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*Original Article*

# Achieving Zero Hunger Goal in ASEAN-8: Impact of ICT on Prevalence of Undernourishment

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**Abstract:** The prevalence of undernourishment is a key indicator of the Sustainable Development Goal (SDG) "Zero Hunger." Despite some progress, undernourishment remains a major issue in the ASEAN region, with most countries recording rates above the targets set by the Food and Agriculture Organization (FAO). This study investigates the direct and indirect impacts of Information and Communication Technology (ICT) on the prevalence of undernourishment across eight ASEAN countries from 2015 to 2022. The analysis uses panel data regression with path analysis, applying the Chow test, Hausman test, and classical assumption test to determine the optimal model. The Sobel test is also employed to examine the significance of mediating variables. The results show that ICT directly reduces undernourishment and indirectly affects it through improvements in GDP per capita, education, and healthcare. These findings highlight the critical role of ICT in advancing sustainable development and addressing food insecurity. On the basis of the results, ASEAN countries are encouraged to promote ICT integration in key sectors, particularly education, health, and the economy. Strengthening digital infrastructure, implementing technology-based training programs, and enacting policies that support inclusive economic growth can enhance the impact of ICT on reducing undernourishment. By pursuing these strategies, ASEAN nations can accelerate digital transformation and move closer to achieving the "Zero Hunger" target. This study provides empirical evidence supporting the use of ICT as a strategic tool for improving food security and fostering long-term development across the region.

**Keywords:** Undernourishment; Information and Communication Technology (ICT); Sustainable Development Goals (SDGs); Food Security; ASEAN countries.



## 1. Introduction

One of the main goals of the Sustainable Development Goals (SDGs), currently a global issue, is to end hunger (zero hunger) by 2030. Zero hunger includes not only the direct elimination of hunger but also ensuring access to nutritious and sufficient food throughout the year for all people. According to a report by the Food and Agriculture Organization (2023), the prevalence of undernourishment remains a major

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challenge in Southeast Asia, especially amidst dynamic economic, social, and environmental changes. Figure 1 shows the prevalence of undernourishment in 8 ASEAN countries for over a decade. In the last three years, during the COVID-19 pandemic, the prevalence of undernourishment in several ASEAN countries has been increasing trend, such as Indonesia, Myanmar, the Philippines, and Timor Leste. In addition, 7 of them still have a prevalence rate of undernourishment above 5% which is still higher than the FAO target of below 2.5%.

Information and Communication Technology (ICT) is increasingly recognized as an important factor in supporting the success of zero hunger targets. ICT can potentially improve food supply chain systems, increase distribution efficiency, and strengthen access to market information and agricultural technology. In the ASEAN context, ICT development has shown a positive trend in the last decade. According to the report, the International Telecommunication Union (ITU, 2023), average internet penetration in the region has reached over 70%, with significant increases in developing countries such as Indonesia, Vietnam, and the Philippines. However, the direct impact of ICT on the prevalence of undernourishment is often influenced by various mediating factors. GDP per capita, education level, and public health status are three important dimensions that can mediate this relationship. GDP per capita reflects people's purchasing power, which can affect food accessibility. Education increases the capacity of individuals to understand the importance of nutrition and healthy diets. Meanwhile, health plays a role in determining food needs and consumption.

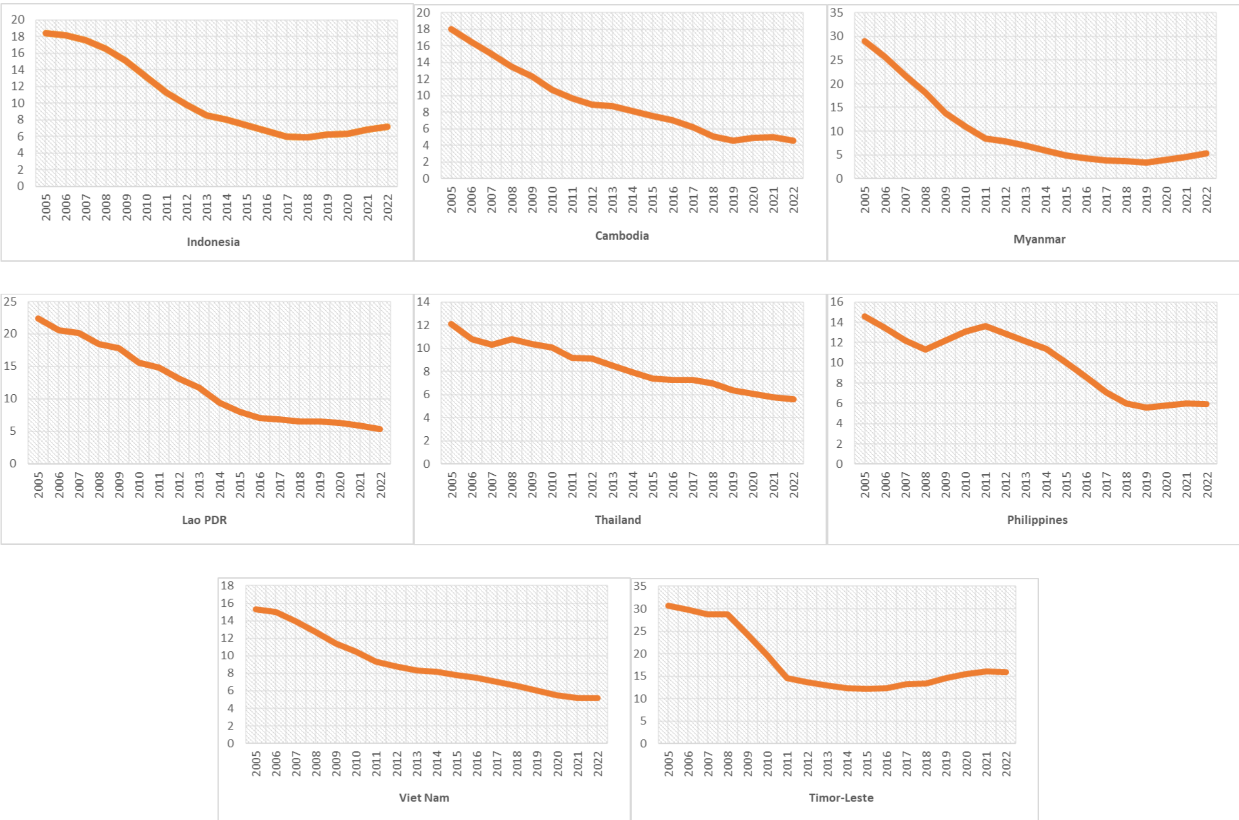


**Figure 1.** Prevalence of Undernourishment in ASEAN-8

Source: FAOSTAT (2022)

Previous study has shown a significant relationship between ICT and improved socio-economic welfare. For example, a study conducted by Wang et al. (2021) and Samadder & Rao (2023) found that ICT adoption contributes to improved socio-economic development. In addition, Samadder & Rao (2023) confirmed that ICT access can improve the agricultural sector's efficiency and expand market access for smallholder farmers. Another study by Sundram (2023) revealed that increased internet access could help rural households in Southeast Asia increase food consumption through access to market information and modern agricultural technology. Research conducted by Lechman & Popowska (2022) shows that improving digital infrastructure in developing countries can significantly reduce poverty and improve access to healthcare. In addition, Chen & Zhao (2021) and (Zulfa et al., 2023) identified that the digitization of the financial sector through mobile banking also has a positive impact on people's purchasing power capacity

Research exploring the indirect influence of ICT on the prevalence of undernourishment through intermediary factors such as GDP per capita, education, and health in the ASEAN Region is limited. This study aims to fill that gap and explain how ICT advancements can boost economic growth, improve educational outcomes, and strengthen health systems, thereby addressing the widespread problem of undernourishment. Through a comprehensive examination of these variables, this study contributes to the broader discourse on sustainable development and food security, providing insights into policy implications that can foster a healthier and more nutritious population in the ASEAN region, with the hope of making an empirical contribution towards achieving the zero-hunger target in the ASEAN Region.

## 2. Literature Review

### 2.1. Prevalence of Undernourishment

Prevalence of undernourishment is an indicator used to measure the proportion of the population with food consumption levels below the minimum energy requirements. According to the report of FAO (2023), this prevalence is one of the main challenges in achieving the zero hunger target in the SDGs. This indicator reflects food insufficiency due to various factors such as limited economic accessibility, unequal distribution, and low availability of quality food. Previous studies have shown that economic, social, and technological factors influence the Prevalence of undernourishment. Sundram (2023) and Hamdani et al. (2023) on their studies suggested that adopting agricultural technologies and digitizing food distribution could reduce this prevalence in rural areas. Smith & Haddad (2015) also emphasized the importance of a cross-sectoral approach, including the application of communication technologies in addressing undernourishment. These resources provide a more comprehensive perspective on related challenges and solutions, especially in countries that still have high prevalence rates, such as Timor-Leste, Indonesia, and the Philippines.

### 2.2. ICT and Prevalence of Undernourishment

ICT is beginning to be recognized as an essential tool in addressing the Prevalence of undernourishment. Research by Aker & Mbiti (2010) shows that using mobile phones in rural Africa helps farmers access market price information and technology, significantly reducing the risk of undernourishment. ICT can streamline food distribution, ensuring that nutritious food can reach underserved populations, especially in rural areas. Mobile technology can also connect farmers directly with consumers, reducing middlemen and increasing the availability of fresh produce (Bloem et al., 2013; Domguia et al., 2023). In addition, ICTs can facilitate better data collection on nutritional status, diet, and health outcomes that are critical for effective intervention programs. Better communication technologies can increase public awareness and education about nutrition, encouraging healthier dietary choices (Deurenberg & Siong, 2016). Research by Mbuya et al. (2019) confirmed that ICT platforms can disseminate information on healthy eating practices, encourage community discussions around nutrition, and promote collective action against malnutrition. Research by Anser et al. (2021) shows that ICT adoption can improve food security by up to 15%.

### 2.3. ICT and Economic Welfare

ICT is important in increasing GDP per capita by promoting economic growth through various mechanisms. The integration of ICT into the economy facilitates technology diffusion, improves decision-making, and lowers production costs, which ultimately leads to increased output and demand for goods and services (Das et al., 2016; Suriani & Ridzqi, 2019). ICT infrastructure development, such as mobile and internet access, has been shown to have a significant positive impact on GDP per capita, especially in developing regions (Shtewi & Almajdob, 2024; Qureshi & Najjar, 2015). Lechman & Popowska (2022) found that implementing digital technologies in developing countries directly increases productivity and creates employment opportunities that can increase GDP per capita. In addition, better communication technologies enable farmers to access markets more efficiently, increasing their income and purchasing power for nutritious food (Ruhyana & Essa, 2020; Suriani & Sartiyah, 2020).

### 2.4. ICT and Education

The integration of ICT into education can enhance the teaching and learning process, offering a wide array of benefits that meet various educational needs. By utilizing digital tools, educators can create an interactive environment that encourages engagement and inclusiveness, ultimately improving educational outcomes. ICT provides unprecedented access to a wealth of information through the internet. Mobile learning platforms facilitate education for diverse populations, including those in underserved areas, in order to promote educational equity (Anastasopoulou et al., 2024; Alrikabi et al., 2024). Research by Liabo et al. (2016) found that programs that embed technology in the classroom benefit socially disadvantaged students, helping to bridge the education gap. ICT through improved education plays a role in reducing undernourishment. By improving access to nutrition information and education, ICT can empower individuals and communities to make informed dietary choices, ultimately improving nutritional status (Domguia et al., 2023). Programs that utilize ICT in schools have effectively promoted healthy eating behaviors among adolescents, leading to better nutritional outcomes (Henriques et al., 2023; Melo, 2017). Research by Munawwaroh et al. (2022) and Seyyedi et al. (2020) found that apps and online resources can effectively disseminate nutrition knowledge, especially to mothers, which is critical for child nutrition. A smartphone-based education program significantly improved mothers' nutrition literacy, leading to better feeding practices and reduced child malnutrition.

### 2.5. ICT and Health

ICT contributes to improving the quality of health and extending life expectancy through expanding access to medical services, increasing public knowledge about health, and strengthening interactions between patients and medical personnel. ICT enables telemedicine, which allows patients to consult with healthcare professionals remotely, which is particularly beneficial in rural areas. Online platforms for making appointments and managing prescriptions simplify healthcare processes, reduce waiting times, and improve patient satisfaction (Allemann & Poli, 2020). The spread of ICT tools, such as mobile phones and the internet, has been associated with increased health literacy, leading to better health choices and behaviors. Educational programs delivered through ICT can target chronic conditions, promoting preventive measures and lifestyle changes that contribute to longer life expectancy (Lee et al., 2016). Investment in ICT is positively correlated with health indicators, including life expectancy, as seen in studies in Pakistan and the Middle East. Better ICT infrastructure supports economic growth, which in turn improves living standards and health outcomes (Ahmed & Almoree, 2024; Ronaghi, 2022; Sugiharjo et al., 2024).

ICT through health interventions can provide wider dissemination of information, optimize the quality of health services, and support data-driven decision-making, which drives significant improvements in nutrition. Digital platforms improve the skills and motivation of community health workers, ensuring better service delivery and utilization of health programs (Maitra et al., 2017). Research by Singh et al. (2023) and Lingala et al. (2020) found that digital health technologies can enhance data-driven interventions, improve access to healthcare resources, and facilitate community collaboration, thereby effectively addressing undernutrition. These strategies are fundamental in developing countries facing resource constraints, as highlighted in managing acute malnutrition.

## 3. Materials and Methods

This study aims to determine the role of ICT in reducing the prevalence of undernourishment in 8 ASEAN countries, they are Indonesia, Cambodia, Myanmar, Laos, Thailand, the Philippines, Vietnam, and Timor-Leste with a data period of 8 years (2015-2022), so there are 144 observations. Three other ASEAN countries, namely Singapore, Brunei Darussalam, and Malaysia, are not included in the research object because they already have a prevalence rate of undernourishment below the FAO target, below 2.5%. The operational definition of variables and data sources can be seen in Table 1.

**Table 1.** Summary of variable descriptions.

| Variable(s) | Code(s) | Indicators of measurement | Source(s) |
|---|---|---|---|
| Prevalence of undernourishment | POU | The proportion of population whose habitual food consumption is insufficient to provide the dietary energy levels required to maintain a normal, active, and healthy life. | Food and Agriculture Organization |
| Information and Communication of Technology | ICT | The proportion of the population with access to the internet. | World Development Indicator |
| The economic welfare of the community | GDP | Gross domestic product per capita at constant 2015 price in USD | World Development Indicator |
| Education | EDU | Mean years school | Human Development Report |
| Health | HLT | Life expectancy at birth in years | Human Development Report |

This study employs path analysis, incorporating mediating variables such as GDP per capita, education, and health, to assess whether these variables directly or indirectly influence the model's relationships. Path analysis utilizes multiple regression to examine the causal effects between the independent and dependent variables (Retherford & Choe, 1993). The Sobel test assesses the significance of mediating variables in path analysis. It evaluates whether the mediating variables significantly mediate the indirect relationship between the independent and dependent variables (Mackinnon, 2008). The research path analysis can be seen in Figure 2. All variables are transformed into natural logarithms to overcome violations of heteroscedasticity assumptions. There are three equations of the model. The equation model to determine the effect of ICT on the mediating variable is as follows:

$$\ln GDP_{it} = \alpha_0 + \alpha_1 \ln ICT_{it} + \varepsilon_{1it} \quad (1)$$
$$\ln EDU_{it} = \alpha_0 + \alpha_2 \ln ICT_{it} + \varepsilon_{2it} \quad (2)$$
$$\ln HLT_{it} = \alpha_0 + \alpha_3 \ln ICT_{it} + \varepsilon_{3it} \quad (3)$$

The equation model to determine the effect of each independent variable on the prevalence of undernourishment in (dependent variable) is as follows:

$$\ln POU_{it} = \beta_0 + \beta_1 \ln ICT_{it} + \beta_2 \ln GDP_{it} + \beta_3 \ln EDU_{it} + \beta_4 \ln HLT_{it} + \varepsilon_{4it} \quad (4)$$

Where POU is the prevalence of undernourishment, ICT is information, technology, and communication, GDP is GDP per capita, EDU is education, HLT is health, $\alpha_0$, $\beta_0$ are constants, $\alpha_i$, $\beta_i$ are regression coefficients and $\varepsilon_{it}$ is an error term.

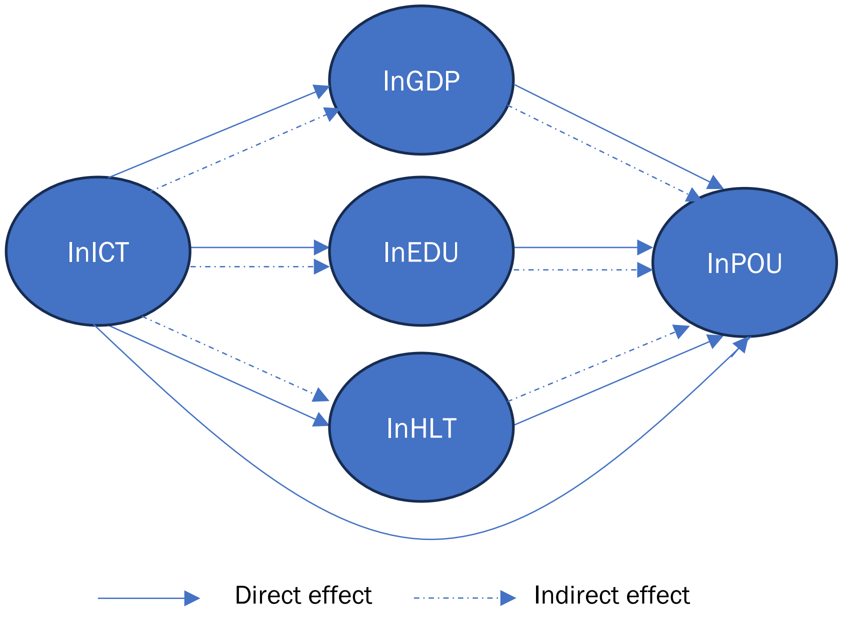


**Figure 2.** Research Path Analysis

The initial step in panel data regression is selecting the most appropriate model, which can be the Common Effect Model (CEM), Fixed Effect Model (FEM), or Random Effect Model (REM). This selection process begins with the Chow test to decide whether the model is CEM or FEM, where the null hypothesis represents CEM and the alternative hypothesis represents FEM. If REM is considered suitable, the Hausman test is conducted to determine whether FEM or REM is the preferred model, with the null hypothesis indicating FEM and the alternative hypothesis indicating REM.

## 4. Results and Discussion

The descriptive statistics presented in Table 2 illustrate the characteristics of the variables, including the mean, standard deviation, maximum value, and minimum value. Based on the data distribution characteristics, all variables have a small data distribution because the standard deviation value is below the mean and median values.

### 4.1. Model Selection

In Model 1, the Chow test results show a p-value of less than the 5% significance level ($0.0000 < 0.0500$), indicating that $H_0$ is rejected, and Ha is accepted. This concludes that the Fixed Effect Model (FEM) is the chosen model. Subsequently, the Hausman test also produces a p-value below the significance level, leading to the rejection of $H_0$, confirming that FEM is the preferred model. Since both tests consistently identify FEM as the best model, the Breusch-Pagan Lagrange Multiplier test is no longer necessary. Models 2, 3, and 4 also obtain the same result. The details of the test results can be seen in Table 3.

**Table 2.** Summary of variable descriptions

| | POU | ICT | GDP | EDU | HLT |
|---|---|---|---|---|---|
| Mean | 10.9743 | 26.9844 | 2411.9870 | 6.4961 | 69.4389 |
| Median | 9.3500 | 23.0106 | 2130.6210 | 6.6110 | 69.0275 |
| Maximum | 30.7000 | 87.9772 | 6453.8940 | 9.1460 | 79.6800 |
| Minimum | 3.4000 | 0.0652 | 518.9696 | 3.2440 | 56.5060 |
| Std. Dev. | 5.8325 | 22.7528 | 1473.7600 | 1.7946 | 4.4694 |
| Skewness | 1.3360 | 0.6651 | 1.0714 | -0.1579 | 0.1712 |
| Kurtosis | 4.7456 | 2.5136 | 3.4218 | 1.6260 | 2.7857 |
| Observations | 144 | 144 | 144 | 144 | 144 |

The descriptive statistics presented in the Table 2 summarize key characteristics of five variables across 144 observations: Prevalence of Undernourishment (POU), Information and Communication Technology access (ICT), Gross Domestic Product per capita (GDP), Education index (EDU), and Health index (HLT). The average (mean) value for POU is 10.97%, indicating that on average, around 11% of the population experiences undernourishment. ICT shows a mean penetration rate of approximately 27%, while the average GDP per capita is around USD 2,412. The average values for education and health indexes are 6.50 and 69.44, respectively. The median values for all variables are slightly lower than their means, suggesting a right-skewed distribution for most variables, especially POU, ICT, and GDP. This skewness is confirmed by the skewness statistics: POU (1.3360), ICT (0.6651), and GDP (1.0714) all show positive skew, indicating the presence of higher extreme values. Conversely, EDU has a slightly negative skew (-0.1579), while HLT is nearly symmetric (0.1712).

The maximum and minimum values further highlight the variability within the dataset. POU ranges from a low of 3.4% to a high of 30.7%, ICT ranges dramatically from just 0.07% to 87.98%, and GDP per capita varies between USD 519 and USD 6,454. The standard deviations reflect this dispersion, with GDP showing the highest variability (SD = 1,473.76), followed by ICT (SD = 22.75) and POU (SD = 5.83). The kurtosis values indicate the flatness of the data distributions. POU has a leptokurtic distribution (4.75), suggesting a sharper peak and heavier tails compared to a normal distribution. ICT and GDP have kurtosis values near 3, indicating near-normal distributions, while EDU shows a platykurtic distribution (1.626), implying a flatter distribution curve. Overall, the data reveal considerable variation across ASEAN countries in terms of nutrition, technological development, economic performance, and social indicators, offering a strong basis for further analysis of the relationships among these variables.

**Table 3.** Result of Best Model Selection Test

| Model | Probability | | Selected Model |
|---|---|---|---|
| | Chow Test | Hausman Test | |
| Model 1 | 0.0000 | 0.0003 | FEM |
| Model 2 | 0.0000 | 0.0003 | FEM |
| Model 3 | 0.0000 | 0.0025 | FEM |
| Model 4 | 0.0000 | 0.0000 | FEM |

The results presented in Table 3 show the outcomes of the best model selection tests conducted for four different models using the Chow test and the Hausman test. The Chow test is used to determine whether the Pooled Least Squares (PLS) model or the Fixed Effects Model (FEM) is more appropriate, while the Hausman test is employed to choose between the Fixed Effects Model (FEM) and the Random Effects Model (REM). For all four models (Model 1 to Model 4), the probability values for both the Chow test and the Hausman test are highly significant, with values well below the 0.05 threshold. The Chow test consistently yields a p-value of 0.0000, indicating that the Fixed Effects Model is statistically preferable to the Pooled OLS model. Similarly, the Hausman test results also show p-values below 0.005 for each model (ranging from 0.0000 to 0.0025), suggesting that the Fixed Effects Model is more suitable than the Random Effects Model. On the basis of these test results, the Fixed Effects Model (FEM) is identified as the most appropriate estimation method for all four models. This indicates the presence of significant individual heterogeneity across the cross-sectional units, justifying the use of FEM in this study's analysis.

## 4.2. Classical Assumptions

Furthermore, the classical assumption test is carried out on the research model. Multicollinearity and heteroscedasticity are the assumption tests to perform in panel data regression (Napitupulu et al., 2021). One of the criteria for obtaining a BLUE (Best Linear Unbiased Estimator) estimator is the absence of perfect multicollinearity among the independent variables. Perfect multicollinearity is characterized by the value of the correlation coefficient between the independent variables approaching 1 (Gujarati, 2004). Based on the correlation coefficient values in Table 4., no perfect multicollinearity was detected among the independent variables studied. Next, a heteroscedasticity test was conducted. This test is used to see whether the residuals of the former model have a constant variance. Based on the results of the heteroscedasticity test in Table 5, it is concluded that the four models are free from heteroscedasticity, as seen from the p-value > 5% alpha. Because the entire model has met the classical assumptions, the analysis can proceed to interpreting the regression results.

**Table 4.** Result of Correlation Matrix

| Variable(s) | lnICT | lnGDP | lnEDU | lnHLT |
|---|---|---|---|---|
| lnICT | 1.000 | 0.718 | 0.705 | 0.705 |
| lnGDP | 0.718 | 1.000 | 0.861 | 0.810 |
| lnEDU | 0.705 | 0.861 | 1.000 | 0.716 |
| lnHLT | 0.705 | 0.810 | 0.716 | 1.000 |

Table 4 presents the results of the correlation matrix, which displays the pairwise correlation coefficients among the logarithmic forms of the independent variables: lnICT (Information and Communication Technology), lnGDP (Gross Domestic Product per capita), lnEDU (Education index), and lnHLT (Health index). All correlation values are positive and relatively high, indicating strong linear relationships among the variables. The highest correlation is observed between lnGDP and lnEDU, with a coefficient of 0.861. This suggests a very strong positive association, implying that higher GDP per capita is closely linked to improved education levels. Similarly, lnGDP also shows a strong correlation with lnHLT (0.810), indicating that economic prosperity tends to coincide with better health outcomes. lnICT is moderately and positively correlated with the other variables, showing coefficients of 0.718 with lnGDP, 0.705 with lnEDU, and 0.705 with lnHLT. These relationships suggest that greater ICT penetration is generally associated with higher economic performance, improved education, and better health services. Although the correlations are strong, none exceed 0.90, which helps to alleviate immediate concerns about multicollinearity. However, the relatively high correlations, particularly among lnGDP, lnEDU, and lnHLT, warrant caution and may require further diagnostic tests, such as Variance Inflation Factor (VIF) analysis, in subsequent regression modeling to ensure robust estimation results.

**Table 5.** Result of Heteroscedasticity Test

| Model | Independent Variable(s) | Prob. |
|---|---|---|
| Model 1 | lnICT | 0.5083 |
| Model 2 | lnICT | 0.5648 |
| Model 3 | lnICT | 0.3469 |
| Model 4 | lnICT | 0.7397 |
| | lnGDP | 0.7654 |
| | lnEDU | 0.3976 |
| | lnHLT | 0.2794 |

Table 5 presents the results of the heteroscedasticity test for four models, examining whether the variance of the residuals is constant across observations. The test focuses on the independent variables: lnICT, lnGDP, lnEDU, and lnHLT, with their respective probability (p-value) results. For all models and variables tested, the p-values are above the conventional significance level of 0.05. Specifically, the p-values for lnICT range from 0.3469 to 0.7397 across Models 1 to 4, indicating no significant evidence of heteroscedasticity related to this variable. In Model 4, additional independent variables, lnGDP (0.7654), lnEDU (0.3976), and lnHLT (0.2794) also show non-significant p-values. These results imply that the null hypothesis of homoscedasticity (constant variance of residuals) cannot be rejected for any of the models or variables. Therefore, the assumption of homoscedasticity is satisfied, supporting the validity of the regression estimates and suggesting that the models do not suffer from heteroscedasticity-related bias or inefficiency.

### 4.3. Direct Effect

The overall estimation results are presented in Table 6. Model 1 examines the effect of ICT on GDP per capita. The estimation results show that the p-value for ICT is smaller than the 5% significance level, indicating that ICT significantly affects GDP per capita. The positive regression coefficient value indicates that increased ICT can increase GDP per capita. This is in accordance with what was stated by Das et al. (2016), Shtewi & Almajdob (2024) and Qureshi & Najjar (2015). ICT can increase GDP per capita by accelerating access to information, improving production efficiency, and expanding economic opportunities. The use of ICT encourages the automation of business processes, reduces operational costs, and increases labor productivity. With increased efficiency and innovation, people's income increases, which in turn has a positive impact on GDP per capita.

**Table 6.** Estimation Result of Direct Effect

| Variable(s) | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| lnICT | 0.1443*** | 0.0684*** | 0.0158*** | -0.0476*** |
| | (0.0066) | (0.0038) | (0.0007) | (0.0136) |
| lnGDP | | | | -1.0995*** |
| | | | | (0.0653) |
| lnEDU | | | | -0.4448*** |
| | | | | (0.4448) |
| lnHLT | | | | -2.1551*** |
| | | | | (0.5477) |
| C | 7.2412*** | 1.6541*** | 4.1979*** | 20.7097 |
| | (0.0000) | (0.0110) | (0.0019) | (2.2767) |
| R-squared | 0.9676 | 0.9575 | 0.9741 | 0.9631 |
| Adjusted R-squared | 0.9657 | 0.9550 | 0.9725 | 0.9601 |
| F-Statistics | 503.8385 | 380.0566 | 634.2587 | 313.6339 |
| Prob (F-statistic) | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Note: Standard error in parentheses; **significant at 5% ***significant at 1%

Model 2 examines the effect of ICT on education. The regression results show that the p-value for ICT is smaller than the 5% significance level, indicating that ICT significantly affects education. The positive regression coefficient indicates that increasing ICT can improve education. This is in accordance with what was stated by Anastasopoulou et al., (2024), Alrikabi et al. (2024), and Liabo et al. (2016). ICT improves education by providing widespread access to digital learning resources, enabling distance learning, and facilitating better interaction between teachers and students. Technologies such as e-learning platforms, video conferencing, and educational apps help students learn independently and flexibly, even in remote areas. In addition, ICT supports the development of relevant digital skills for the modern era, thereby improving the quality of education and its relevance to labor market needs.

Model 3 examines the effect of ICT on health. The regression results show that the p-value for ICT is smaller than the 5% significance level, indicating that ICT significantly affects health. The positive regression coefficient indicates that an increase in ICT can improve health. This is in accordance with what is stated by Allemann & Poli (2020), Lee et al. (2016), Ahmed & Almoree (2024), and Ronaghi (2022). ICT Improves healthcare by making it easier to access medical information, supporting diagnoses, and speeding up communication between patients and healthcare professionals. Technologies such as telemedicine enable remote consultations, while health apps help with real-time monitoring of patient conditions. In addition, digitizing data in medical records improves the efficiency of medical services and decision-making. Thus, ICT supports faster, more affordable, and equitable health services, even in remote areas.

Model 4 examines the influence of ICT, GDP per capita, education, and health on the prevalence of undernourishment. The regression results show that the p-values for all independent variables are smaller than the 5% significance level, indicating that all variables significantly affect the prevalence of undernourishment. The negative regression coefficients of all variables indicate that an increase in ICT, GDP per capita, education, and health can reduce the prevalence of undernourishment. This is under what was stated by Aker & Mbiti (2010), Bloem et al. (2013), Domguia et al. (2023), Deurenberg & Siong (2016) (2016), (Mbuya et al., 2019), dan Anser et al. (2021). ICT can reduce the prevalence of undernourishment by improving the efficiency of the food supply chain, facilitating access to market information, and supporting more equitable distribution. Digital applications allow farmers to access weather data, market prices, and agricultural technology, resulting in optimized food production. In addition, e-commerce platforms can connect farmers directly with consumers, reducing crop losses and ensuring food availability. With ICT, inequality in food distribution can be minimized, increasing access to adequate and nutritious food.

### 4.4. Mediation Effect

The mediation effect was estimated using the Sobel test approach to calculate the indirect impact of ICT on the prevalence of undernourishment. The results are presented in Table 7. The Sobel test results obtained from Table 7 show that GDP per capita, education, and health mediate the impact of ICT on the prevalence of undernourishment. During the study period, ICT indirectly contributed to the decrease in the prevalence of undernourishment in ASEAN-8 through increased GDP per capita. About 77% of the total effect of ICT on reducing the prevalence of undernourishment is due to GDP per capita. Then, the indirect effect of ICT on reducing the prevalence of undernourishment through increasing education is about 39% of the total effect. Finally, the indirect effect of ICT on reducing the prevalence of undernourishment through improving health is about 41% of the total effect. The indirect effect of ICT on the prevalence of undernourishment is reflected in its role in enhancing national productive systems, strengthening education systems, and improving access to healthcare. The findings suggest that countries prioritizing ICT adoption in the production, education, and health sectors have the potential to accelerate efforts to reduce hunger significantly.

**Table 7.** Result of Sobel Test

| Description | Mediating Variable(s) | | |
|---|---|---|---|
| | lnGDP | lnEDU | lnHLT |
| Sobel-test | -13.3402***<br>(0.0119) | -3.6480***<br>(0.0083) | -3.8764***<br>(0.0088) |
| Indirect Effect | -0.1587 | -0.0304 | -0.0341 |
| Mediated effect | 76.9035% | 38.9735% | 41.6924% |

Note: Standard error in parentheses; **significant at 5% ***significant at 1%

## 5. Conclusions

This study determines the direct and indirect effects of ICT on the prevalence of undernourishment in 8 ASEAN countries. The method used is panel data regression with path analysis for 2015-2022. Some necessary conditions, such as the Redundant test, Hausman test, Lagrange Multiplier test, classical assumption test, and Sobel test, are used for mediation effect. The results show that ICT directly affects the prevalence of undernourishment and indirectly affects GDP per capita, education, and health. Policy recommendations from the results include increasing the adoption and utilization of information and communication technology (ICT) more widely in ASEAN countries. The government needs to encourage the integration of ICT in the education, health, and economic development sectors to improve productivity and access to basic services. Investments in digital infrastructure, such as more widespread and affordable internet networks, are essential to accelerate digital transformation. In addition, ICT-based training and education should be strengthened to improve people's skills in using technology optimistically. These efforts must be accompanied by the development of policies that support the increase of GDP per capita, such as micro, small, and medium enterprise (MSME) development programs and initiatives to expand access to quality health and education services. With this approach, ICT can play a more significant role in reducing the prevalence of undernourishment in the ASEAN region to realize the goal of zero hunger.

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