to regard collaboration between local governments in providing land and the central government in providing subsidies for the private sector to build BTS. Second, the government must also supply information through the internet to enhance the productivity of agricultural households. This can be achieved by developing an online platform for buying and selling agricultural products, disseminating price and weather information, and providing agricultural technology guidance. Access to agricultural knowledge through the internet can significantly contribute to food security. Third, the government should prioritize efforts to increase internet use among agricultural households. Female household heads still need to improve internet use through increased digital literacy and education regarding internet use.

The present study utilizes cross-section data. Thus, the changes in household food insecurity cannot be determined between years. Also, the internet use variable was generally utilized to improve productivity without considering internet usage by purpose. Consequently, future research should be designed considering the usage of panel data and internet variables in detail based on internet use.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40100-023-00264-9.

Additional file 1. Table S1 Endogeneity testing. **Table S2** Tetrachhoric correlation analysis for testing the validity of instrumental variable. **Table S3** Impact of internet use and control variables on per capita income. **Table S4** Mediatory impact of per capita income on food insecurity of agricultural household.

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D.M.A. contributed to conceptualisation, investigation, data curation, methodology, and writing. D.H. was involved in conceptualisation, methodology, reviewing, and supervision. P.A.W. contributed to reviewing, writing, and editing. All authors read and approved the final manuscript.

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Availability of data and materials
The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Declarations

Competing of interests
The authors declare no competing of interests.

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