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ORIGINAL ARTICLE

Does information and communication technology improve labor productivity? Recent evidence from the Southeast Asian emerging economies

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Abstract
The comprehension of the textbook and augmented Solow growth model has been studied to picture the consequences of workforce growth and capital. In the age of digitalization, Information and Communications Technology (ICT) is also the first necessity identified factors affecting labor productivity. This paper revisits the augmented Solow growth equation by integrating ICT as an explanator that improves labor productivity in Southeast Asian emerging economies. We used a Two-Way Random-Effects Model to regress the impact of workforce growth rate, physical capital, and human capital on labor productivity. The results show that using human capital is essential to improve output in emerging market countries rather than only using physical capital. According to our adjusted ICT factors, our analysis reveals that using the Internet and mobile cellular significantly boosts labor productivity. Moreover, the analysis of total factor productivity shows that most Southeast Asian economies highly depend on implementing ICT, especially the contribution of Internet usage and mobile cellular. Therefore, this study contributes to further studies and policy recommendations in improving the introduction of Internet usage and installation, especially for the emerging Southeast Asian.

KEYWORDS
augmented Solow growth model, information and communications technology (ICT), Internet users, labor productivity, mobile broadband, mobile cellular

1 | INTRODUCTION

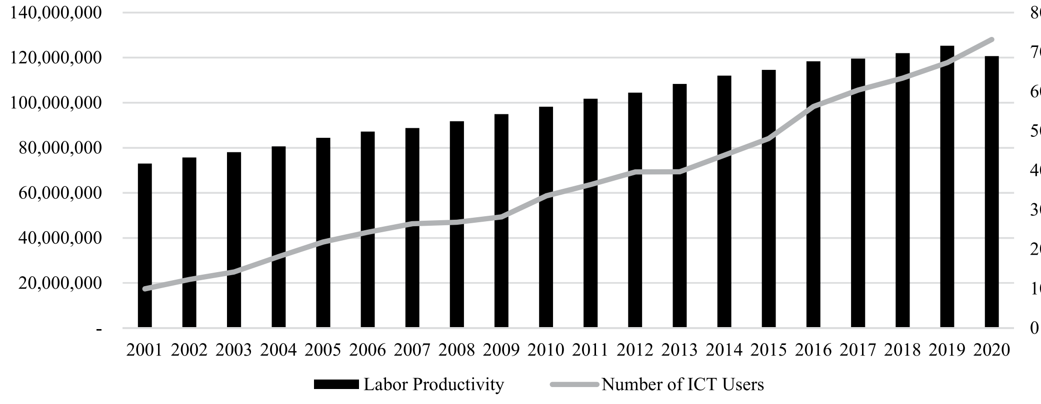
Production has an essential contribution to the growth of national welfare, improvement of societies' standards of living, and development of the economy (Gumpert, 2019; Lee, Hong, & Chang, 2020; Maharani & Woyanti, 2022; Nguyen, 2019; Shahnazi, 2021). The aggregate development of production can be measured by how many products have been created by several workers in a country, which is so-called labor productivity (Hutter & Weber, 2021; Laddha et al., 2022). The use of labor productivity measures the number of created products and provides an overview of the amount of labor absorbed by the firms. Therefore, it provides an overview for policymakers regarding the policies implemented to improve labor productivity.

The variability of factors affecting labor productivity becomes a significant issue to be explored (Hutter & Weber, 2021; Kim, Park, & Komarek, 2021; Twumasi et al., 2021). Many studies of labor productivity determinants have been carried out by re-examining the Solow growth model. Previous studies concerned the effect of physical capital on productivity (Li & Su, 2022; Magazzino & Mele, 2022; Oliver Huidobro et al., 2022; Rahman & Shahari, 2017). Following the augmented Solow growth model, the studies extended the need for human capital in labor productivity (He et al., 2022; Hutter & Weber, 2021; Kufenko et al., 2020; Le et al., 2022; Mazhar & Rehman, 2022; Okunade et al., 2022; Park & Seo, 2016). In the technology age, textbooks and augmented models are modified following the modernization factors affecting productivity, especially the effect of Information and Communications Technology (ICT).

The contribution of ICT to investment attraction, output improvement, and economic growth development is significantly occurring (Abramova & Grishchenko, 2020; Espinoza et al., 2020; Laddha et al., 2022; Shahnazi, 2021). The implementation of ICT provided at least two contributions to productivity (Kim, Park, & Komarek, 2021). First, it improves efficiency by creating more innovation and decreasing the cost of production. Second, it contributes to analyzing production issues' presence and gives solutions and new opportunities.

Most developed countries benefit from ICT installation (Espinoza et al., 2020; Kim, Park, & Komarek, 2021). They report faster and more efficient activities for producing output through the appearance of business information system models, online-order transportation, e-commerce, digital streaming, financial cloud, and other related aspects., with much more efficient processes. Studies of the effect of ICT on labor productivity have emerged recently (Abramova & Grishchenko, 2020; Alam & Mamun, 2017; Hsieh & Goel, 2019; Nguyen et al., 2022; Vu & Hartley, 2022). They confirm the presence of computer hardware and software investment in improving productivity growth. However, most provide determination for developed countries with more prolonged ICT investment than developing countries.

However, other previous studies reveal some disconnections between the implementation of Internet broadband and the output productivity produced by the worker (Alam & Mamun, 2017; Asongu & Odhiambo, 2023; Bertschek et al., 2013; Hagsten, 2016). Alam and Mamun (2017) explained the disconnection between broadband installation and labor productivity due to the specific remote area. Most of the labor there gained fewer benefits from broadband installation. In a specific case of Sub-Saharan African countries, Asongu and Odhiambo (2023) reveal that broadband subscriptions



10 **FIGURE 1** The movement of labor productivity and number of ICT users in Southeast Asian Developing Economies 2001–2020. *Source*: World Bank and ITU.

decrease labor productivity, especially women workers. Bertschek et al. (2013) used the sample firms in Germany to provide a different reason for the case due to the socialization and learning process in the introduction of broadband, which had a disconnection with labor productivity. Moreover, the result of Hagsten (2016) was confirmed by Alam and Mamun (2017), who provided varied results due to various areas. Therefore, since a considerable contradiction results from the effect of ICT on labor productivity, we conclude that the effect of the implementation of the Internet of thing (IoT), mobile broadband, and mobile cellular subscription, whether promoting or weakening labor productivity, is still an interesting debate to be explored bringing to the different sample and representation of proxies of ICT.

Besides, ICT infrastructures have also been massively implemented in developing countries to support their economic productivity (Fan et al., 2021; Kim, Park, & Komarek, 2021; Laddha et al., 2022; Lee, Hong, & Chang, 2020; Nguyen et al., 2022; Sun & Guo, 2022; Suryoko et al., 2023; Twumasi et al., 2021). Figure 1 shows that the movement of labor productivity in the last 20 years follows the number of ICT users in Southeast Asian developing economies. In 2001, the number of ICT users was around 9.94% of the total population in five countries of Southeast Asia. The number has increased after 20 years to approximately 73.19%. It was in line with labor productivity from around 73 million U.S. dollars in 2001 to 121 million U.S. dollars in 2020. However, we cannot conclude that ICT infrastructure ideally improves labor productivity. Therefore, it needs to be empirically analyzed. Regarding the previous empirical dialectic of whether the implementation ICT and labor productivity connect or disconnect, and their movement data in Southeast Asia, we, therefore, try to fill the gap by analyzing the effect across ICT variables (Internet users, mobile broadband, and cellular subscription) on labor productivity using the case of selected Southeast Asian economies.

This study estimates the panel's variety of parameters. We employ the fixed and random effect models to examine the textbook and modify the Solow model for growth. We spotlighted on the use of ICT factors on productivity of labor. Our study contributes to three extended factors. First, we compare physical and human capital use by revisiting the original textbook and augmented Solow growth model. Second, we extend the augmented Solow growth equation by investigating the various effect of ICT on productivity of labor at the aggregate level. Third, since the rare studies, this manuscript allows us to compare ICT (Internet users, mobile broadband, and cellular subscription) variables in the recent implementation of ICT in developing countries, especially in selected Southeast Asian economies. Finally, we also provide the total factor productivity calculation and the beneficence of each output and input toward the output productivity. This cross-information will help provide practical policy recommendations for issues in the age of technology.

2 | SCIENTOMETRICS REVIEW

Labor productivity and ICT have emerged as debated topics in the last decade. The comprehension studies contended the development of technology infrastructure on productivity of labor. To prove a specific topic and guide our estimation in finding a research gap by reviewing kinds of literature related to the topics of labor productivity and ICT, we provide a bibliometrics analysis. We focused on the manuscripts related to the topic of labor productivity and the implementation of ICT, which were published in the journals indexed by Scopus and Web of Science (WOS), including 226 and 201 papers, respectively. Using RStudio tools helps us remove 90 duplicated articles and combined papers from both sources. Our thematic evolution analysis, presented in Figure 2, differs into three time slices: 2001–2013, 2014–2019, and the newest slice is from 2020 to 2022. The result of thematic evolution analysis reveals that research changes from the hugest theme in productivity into labor productivity and the most specific theme in information communication technology or ICT.

Figure 3 shows a co-occurrence network analysis. The result reveals that foregoing research focused on the causality between labor productivity and ICT have five main clusters: productivity, labor productivity, system, mobile phone, and entry, with various frequencies of all clusters. We found 187 articles related to productivity with 1038 frequencies of the cluster. Most studies are clustered into the topic of productivity and ICT in the general concept of production (Aboal & Tacsir, 2018; Bartelsman et al., 2019; Choi et al., 2018; Hasan et al., 2018; Scholz et al., 2018; Seon, 2021). They provide an analysis of the ICT used toward productivity.

Productivity is the number of output produced by a firm in a specific period associated with innovation, and the ICT implemented (Aboal & Tacsir, 2018; Bartelsman et al., 2019). Furthermore, productivity is connected to investment volatility, especially in funding technology capital (Choi et al., 2018). Specifically, Hasan et al. (2018) used qualitative deep interviews and explained that mobile ICT enhances communications and information, increasing construction project productivity. The study of Vu (2013) employed the generalized method of moments (GMM) and noted the appositive contribution of ICT on productivity and economic growth aggregately.

Our co-occurrence network analysis provides a more specific theme of labor productivity. Most studies show a significant investigation of the causality between ICT infrastructure and labor productivity (Appiah-Otoo & Song, 2021; Avram et al., 2019; Falentina et al., 2021; Gupta

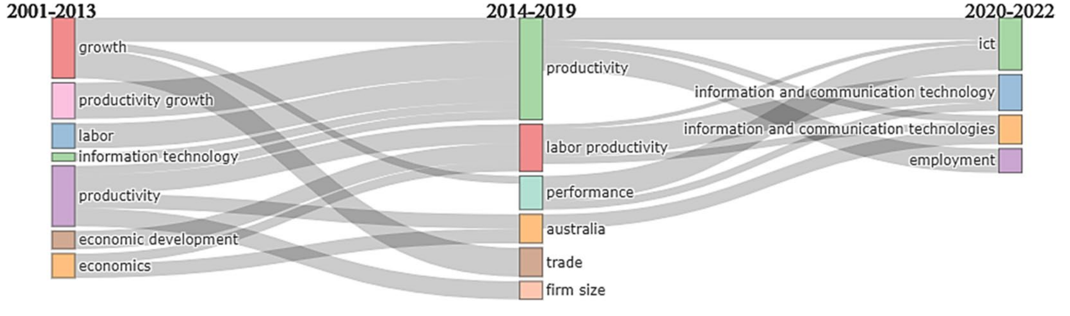


FIGURE 2 Longitudinal thematic movement of ICT investment in labor productivity research. *Source*: Author's Computation based on Bibliometrics Analysis.

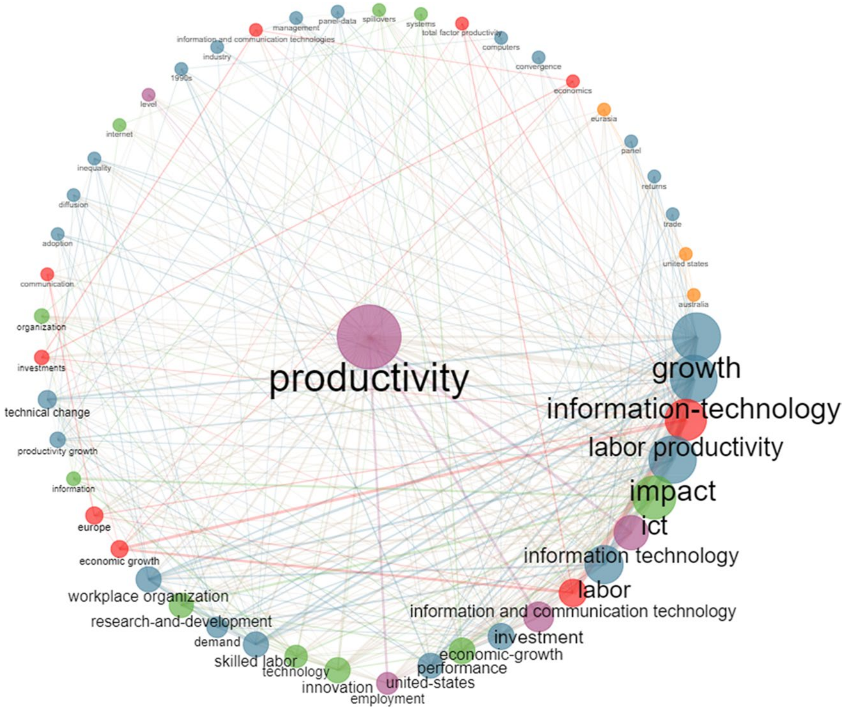


FIGURE 3 Co-occurrence network of ICT investment in labor productivity research. *Source*: Author's Computation based on Bibliometrics Analysis.

& Kumar, 2018; Hintzmann et al., 2021; Leviäkangas et al., 2017; Shabani & Shahnazi, 2018; Viollaz, 2021). Appiah-Otoo and Song (2021) and Avram et al. (2019) used GDP per capita as a proxy for the output produced by workers. The use of GMM, Appiah-Otoo and Song (2021) shows that developing countries gained more from ICT installations by improving labor productivity, and Avram et al. (2019) explain that ICT skills improve labor productivity in selected European labor markets by implementing vector autoregressive (VAR) for their analysis.

In a more specific sample, Falentina et al. (2021) provide a positive result of digitalization engaged to ICT on labor productivity. They use OLS and IV methods to prove that the implementation of Internet use improves profit per worker per month of SMEs in Yogyakarta, Indonesia. Moreover, Gupta and Kumar (2018) implemented the Malmquist productivity index of data envelopment analysis and linear programming method, showing that ICT usage also improves the labor productivity of small firms by increasing technologically skilled labor in India. The study of Viollaz (2021) supports the result of Gupta and Kumar (2018) and Falentina et al. (2021). By employing OLS, they noted that adopting the Internet improves the labor productivity of small firms in Peru. Due to the implementation of technology in a specific region, it also has a positive impact on other regions. The study of Shabani and Shahnazi (2018) employed the global Morans index, revealing the positive technology spillover effect among Iranian provinces.

Previous studies also prove the whether investment and labor productivity related or not. Investing in intangible assets positively affects labor productivity (Hintzmann et al., 2021). Based on their OLS analysis, investment in intangible tools should follow the characteristics of countries needed to promote labor productivity growth in European Union member states. Inversely, labor productivity is less impacted by investment in ICT infrastructure (Leviäkangas et al., 2017). Through the implementation of Spearman rank correlation analysis, the research of Leviäkangas et al. (2017) reveals that gross value added (GVA) in terms of labor is related to the low investment in digitalization.

The third cluster relates to the system theme. The research tried to realize an ICT system to improve productivity (Baek & Im, 2022; Kim, Ham, et al., 2019; Kim, Jung, et al., 2019; Narvaez et al., 2017). By criticizing the agricultural sector, Baek and Im (2022) and Narvaez et al. (2017) provided tools to increase farms' production. Moreover, they conclude that using mobile robots and automation helps reduce costs and improve overall productivity. Kim, Ham, et al. (2019) and Kim, Jung, et al. (2019) made webcams and open-source operation to capture operational data using an easy-integrated system. They conclude that monitoring difficulty decreases by reducing operational duration, energy consumption, and negative externality. Most studies in the thematic system suggest a positive impact of technology implementation on productivity however, none of the studies implemented in a larger regional sample.

The theme of entry in productivity becomes the fourth cluster. The theme focused on taxation and exit-entry of labor with inverse correlations (Guo et al., 2019; Seon, 2021). In the case of government regulation, more progressive taxation also connects to lower aggregate productivity through movement inputs from productive to less productive establishments (Guo et al., 2019). Inversely, Seon (2021) analyses that the dynamic of the ICT industry has slowed productivity due to the entry and exit of labor. Decomposition analysis helps them give a specific analysis that differs between exit and labor entry.

The fewest and rarely introduced cluster is mobile phones. It analyses the implementation of mobile communication on labor support. A current study by Gu et al. (2022) explored the effect of smartphone adoption by rural communities on their outcome. They used random effect (RE), panel instrumental variable (IV), Bernoulli quasi-maximum likelihood estimation (QMLE), and maximum likelihood structural equation modeling (ML-SEM) to reduce the biases of their analysis. The result shows that smartphone ownership supports labor migration from on-farm to off-farm and improves their well-being.

According to previous studies, most of them need to provide a variety of ICT support, especially the usage and installation of the Internet on labor productivity. We, therefore, fill the gap by including the usage of the Internet, mobile broadband, and cellular subscriptions in improving labor productivity. Our analysis focused on implementing the Internet regarding the ICT infrastructure development in Southeast Asian countries.

3 | METHOD

3.1 | Data source and variable measurement

The data on the GDP, labor force, workforce growth rate, investment, and human capital of the Southeast Asian countries were retrieved from the World Bank and International Monetary Fund (IMF) dataset. We extended the Augmented Solow growth model by integrating Internet users, mobile broadband subscriptions, and mobile cellular subscriptions as additional independent variables. The data are gained from the international telecommunication unions (ITU). This study compares whether physical or human capital improves output per worker based on the original textbook and augmented Solow growth model. Furthermore, we also analyzed the contribution of ICT installment on output in terms of labor. We applied the models for selected Southeast Asian emerging economies, namely Brunei Darussalam, Indonesia, Malaysia, the Philippines, and Thailand, from 2001 to 2020.

The determinants of output per worker are analyzed by considering six variables. The dependent variable is the output per worker of selected Southeast emerging economies. To calculate this variable, we divide the real GDP by the working-age population of 15–64 years old. The independent variables

TABLE 1 Resume of data.

	Definition	Calculation	Source
$\ln\left[\frac{Y}{L}\right]_{it}$	Output per worker	Real GDP divided by working age population (15–64 y.o.) as a proxy of output per worker of the country (i) at the time (t) in logarithm	World Bank
$\ln[s_k]_{it}$	Physical capital	Capital gross formation as investment divided by working age population (15–64 y.o.) as a proxy of physical capital or saving of country (i) at the time (t) in percentage	Capital gross formation from IMF and working age population from World Bank
$[n]_{it}$	Workforce	The workforce growth rate of the country (i) at the time (t) in percentage	World Bank
$\ln[s_h]_{it}$	Human capital	The secondary school enrolled as the human capital of the country (i) at the time (t) in logarithmic	World Bank
$\ln\,[NIU]_{it}$	Number of Internet users	Percent of people in the community who utilize the Internet of the country (i) at the time (t)	The international telecommunication union (ITU)
$\ln\,[MBS]_{it}$	Mobile broadband subscription	Active mobile broadband subscriptions for every 100 residents, or the total of regular and specialized mobile broadband subscriptions to the open network of the country (i) at the time (t)	The international telecommunication union (ITU)
$\ln\,[MCS]_{it}$	Mobile cellular subscription	The number of subscribers to a public cell phone service that offers cellular connectivity to the PSTN or the total mobile-cellular subscriptions for every 100 residents of the country (i) at the time (t)	The international telecommunication union (ITU)

Source: Authors' compilation.

are savings, labor force growth rate, and technology. Savings (s) divide capital gross formation by real GDP to cover the average proportion of real GDP investment, called physical capital. We employed the workforce growth rate data in percentages to show the effect of the workforce growth rate. The data of output per worker is logarithmically transformed. The information is used to describe the textbook Solow growth model. Enrollment in secondary schools is another way we measure human capital. The data is converted logarithmically to explain the enhanced Solow growth model. Finally, we add the ICT variables to the modified version of the enhanced Solow growth model the definition, calculation, and source of variables are resumed in Table 1.

3.2 | Empirical model and analysis

The primary purpose is to analyze the determinants of output per worker of the Southeast Asian emerging market economies. We first modified the textbook Solow growth model to provide a simple estimation technique, as follows:

$$\ln\left[\frac{Y}{L}\right]_{it} = \propto_{it} + \frac{\propto}{1-\propto}[s]_{it} - \frac{\propto}{1-\propto}[n+g+\delta]_{it} + \varepsilon_{it} \tag{1}$$

Then we transformed by applying Equation (4) above in our panel dataset, as follows:

$$\ln\left[\frac{Y}{L}\right]_{it} = \propto_{it} + \frac{\propto}{1-\propto}[s]_{it} - \frac{\propto}{1-\propto}[n+g+\delta]_{it} + \mu_t + \varepsilon_{it} \tag{2}$$

where i is the country specification, the $\ln\left[\frac{Y}{L}\right]_{it}$ is the output per labor at a time (t) in the logarithmic term. The $\ln\,[s]_{it}$ denotes saving rates at time (t) logarithmic term. $\ln\,[n + g + \delta]_{it}$ represents the workforce growth rate at the time (t) percentage term. The μ_t is a time-specific shock. We, therefore, suppose that savings and population increase are explanatory of cross-country shock ε_{it} corrected by g and δ.

By including a variable assessing human capital expenditures in the framework of schooling rather than health and training, we also examined the existence of the enhanced Solow growth model. The use of secondary school enrolled for each country analysis encounters difficulties in measuring human capital. Equation (2) was estimated by adding human capital ($\ln[s_h]_{it}$) to analyze the augmented Solow growth model as follows:

$$\ln\left[\frac{Y}{L}\right]_{it} = \propto_{it} + \frac{\propto}{1-\propto}\ln[s_k]_{it} - \frac{\propto}{1-\propto}[n+g+\delta]_{it} + \ln[s_h]_{it} + \mu_t + \varepsilon_{it} \tag{3}$$

Finally, to evaluate the causality of ICT variables and labor productivity, we propose the number of Internet users ($\ln\,[NIU]_{it}$), mobile broadband subscription ($\ln\,[MBS]_{it}$), and mobile cellular subscription ($\ln\,[MCS]_{it}$) variables. We modified the augmented Solow growth model from Equation (3) as follows:

$$\begin{aligned}\ln\left[\frac{Y}{L}\right]_{it} = \propto_{it} + \frac{\propto}{1-\propto}\ln[s_k]_{it} - \frac{\propto}{1-\propto}[n+g+\delta]_{it} + \ln[s_h]_{it} \\ + \ln[NIU]_{it} + \ln[MBS]_{it} + \ln[MCS]_{it} + \mu_t + \varepsilon_{it}\end{aligned} \tag{4}$$

We, therefore, estimate Equation (4) to revisit the augmented Solow growth model by integrating three ICT variables.

3.3 | Estimation strategy

This study used two-step estimations. Firstly, we used causality analysis using a panel dataset and thus employed the two-way fixed-effects and random effect models (by country and time) to account for the unobserved country and time effects. Laddha et al. (2022) explained that the fixed effect model could be easily estimated under endogeneity issues. We can handle it without employing instrument variables by capturing unidentified heterogeneity in panel data. Both analyses have their benefits based on which one is appropriate to apply to the model built. Therefore, the Model selection is used to construct a suitable model across fixed and random effects.

The selection of the fittest model by estimating coefficients is based on the Breusch–Pagan Lagrange Multiplier Test by Breusch and Pagan (1980) and the Hausman Test by Hausman and Taylor (1981). Our analysis follows the criteria for choosing an appropriate model and analysis method. A fixed effects model is appropriate unless the data available are virtually population-wide and not randomized. In contrast, random effects are more suitable when concluding a population average or when components are considered to be samples of a larger group, as is the issue for our origin and destination state pairings. For the Breusch–Pagan Lagrange Multiplier Test, if the probability of Chi-square is greater than the critical value ($\alpha = 0.01$, 0.05, and 0.1), we accept the fixed effect is more robust than the random effect model (Laddha et al., 2022). For the Hausman Test, we accept the fixed effect over the random effect model because the probability of Chi-square is greater than the critical value ($\alpha = 0.01, 0.05$, and 0.1).

Secondly, since the objective of this study is to examine the impact of information and communication technology (ICT) on worker productivity. In order to provide a comprehensive analysis, we expand our investigation following Ahmed (2017) by calculating the total factor productivity (TFP). The calculation of TFP is situated on the growth accounting application by Jorgenson and Griliches (1967). We follow the steps and calculate the difference between the aggregate output per worker and the filled average of the physical capital, workforce, human capital, and ICT factors. Ahmed and Kialashaki (2023) advise that the subsequent stage involves the computation of sustainability indicators, which encompass the Total Factor Productivity (TFP) that serves as a proxy for technological advancement through the use of the residual term. Therefore, to provide, we transform the Equation (4) as follows:

$$\ln \mathrm{TFP}_{it} = \ln\left[\frac{Y}{L}\right]_{it} - \left(\begin{array}{c} \propto_1 \ln[s_k]_{it} + \propto_2[n+g+\delta]_{it} + \propto_3 \ln[s_h]_{it} + \propto_4 \ln[\mathrm{NIU}]_{it} + \propto_5 \ln[\mathrm{MBS}]_{it} \\ + \propto_6 \ln[\mathrm{MCS}]_{it} \end{array}\right) \tag{5}$$

Where $i = 1, \ldots, 5$, and $t = 2001, \ldots, 2020$. The values of the weights represent the distribution of value portions, such as $\ln\left[\frac{Y}{L}\right]_{it}$ is the labor productivity, $\propto_1 \ln[s_k]_{it}$ is the contribution of physical capital, $\propto_2 [n + g + \delta]_{it}$ represents the contribution of the workforce, and $\propto_3 \ln[s_h]_{it}$ is the contribution of human capital. The other three weights are $\propto_4 \ln[\mathrm{NIU}]_{it}$ as the contribution of the first ICT implementation, number of Internet users, $\propto_5 \ln[\mathrm{MBS}]_{it}$ as the contribution of mobile broadband subscription, and $\propto_6 \ln[\mathrm{MCS}]_{it}$ as the contribution of mobile cellular subscription.

4 | RESULT AND DISCUSSION

Our analysis starts from the summary statistics of the data analyzed. We employ 100 observations following the five countries as cross-sections and 20 years of each. The data dispersion across variables is relatively narrow. Over the sample period, the number of Internet users is relatively small (37.18% of the total population in each country). The rest are societies that do not connect to the Internet, which is 62.82% of the population. Moreover, on average, mobile broadband subscription to the public Internet has lower subscribers than Internet users. The result of descriptive statistics that provide another parameter of standard deviation, minimum, and maximum values of the sample is presented in Table 2.

This study uses panel ordinary least squares for causality analysis. Before we set the analysis, we choose a model to provide the best fit for model analysis confidently. To evaluate whether the model fits the data better, fixed effect or random effect, we use the Bruesch and Pagan Lagrangian multiplier test and Hausman test. The criteria of the best model used are described in our previous section. Table 3 displays the outcome of selecting the best model.

The result of choosing the model presented in Table 4 shows that our textbook Solow growth model fits with the random effect model due to the result of Bruesch and Pagan Lagrangian multiplier test Chi-square is 730.95 with probability 0.0000, which is lower than our critical value ($\alpha = 0.01$, 0.05, and 0.1). Our Hausman test perfectly supports the Bruesch and Pagan Lagrangian multiplier test

TABLE 2 Summary statistics.

	Number of obs.	Mean	Std. deviation	Minimum	Maximum
$\left[\frac{Y}{L}\right]_{it}$	100	12,500,000	25,400,000	58,558	80,400,000
$[s_k]_{it}$	100	0.1243	0.3645	−1.8461	0.4568
$[n]_{it}$	100	68.6567	4.7683	61.7700	79.0600
$[s_h]_{it}$	100	85.1206	13.3414	55.5404	120.6512
$[NIU]_{it}$	100	37.1836	26.5720	2.0186	95.0000
$[MBS]_{it}$	100	22.9261	59.7953	−140.7292	146.4997
$[MCS]_{it}$	100	78,900,000	98,900,000	143,004	435,000,000

Source: Authors' calculation.

TABLE 3 The result of choosing the model.

Test	Textbook Solow growth model	Augmented Solow growth model	Augmented Solow growth model integrated ICT
Bruesch and Pagan Lagrangian multiplier test	730.95 (0.0000)	623.67 (0.0000)	0.00 (1.0000)
Hausman test	0.01 (0.9942)	0.01 (0.9998)	91.46 (0.0000)

Note: Bruesch and Pagan Lagrangian multiplier test and Hausman test provide Chi-square, and the number inside parentheses is the probability of Chi-square

Source: Authors' calculation.

TABLE 4 The result of random effect model for textbook and augmented Solow growth model.

Variable	Textbook Solow growth model	Augmented Solow growth model
c	0.2040043*** (0.04967)	3.938366 (2.58147)
$[s_k]_{it}$	0.2130372*** (0.792,366)	0.016246 (0.039265)
$[n]_{it}$	12.17834 (3.414804)	1.208521** (0.552684)
$[s_h]_{it}$		0.915059*** (0.095462)
R^2	0.1893	0.6077

Note: The value in the parenthesis ( ) is the standard deviation, and the asterisks (*, **, and ***) denote the significance of the threshold at 1%, 5%, and 10%, respectively.

Source: Authors' Calculation.

with Chi-square 0.01 and its probability 0.9942. The augmented Solow growth model reveals a similar result in better employing the random effect model over the fixed effect model. However, our modified augmented Solow growth model concludes that we prefer the fixed effect model to the random effect model.

The main findings in Table 4 present the causality analysis of the textbook and augmented Solow growth model. Both analyses are based on the random effect model following the suggested result of the Bruesch and Pagan Lagrangian multiplier test and the Hausman test for choosing the fittest model. The textbook Solow growth model employing physical capital and workforce growth rate shows a significant effect of the number of capitals used on output per worker. The theory postulated that under the conditions of diminishing marginal returns of capital, external overpopulation, and rate of return, no depreciation, and technical advancement, the model suggests that steady-state condition for every income per capita is externally determined by savings and demographic growth rate

TABLE 5 The result of fixed effect model for augmented Solow growth model integrated ICT.

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	Model 1	Model 2	Model 3	Model 4
c	6.749533*** (2.141671)	7.122548*** (2.037318)	6.691476** (2.59793)	7.277373*** (2.012297)
$[s_k]_{it}$	−0.06494* (0.034236)	−0.02809 (0.032395)	0.001022 (0.037713)	−0.08027** (0.034359)
$[n]_{it}$	0.663046 (0.466,404)	0.829802* (0.449,821)	0.79159 (0.55242)	0.416589 (0.455,408)
$[s_h]_{it}$	0.440834*** (0.115911)	0.477797*** (0.102518)	0.6881*** (0.132302)	0.423467*** (0.105338)
$[NIU]_{it}$	0.067075** (0.027428)	0.111517*** (0.017216)		
$[MBS]_{it}$	−0.00033 (0.000306)		0.00074** (0.000313)	
$[MCS]_{it}$	0.082703*** (0.029421)			0.130159*** (0.019275)
R^2	0.7553	0.7315	0.6304	0.7387
F-test	11,328.49 [0.0000]	15,236.40 [0.0000]	12,020.62 [0.0000]	13,363.97 [0.0000]

3 *Note*: The value in the parenthesis ( ) is the standard deviation, and the asterisks (*, **, and ***) denote the significance of the threshold at 1%, 5%, and 10%, respectively.

Source: Authors' Calculation.

(Brannan, 2019; Lee, Hong, & Chang, 2020; Park & Seo, 2016; Raczynski, 2019). Our result presents
17 an increase of 1% in physical capital and an improved 21% in labor productivity. Our study aligns with the results of Magazzino and Mele (2022) and Park and Seo (2016), who conclude that an affirmative effect of physical investment on productivity—the support of physical infrastructures such as machinery, computers, and other tangible tools matters.

21 Several empirical studies have enhanced the Solow model using cross-country data to imply the influence of human capital on the course of economic progress (Alvarez-Cuadrado, 2019; Hsieh & Goel, 2019; Lee, Hong, & Chang, 2020; Park & Seo, 2016; Raczynski, 2019). According to our estimation, the augmented Solow growth has a different result from the previous model. The variable of physical capital has an insignificant effect on output per worker. However, human capital supports labor productivity with a significant confidence level. We confidently present a one percent increase in human capital used. The output would respond to a 92% increase in labor productivity. It supports the previous analysis of Okunade et al. (2022), Mazhar and Rehman (2022), and He et al. (2022). They provide results of higher human capital and boost productivity due to the condition of labor. Higher health conditions, education level, and labor skills would improve labor productivity.

With adjustments in a series of years and cross-country variables, we estimate the presence across different measures of ICT implemented on labor productivity in Southeast Asian developing coun-
8 tries. Our study employs a fixed effect due to the confidence suggestion of the Bruesch and Pagan Lagrangian multiplier test and Hausman test results. Table 5 provides four models of augmented Solow growth model integrated ICT with a different application of modified variables. Model 1 presents the overall ICT variables' effect on output per worker. The result reveals that some Internet users and mobile cellular subscriptions confirm an affirmative and significant causality with 5 and 1% confidence levels, respectively. This finding supports the previous studies (Hsieh & Goel, 2019; Laddha et al., 2022; Lee, Hong, & Chang, 2020). However, mobile broadband cellular is not statistically significant. Alam and Mamun (2017) suggest that the societies in the sample area benefit less from installing broadband. We conclude that Internet tools have been implemented and have recently gotten viral users compared to more developed countries.

This study analyzed a single ICT variable's effect on labor productivity to provide a more robust estimation. Models 2 through 4 present the single effect of many Internet users, mobile broadband, and cellular subscriptions. Model 2 shows several Internet users' positive and significant effects on output per worker at a 1% significant level. It confirms that Internet users' improvement supports

TABLE 6 Productivity indicators of selected Southeast Asian countries.

	Brunei Darussalam	Indonesia	Malaysia	'the Philippines	Thailand
$\left[\frac{Y}{L}\right]_{it}$	11.4833	17.9200	11.2081	12.6453	12.2641
$[s_k]_{it}$	−0.0185	0.0070	−0.0152	−0.0130	−0.0007
$[n]_{it}$	2.8105	2.8021	2.7711	2.7518	2.8772
$[s_h]_{it}$	2.0088	1.8974	1.9365	1.9533	1.9730
$[NIU]_{it}$	0.2615	0.1554	0.2710	0.1824	0.2124
$[MBS]_{it}$	−0.0167	0.0011	−0.0128	−0.0070	−0.0022
$[MCS]_{it}$	1.0585	1.5421	1.4161	1.4901	1.4796
TFP_{it}	5.3790	11.5149	4.8412	6.2877	5.7249

Source: Authors' Calculation.

laborers' capability and skill improvement toward technology implementation (Abramova & Grishchenko, 2020; Hutter & Weber, 2021; Shahnazi, 2021; Twumasi et al., 2021; Wang et al., 2021). Model 3 recognizes the previous result of the insignificant effect of mobile broadband cellular with the singular affirmative and statistically significant effect on output per worker. Therefore, this model does not confirm the findings of Alam and Mamun (2017), Asongu and Odhiambo (2023), Bertschek et al. (2013), and Hagsten (2016), who provided a disconnection between labor productivity and Internet broadband installation.

Finally, the coefficient of the mobile cellular subscription variable presented in model 4 has a similar pattern with output per worker and the observed results exhibit statistical significance at a 1% confidence level. Hasan et al. (2018) explained that better communication improved construction productivity by enhancing mobile broadband. This result also confirms the previous empirical studies that postulated that connection infrastructures improve labor productivity (Espinoza et al., 2020; Fan et al., 2021; Kim, Park, & Komarek, 2021; Laddha et al., 2022; Lee, Hong, & Chang, 2020; Lee, Hong, & Chang, 2020; Nguyen et al., 2022; Rahman & Shahari, 2017; Vu & Hartley, 2022). Overall, we confidently confirm that implementing ICT variables such as the number of Internet users, installation of mobile broadband, and mobile cellular improves labor productivity in Southeast Asian developing economies.

We proceed to our second analysis of traditional calculation of TFP, by providing the analysis result for each country based on Equation (5). The analysis compared the productivity of output per worker and inputs such as physical capital, labor workforce, human capital, number of Internet users, mobile broadband subscription, and mobile cellular subscription. Ahmed and Kialashaki (2023) suggest that using TFP reduces the weakness of a single productivity analysis of the relationship between output per worker and the input measurements.

Table 6 presents productivity indicators of each input and output of selected Southeast Asian economies from 2001 to 2020. The findings indicate that the mean total factor productivity, as measured by annual output productivity, is influenced by the incorporation of physical capital, labor force, human capital, and ICT deployment within the model was around 4.84–11.52. Overall, TFP intensity throughout the analysis is increasing for each selected economy. The increase in TFP intensity is considered an increasing economy in Southeast Asia as captured by the output produced over the period. Since we have positive correlations of three ICT implementations, the contribution of ICT cannot be separated from the increasing productivity. The peak of TFP was in 2019 for each country, as supported by the peak of ICT implementations such as the most frequent number of Internet users, the highest mobile broadband, and cellular subscription.

Moreover, the contribution of physical capital and mobile broadband implementation were little dropped in most selected economies from −0.0007 to −0.0185 and from −0.0022 to −0.0167, respectively, which these decreases have a bit contributed to the burden of annual output productivity. This means that the use of physical capital and the installation of mobile broadband in Southeast Asian countries could not reduce the yearly production cost. The result is in line with the previous analysis of the augmented Solow growth model integrated into and Alam and Mamun (2017) reveal a reason that some areas in Southeast Asian countries do not gain the benefit of mobile broadband installation.

Since Southeast Asia has a famous large workforce, the support of labor workforce contribution was high (average from 2.7518 to 2.8772). Besides, the human capital also increases from 1.9365 to 2.0088 in terms of annual average, reflecting an increase in higher-pad skills regarding the support of expenditure in the education sector. Furthermore, the contribution of Internet users shows significant support from 0.1554 to 0.2710. Mobile cellular subscription has a similar positive contribution (1.0585–1.5421) toward productivity from 2001 to 2020. The productivity of selected economies is mainly supported by implementing the Internet of Things and installing mobile cellular in Southeast Asia. These results respectively support the study of Ahmed (2017) that ICT and human capital intensities have significant support productivity.

5 | CONCLUSIONS

The contribution of labor productivity to national growth is indispensable. It provides the development of output and informs the labor activity and efficiency of production activities. Therefore, research on labor productivity determinants emerges due to its essentials. Revisiting the Solow growth model of labor productivity with integrated ICT variables gives some essential evidence. First, the textbook Solow's growth model shows the importance of physical capital. Second, the augmented Solow growth model reveals that human capital would improve labor productivity. Third, the number of Internet users, mobile broadband subscriptions, and mobile cellular subscriptions significantly contribute to labor productivity by increasing labor skills, implementing technology in production, and improving the efficiency of overall business processes. Fourth, most of the inputs, output, and calculated TFP confirm the support of annual average productivity except for the physical capital and the implementation of broadband subscriptions.

This study contributes to policy recommendations such as providing more labor with technology-skilled training and providing technology courses for labor, implementing ICT networks (specifically IoT and cellular subscription), especially for remote areas and seeking assistance from developed countries. Therefore, implementing ICT improves output, makes societies educated, and reduces poverty. Finally, the study is limited to the case of sample in selected emerging economies and availability of data from other measurements of ICT. It is preferable to conduct additional research to cover the gap through comparing the different level of economy and additional technological innovation data adopted by industry and technological skill absorption per worker in supporting productivity.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available in the following resources public domain:—International Monetary Fund, https://data.imf.org/regular.aspx?key=61545852—

The International Telecommunication Union (ITU), https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.a—World Bank, https://databank.worldbank.org/source/world-development-indicators.

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