# Labor Productivity in Southeast Asian Emerging Market Countries: The Role of Education and Digitalization (2000-2023)

[1]M. Munip Utama
[2]Rizqon Halal Syah Aji
[3]Pheni Chalid

[1,2,3]State Islamic University Syarif Hidayatullah Jakarta -Indonesia
Corresponding author: m.munip.utama@gmail.com

***Abstract***
*This study investigates the impact of investment in education and digitalization on labor productivity in four emerging market countries in Southeast Asia (Indonesia, Malaysia, the Philippines, and Thailand). The study uses dynamic panel data (2000-2023) and fixed effects models to examine the effects of education investment (proxied by average schooling attainment) and digitalization (proxied by internet penetration) on labor productivity (measured by GDP per employed person). The findings show that current labor productivity is strongly influenced by labor productivity in previous years. Education investment does not show a significant effect on overall labor productivity. However, Malaysia and the Philippines show that the percentage of internet users, which reflects digital literacy, significantly affects their workforce productivity. In contrast, the percentage of internet users in Indonesia and Thailand does not yet fully reflect digital literacy, which can significantly affect productivity. Further analysis shows that education investment and digitalization jointly significantly affect labor productivity in all countries studied.*
***Keywords**: labor, productivity, education, digitalization*
***JEL**: C33, I25, O33, O40*

## A. INTRODUCTION

Productivity is a crucial factor in a nation's economic growth. Investing in human resources through education, healthcare, skills training, and information provision empowers individuals to contribute effectively to economic activities (Becker, 1962a; Schultz, 1961).

A competent workforce, shaped by knowledge and skills acquired through education, is key to higher productivity (Baharin et al., 2020; Wahyuni & Monika, 2017). Thus, building public education is an effort to produce quality and productive workers because the level of worker productivity will affect the level of wages received (Dini & Aji, 2022).

Interpreting knowledge as one of the factors of production can explain that increasing productivity is directly related to investment in human resources (Brezis & Brand, 2016). Technology is considered an endogenous factor because it results from human knowledge development itself. Studies conducted by Romer (1990) and supported by Matthess dan Kunkel (2020) show that Technology acts as a medium for incorporating knowledge into machines, enhancing labor efficiency (Mankiw et al., 2016)

The decline in software and robot production costs (ARK Investment Management, 2016) and the emergence of new jobs created by the internet underscore the transformative power of Technology. While some jobs are replaced by automation, new opportunities are created, requiring different skills and capabilities.

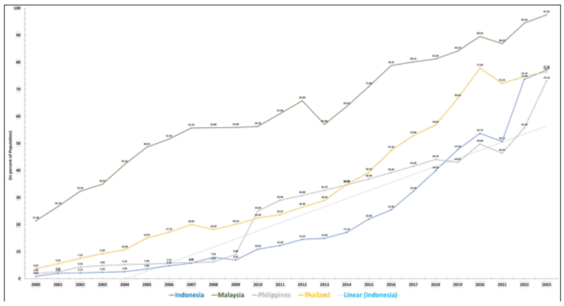
The Industry 4.0 revolution, characterized by integrating information and communication technology into various industries, has significantly altered production models (Nurjanah et al., 2017). This revolution has impacted business models, shifting from conventional to digital or virtual processes.

Artificial intelligence (AI) powered production machines automate tasks, while the Internet of Things (IoT) facilitates distribution, and Self-Service technology empowers consumers (Ferschli et al., 2021).

Digitalization's impact on the labor market is undeniable. Increased accessibility to digital technologies due to improved infrastructure fosters the emergence of informal jobs and disrupts traditional roles. Jobs like YouTubers, streamers, and product reviewers exemplify the new opportunities created by the digital era, while jobs like motor vehicle assemblers are partially replaced by robots, leading to the emergence of new roles like robot technicians and AI specialists Bejaković dan Mrnjavac (2020).

The OECD and ILO report (2019) revealed that the proportion of informal workers in the Arab and Asia Pacific regions has reached 68%. The 2016 World Development Report highlights three key ways in which digitalization impacts businesses, individuals, and governments: firstly, through inclusivity, it reduces information access costs, expands markets, creates jobs, and increases access to public services. Secondly, digitalization fosters efficiency by streamlining resource utilization. In businesses, it can replace workers or non-ICT capital with robots or ICT capital while increasing worker productivity. Within the government, it improves service delivery through information management systems and online services. Finally, digitalization drives innovation by fueling competition in the business world, promoting product innovation and new ways to assess consumer welfare through rating systems and social media.

The rapid development in the internet penetration rate in four emerging market countries in Southeast Asia—Indonesia, Malaysia, the Philippines, and Thailand—stands as a phenomenon that captures attention and



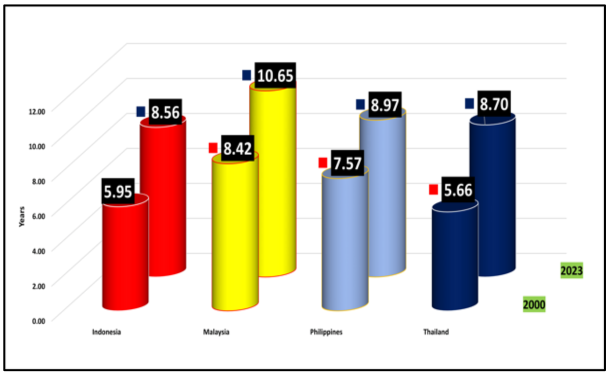

Source: World Bank, drawn by author's 2023

**Figure 1.** Individuals using Internet % of population 2000-2023

reflects the success of efforts to enhance internet accessibility and affordability in the region. For instance, in the year 2000, the percentage of internet users in Indonesia was a mere 3.5%, whereas in 2023, this figure experienced a significant surge, reaching 77.0%, marking a remarkable growth of 73.5%.

A similar trend is observed in Malaysia, the Philippines, and Thailand, with each country showing impressive growth in the percentage of internet users. The key drivers behind this phenomenon involve advancements in information and communication technology, decreased hardware and software costs, increased penetration of telecommunication networks, and government policies supporting the development of internet infrastructure.

Nevertheless, it is crucial to scrutinize that while these figures depict success in providing connectivity, substantial questions arise regarding the actual impact on the digital literacy of the local population. In this perspective, the increase in the percentage of internet users not only reflects the growth in the number of users but also raises questions about the extent to which society can comprehend and effectively adopt this.




Source: UNDP, drawn by author's 2023

**Figure 2.** Mean years of schooling 2000-2023

This research hypothesizes that a synergistic relationship exists between education investment, internet access equality, and digital literacy in enhancing workforce productivity. Increased education investment strengthens knowledge and skills, while improved internet access facilitates knowledge acquisition and skill development. This combined effect fosters digital literacy, ultimately leading to higher productivity.

However, based on several research results in Indonesia, there is still a mismatch between the ability and the field of work carried out as well as differences in the quality of majors and educational institutions still have a significant influence on the unevenness of worker income in Indonesia (Wahyuni & Monika, 2017). In the long run, higher education no longer determines competence or is no longer fully correlated with the measure of ability to produce goods and services (Baharin et al., 2020). This indicates a fundamental educational problem, where the length of time taken to achieve higher education does not guarantee that college graduates can become workers who are ready to enter the workforce (Chalid, 2016).

Understanding the complex interplay between these factors is crucial for policymakers to develop effective strategies for enhancing productivity and promoting economic growth in Southeast Asia. This research aims to provide valuable insights into this dynamic relationship, informing policy decisions and interventions to ensure that digital transformation benefits all workforce segments.

## B. LITERATURE REVIEW

According to Nicholas Gregory Mankiw, labor productivity is defined as Y/L, which is the amount of output divided by the number of workers used. Labor productivity depends on total factor production growth and the capital-labor ratio. To obtain the output per worker figure as a measure of labor productivity, the formula used is:

$$\frac{Y_{it}}{L_{it}} = \left(\frac{K_{it}}{Y_{it}}\right)^{\alpha/(1-\alpha)} \frac{H_{it}}{L_{it}} A_{it} \text{......................(1)}$$

where $\frac{Y_{it}}{L_{it}}$ is output per worker (labor productivity), $\frac{K_{it}}{Y_{it}}$ is the physical capital-output ratio, $\frac{H_{it}}{L_{it}}$ is the number of human resources per worker, and A_it still represents the level of aggregate efficiency in the economy. As suggested by (Hall & Jones, 1999; Hsieh & Klenow, 2010; Klenow & RodríÂguez-Clare, 1997; Mankiw et al.,1992), using the physical capital-output ratio as opposed to the physical capital-labor ratio is more natural for interpreting long-term analysis. Specifically, the physical capital-output ratio is proportional to the investment rate along the balanced growth path. It also helps us to control for indirect effects on physical capital accumulation that may occur when there are exogenous changes in aggregate efficiency (Mendez, 2020).

In endogenous growth theory, the economy's productivity can be simply written as follows:

$$Y = AK \text{...............................................................(2)}$$

where Y is the output, K is the capital stock, and A is a constant that measures the output produced for each capital unit. Note that this production function does not exhibit the property of diminishing returns to capital. An additional unit of capital produces an additional output unit, regardless of how much capital is used. The main difference between this endogenous growth model and the exogenous Solow growth model is the absence of diminishing returns.

The absence of diminishing returns is based on the approach (Romer, 1990) to the variable K, which is no longer interpreted only as a stock of economic factories and equipment but is interpreted more broadly. The best example that can be used is when interpreting knowledge as one type of capital. Knowledge is the primary input for the economy's production in producing goods and services and new knowledge. Knowledge can increase capital returns based on the rate of innovation in science and Technology in recent decades. The reinforcement of this theory is a two-sector model that considers the production function in manufacturing companies and the production function in educational institutions. Then the equation for accumulating resources used is:

$$Y = F[K, (1-\mu)LE] \quad (3)$$

as a production function in manufacturing companies

$$\Delta E = \&(\mu)E \quad (4)$$

as a production function in educational institution research

$$\Delta K = sY - \delta K \quad (5)$$

as a resource accumulation

where μ is the fraction of the workforce in educational institutions, and 1-μ is the fraction in the manufacturing sector. E is knowledge resources (as a determinant of labor efficiency) and is a function that shows how knowledge development depends on the fraction of the workforce in educational institutions. If physical capital K is combined with effective labor in the manufacturing sector [(1-μ)LE], then the production output of goods and services will increase (Y). Therefore, this model can produce persistent growth without assuming changes in production functions on exogenous factors. Persistence is obtained because new knowledge continues to be produced in educational institutions.

Human resource investment is an action that places humans as resources that are expected to be able to influence the high or low real income in the future. Investments can be made in education, health, training and providing good economic information. Research conducted by Gary Stanley Becker, who tried to observe the money return from high school and higher education levels in the United States, produced a general analysis of human capital investment theory (Becker, 1962a).

Education investment is divided into two based on the investor: private investment and public investment. Private investment is a type of education investment carried out by an individual who takes or obtains formal and non-formal education. Meanwhile, public investment is an education investment made by a certain community or government allocated for educational institutions, educational infrastructure such as school buildings, public libraries, training places and financing assistance such as free books and uniforms and can take various other forms. Of course, education also directly contributes to welfare. For example, education increases empowerment and autonomy in key areas of life, such as the capacity for civic engagement, making decisions about one's own health care, and the freedom to choose one's own partner rather than an arranged marriage. However, the basic human capital approach focuses on the indirect ability to improve welfare by increasing income. In this section, the point is illustrated with education investment where an educated person can have wider opportunities to get a job even have the ability to open their own job field (Todaro & Smith, 2014).

In principle, an alternative method for estimating investment in human resources is to look at education results compared to the costs incurred. Where some new abilities are possessed by investing in human resources, which then represent humans and, therefore, cannot be sold out whatever approach is used in the labor market by influencing the number of wages received. Someone who will decide to invest in education must first calculate the costs and benefits that will be received. If the benefits received can exceed the costs incurred, then education investment is the right rational decision to make (Schultz, 1961).

Education investment can increase a person's bargaining power, social status, and self-esteem. According to this theory, some jobs pay better than others because they require human resources with higher abilities. For example, a general practitioner can become a surgeon, but only by extending his formal education for a few more years. Greater additional investment in education is required for a plumber to become a lawyer. Differences in demand can cause some types of human resources to be more valuable than others. Note again the increase in demand for computer programmers that has occurred over the past few decades. During that same period, demand for tax accountant services has fallen as more and more taxpayers have used tax preparation software as a substitute for hiring accountants to help them with their taxes. Both jobs require demanding technical training, but the training received by computer programmers now produces higher returns in the labor market (Frank & Bernanke, 2009).

The primary competence of digital literacy concerns the ability to actively search for and use information, as well as the ability to handle various formats of information, which consist of understanding digital and non-digital formats, creating and communicating digital information, evaluating information, assembling knowledge, information literacy, and media literacy (Bawden, 2008). The basic digital literacy skills that must be possessed by someone are the ability to use computer technology to access resources, find, and identify and learn information effectively to choose and develop the ability to use tools or features that can support one's work, solve problems or create products (Santoso et al., 2019).

Basically, digital literacy involves various types of skills, including skills to use software and other technologies to manage digital information, as well as the ability to use search logic, such as using boolean logic which is a technique for filtering information using mathematical logic that produces true or false output. Another ability is the use of truncation symbols, which is a method of searching for information that uses certain symbols compared to using letters or words to expand the information sought and speed up searches compared to typing one letter or word at a time that needs to be used to search through search engines or databases (Alfonzo & Batson, 2014).

Research that focuses on observing human resources from various perspectives has been carried out by many economists around the world, such as those carried out by (Becker, 1962a; Cornish, 1851; Krueger, 1993; Romer, 1990; Schultz, 1961) to (Ichniowski et al., 1997) and recent studies conducted by (Aji et al., 2020; Puspasari & Handayani, 2020; Wahyuni & Monika, 2017; Wang & Liu, 2016), to (Putriana & Aji, 2022).

The research conducted in Malaysia by (Arshad & Malik, 2015) entitled "Quality Of Human Capital And Labor Productivity: A Case Of Malaysia" through education levels proxied by primary education, secondary education and workforce with tertiary education levels and life expectancy as a proxy for the health condition of the workforce, it is known that high levels of education and good health conditions of the workforce will be in line with the high and good ability of the workforce in producing goods and services. This means that pursuing higher education and improving the health conditions of the workforce will positively and significantly affect labor productivity in 14 territory regions of Malaysia.

A similar study has also been conducted in Vietnam titled "Effects of Foreign Direct Investment and Human Capital on Labor Productivity: Evidence from Vietnam". The study conducted by (Hoang et al., 2019) attempts to observe labor productivity through foreign direct investment and human capital proxied by the human development index. Using the Autoregressive Distributed Lag (ARDL) method, it is known that foreign direct investment and human development index positively and significantly affected labor productivity in Vietnam from 1986-2014, both in the short and long term.

Whereas in Indonesia, research on human resources, specifically observing labor productivity, has been conducted by (Aji et al., 2020; Baharin et al., 2020; Puspasari & Handayani, 2020). According to the research (Baharin et al., 2020) entitled “Impact of Human Resource Investment on Labor Productivity in Indonesia”, in the short term, all levels of education and health conditions of the workforce positively and significantly affect productivity. However, in the long term, only primary and secondary education levels positively and significantly affect labor productivity. On the other hand, higher education possessed by the workforce has a negative effect on labor productivity in the long run. This is due to the mismatch between the high level of education and the level of knowledge and work skills possessed after graduation. On the other hand, the health condition of the workforce in the long term no longer shows a significant effect on increasing labor productivity in Indonesia.

In a more focused regional scope in one of the provinces in Indonesia, Central Java (Puspasari & Handayani, 2020) stated in their research entitled "Analysis of the Effect of Education, Health, and Wages on Labor Productivity in Central Java Province" that labor productivity in Central Java province is positively and significantly influenced by the average length of schooling, with the intention of showing the level of education ever pursued by the workforce. Likewise with life expectancy which supports an increase in labor productivity positively and significantly. The nominal wages received also have a positive and significant effect, where an increase in worker wages will build work motivation, which will then increase productivity.

On the other hand (Aji et al., 2020), in a study titled "Does Education Increase Labor Productivity? An Evidence from Indonesia during Reform Era". In Indonesia, secondary and higher education positively and significantly affects the increase in labor productivity in Indonesia. However, college graduates are not more productive than workers with basic and secondary education. (Putriana & Aji, 2022) They tried to observe further how human resources affect a region's high and low economic growth. This research is entitled "Study on Poverty, Labor Force Participation Rate, Average Length of School as Determinants of Economic Growth in D.I Yogyakarta Province". The results showed that the average length of education of the workforce only had a positive and significant effect on economic growth in Sleman Regency. Whereas in 4 other regencies/cities, namely Bantul Regency, Gunung Kidul Regency, Yogyakarta City and Kulon Progo Regency, although it has a positive effect, it is not significant for economic growth. This means that labor productivity, which is the foundation for measuring economic growth in a region, is not necessarily influenced by the workforce's average length of education.

Then (Dini & Aji, 2022), through their research entitled "Education Investment In Economic Growth Following Provinces In Indonesia In 2014-2020", concluded that primary school participation has a significant effect on economic growth in 4 provinces in Indonesia, namely DKI Jakarta Province, West Java, Central Java and East Java and 30 other provinces it does not have a significant effect. Junior high school (SMP) participation significantly affects economic growth only in the provinces of Indonesia, namely DKI Jakarta and East Java Province. High school (SMA) participation only significantly affects economic growth in 4 provinces in Indonesia, namely DKI Jakarta Province, East Java, Banten and East Kalimantan.

However, Education Investment, as proxied by school participation rates for elementary, junior high and high schools when viewed together, will significantly affect economic growth in 30 Provinces in Indonesia during the period 2014-2020. Economic growth in Riau Province, Bali, West Nusa Tenggara and Papua is not significantly affected. This reinforces the results of research conducted by Rahayu and Rizqon Halal Syah Aji, where high school participation rates do not necessarily increase the ability of human resources to produce goods and services, which then affect economic growth in a region.

Along with the development of Technology, some economists in the world have become interested in observing how Technology affects the business world and productivity. Such as the observation effort made by (Markhaichuk, 2018) in Russia in his research entitled "The Role of Digital Competence in the Impact of Digitalization on Labor Productivity" concluded that the digital literacy level indicator has a positive and significant effect on labor productivity at lag 1,2 and 3 years. The digital transformation experienced by the education world in Russia has had a positive and significant effect on the ability of human resources to produce goods and services at a lag of 1,2 and 3 years. After 2 years, the use of information and communication technology becomes more important in increasing labor productivity.

Furthermore (Rachinger et al., 2019), in "Digitalization and its influence on business model innovation in Austria and Hungary", observed how digitalization affects 2 business models, namely the automotive business and information media business. Using a survey method on employees at 6 automotive companies and 6 information media companies in Austria and Hungary. Both 6 automotive companies and 6 information media companies agreed that digitalization has a positive impact on their business. Especially in supporting new business relationships, collaborating between companies in different industries, product development processes, production of goods, increasing company revenue from both digital products and services offered, increasing production speed, customer satisfaction, and data availability.

A study entitled “Digitalization, Industry Concentration, and Productivity in Germany” conducted by (Ferschli et al., 2021) using a multivariate analysis method found that the German economy has been digitized since 2000. There is a positive and significant relationship between digitalization and industry concentration on labor productivity in Germany's sectoral level. Several of these studies show how important it is to research labor productivity. A review of the results of previous research that has been conducted aims to build information about the object of observation related to this research.

## C. RESEARCH METHODS

In observing social and economic variables, it is difficult to say that there is no correlation between the lag of endogenous variables and their residuals. This takes into account that conditions in previous years will affect all kinds of influences that occur in the current year. Therefore, to meet the analysis needs of this study which also wants to see the dynamic impact of the lag of endogenous variables, namely labor productivity in the previous year, the appropriate regression model to use in this study is a dynamic panel regression model.

The dynamic panel model is able to consider cross-section characteristics between countries and, at the same time, identify the dynamic process between exogenous and endogenous variables. This model is based on a fixed effect model that uses residual variance-covariance to accurately analyze the effect of education investment as proxied by the average length of schooling and digital literacy as proxied by the percentage of internet users on labor productivity as proxied by output per worker (constant 2017 international GDP $ at PPP) in emerging market countries in Southeast Asia for the period 2000-2023 (Mahyus Ekananda, 2016).

The basic assumption is that there are lagged endogenous variables with residuals, while regressors have no relationship with residuals. As long as feasible general least squares (FGLS) estimators are not consistent, to meet the assumption of correlation between lag endogenous variables and their residuals, it can be done by including instrumental variables (VI) into the regression equation (Baltagi, 2005).

This study aims to identify dynamic patterns of influence from education investment and digital literacy variables on labor productivity in each emerging market country in Southeast Asia. The dynamic panel model is used if period t-1, namely the previous year, affects labor productivity in period t. The following is a general equation used (Blundell & Bond, 1998):

$$y_{it} = \delta y_{i,t-1} + \beta'_i x_{it} \dots + \varepsilon_{it} \quad \text{......................(6)}$$

where i is 1, 2, 3, .... n, and t is 1, 2, 3, .... t.
Index i represents the cross-section component, and t represents the time series component.
where;

$y_{i,t-1}$ : cross-section component i at t-1 period
$\alpha_i$ : Intercept
$y_{i,t-1}$ : Independent variable for individual i unit and t-1 period
$X'_{i,t}$ : Exogenous variable
$\beta$ : Variable coefficient
εt : Error

To explain the influence of human resources on labor productivity, this study refers to the theory (Becker, 1962a; Cobb & Douglas, 1928; Phelps, 1966; Romer, 1990; Schultz, 1961; Solow, 1956). With a Cobb-Douglas function approach like the model used by (Aji et al., 2020; Bahrain et al., 2020) where the Cobb-Douglas function can be simply written as follows:

$$Y_t = AK_t^{\alpha} L_T^{\beta} \quad \text{..............................................(7)}$$

where K is the stock of physical capital, L is the number of workers and $\alpha + \beta = 1$, when α is the efficiency parameter at time period t. From this model, by inserting research variables into the general equation used, the analysis model in this study is:

$$LP_{it} = \alpha_i + \beta_{1i}{}^{*}LP_{it-1} + \beta_{2i}{}^{*}EI_{it} + \beta_{3i}{}^{*}DG_{it} + \varepsilon_{it} \quad \text{............................................................(8)}$$

where;
$LP_{it}$ : Labor productivity of i country at t period
$LP_{it-1}$ : Labor productivity of i country at t-1 period

$EI_{it}$ : Education Investment of i country at t period
$DG_{it}$ : Digitalization of i country at t period

The test used in this dynamic panel model is the coefficient of determination test ($R^2$), namely the ($R^2$) adjustment test and the Wald test. The ($R^2$) test is used to see exogenous variables' high and low ability to explain variations in endogenous variables. The coefficient of determination ($R^2$) interval is valued between zero and one. If the coefficient of determination ($R^2$) is close to zero, the X variable has limited ability to affect the Y variable. Conversely, if ($R^2$) is closer to 1, then the X variable has the necessary ability to affect the Y variable. Therefore, the high and low value of ($R^2$) indicates whether a regression model equation is good or bad. However, using the ($R^2$) coefficient of determination test has weaknesses. Its weakness is its bias towards the number of exogenous variables used in the model. The value of ($R^2$) will increase along with the increase in the use of exogenous variables in the model without considering whether the exogenous variables added to the model significantly affect endogenous variables. Therefore, researchers need to use adjusted ($R^2$) to obtain the best model that can be used. This is because increases and decreases in adjusted ($R^2$) depend on the significance of exogenous variables added.

Wald statistics are a joint significance test for exogenous variables that are asymptotically distributed. The Wald test in dynamic panel analysis methods is used to determine the joint effect of exogenous variables on endogenous variables (Arellano & Bond, 1991).

Wald test statistics can be written in equation formulas as follows:

$$W_j = \left[\frac{\widehat{\beta_1}}{SE(\widehat{\beta}_j)}\right]^2 \text{.....................................(9)}$$

Where;
$\beta_j$ : Estimator for $\beta_j$
SE($\beta_j$) : Standart error for βj

Based on the results of the Wald test, the hypotheses used for decision-making are as follows:

1. If the p-value < 0.05, then H0 is accepted and H1 is rejected.
2. If the p-value > 0.05, then H0 is rejected and H1 is accepted.

In this study, the Wald test was used to identify the effect of investing in education and digital literacy on labor productivity.

## D. RESULTS AND DISCUSSION

The results of the coefficient of determination test that has been carried out are useful for seeing the extent to which education investment and digital literacy have the ability to affect labor productivity in emerging market countries in Southeast Asia, resulting in the following equation:

**Table 1.** Coefficient Determination Test

| | |
|---|---|
| **R-Squered** | 0.997895 |
| **Adjusted R-Squered** | 0.997479 |

Source: Eviews estimation results, 2023

The adjusted $R^2$ value is closer to 1, which is 0.997479, so education investment and digital literacy have the necessary ability of 99.7% to affect labor productivity in all emerging market countries in Southeast Asia.

The instrumental variable used in this study is labor productivity in the previous year in 4 countries classified as emerging market countries in Southeast Asia. Based on the results of the regression test that has been carried out, the following are the results of the dynamic panel fixed effect model regression test in each emerging market country in Southeast Asia.

**Table 2.** Wald Test

| No | Country | Wald Test Results | | |
|---|---|---|---|---|
| | | F-Value | P-Value | Signification |
| 1 | Indonesia | 476283.1 | 0.0000 | *** |
| 2 | Malaysia | 9300.255 | 0.0000 | *** |
| 3 | Philippines | 124042.2 | 0.0000 | *** |
| 4 | Thailand | 46904.87 | 0.0000 | *** |

Source: Eviews estimation results, 2023

On the other hand, when the length of education is in line with the development of worker skills, both will increase labor productivity. This can be seen from the results of the Wald test in this study, which shows that education investment and digital literacy significantly affect labor productivity. The increase in the average length of schooling in emerging market countries every year indicates that the ability to emerge market countries' populations to access education is getting better. Then it can be explained that internet usage penetration coupled with an increase in access to education for a country's population can significantly affect labor productivity.

The aspect of higher education alone is not enough to guarantee that higher education can produce the workforce needed in the job market. Because the development of the job market requires new skills that are constantly changing (Becker, 1962b). Human resources are required to remain relevant with the times. Where increasing labor productivity in the era of technological development absorbed in the business world is highly dependent on the ability of educational institutions to produce workers who are adaptive to technological developments (Romer, 1990). According to (Schultz, 1961), besides quantity, the quality attribute of human resources produced by educational institutions is also a very determining factor in obtaining a positive rate of return. So that education can become a human attribute to obtain welfare in the future.

**Table 3.** Previous Year's Labor Productivity on Current Labor Productivity

| No | Country | Dynamic Model Equation | | | |
|---|---|---|---|---|---|
| | | Adjusted R-Squere | F-Value | P-Value | Signification |
| 1 | Indonesia | 0.994783 | 0.0000 | 0.0014 | *** |
| 2 | Malaysia | 0.956324 | 0.0000 | 0.0620 | * |
| 3 | Philippines | 0.985602 | 0.0000 | 0.0000 | *** |
| 4 | Thailand | 0.976168 | 0.0000 | 0.0104 | ** |

Source: Eviews estimation results, 2023

Based on the results of the dynamic panel statistical test above, it is known that the probability value of the instrumental variable for labor productivity in the previous year is 0.0014 < alpha 1% for Indonesia, 0.0620 < alpha 10% for Malaysia, 0.0000 < alpha 1% for the Philippines and 0.0104 < alpha 5% for Thailand. It can be explained that labor productivity in previous years significantly affects current labor productivity in all emerging market countries in Southeast Asia.

The first endogenous variable used in this study is education investment as proxied by the average length of schooling in 4 countries classified as emerging market countries in Southeast Asia. Based on the results of the regression test that has been carried out, the following are the results of the dynamic panel fixed effect model regression test in each emerging market country in Southeast Asia.

The dynamic panel model approach was used to see the effect of education investment as proxied by the average length of schooling of the population in 4 Southeast Asian emerging market countries through P-value, $R^2$ value and adjusted $R^2$ value with a significance level of 0.01 or 1%. The $R^2$ and adjusted $R^2$ values show the influence of the combination of exogenous variables used on endogenous variables, but do not explain the total overall influence. Based on the regression test results, Indonesia's P-value is 0.3875>1%, Malaysia 0.4632>1%, Philippines 0.2571>1% and Thailand 0.1436>1%. It can be concluded that there is no significant effect of the average length of schooling on labor productivity in each emerging market country in Southeast Asia.

**Table 4.** Education Investment on Labor Productivity

| No | Country | Dynamic Model Equation | | | |
|---|---|---|---|---|---|
| | | Adjusted R-Squere | F-Value | P-Value | Signification |
| 1 | Indonesia | 0.994783 | 0.0000 | 0.3875 | |
| 2 | Malaysia | 0.956324 | 0.0000 | 0.4632 | |
| 3 | Philippines | 0.985602 | 0.0000 | 0.2571 | |
| 4 | Thailand | 0.976168 | 0.0000 | 0.1436 | |

Source: Eviews estimation results, 2023

This insignificant effect is quite worrying for emerging market countries in Southeast Asia. Because the length of time spent on education does not fully guarantee an increase in the ability of workers to produce goods and services. The country with the largest economic growth in 2030 is predicted to be enjoyed by countries that have a demographic bonus with a minimum condition of 45% of the population being skilled workers. At the same time, the results of this study show that educational institutions in emerging market countries are still not able to optimally utilize their demographic bonuses.

Some previous studies that align with this study's results include a study conducted by (Abidin et al., 2018), which concluded that in the short term, the average length of schooling still has a negative and significant effect on TFP (Total Factor Productivity). Furthermore, a study (Baharin et al., 2020) shows that in the long run, higher education no longer significantly increases labor productivity. Higher education does not always match a person's job quality, so the high and low level of education of workers does not always determine their ability to complete a job. A study conducted by (Aji et al., 2020) states that the reason why college graduate workers are not more productive than workers with basic and secondary education is due to the mismatch between high levels of education and levels of knowledge and work skills possessed after graduation. According to (Putriana & Aji, 2022), labor productivity, which is the foundation for economic growth in a region, is not necessarily influenced by the average length of education ever pursued by workers in that region.

The second endogenous variable used in this study is digital literacy as proxied by the percentage of internet users in 4 countries classified as emerging market countries in Southeast Asia. Here are the results of the regression test of the effect of digital literacy on labor productivity in each emerging market country in Southeast Asia.

**Table 5.** Digitalization on Labor Productivity

| No | Country | Dynamic Model Equation | | | |
|---|---|---|---|---|---|
| | | Adjusted R-Squere | F-Value | P-Value | Signification |
| 1 | Indonesia | 0.995262 | 0.0000 | 0.8694 | |
| 2 | Malaysia | 0.970325 | 0.0000 | 0.0012 | *** |
| 3 | Philippines | 0.984849 | 0.0000 | 0.0216 | ** |
| 4 | Thailand | 0.974211 | 0.0000 | 0.2264 | |

Source: Eviews estimation results, 2023

Based on the results of the regression test with the dynamic panel model approach above, it can be seen that of the 4 emerging market countries in Southeast Asia, the influence of the percentage of internet users on labor productivity is only significant in 2 countries, namely Malaysia with a P-value of 0.0012 <0.01 and the Philippines with a P-value of 0.0216 <0.05. While in Indonesia and Thailand, the number of internet users does not significantly affect labor productivity. It can be concluded that the percentage of internet users in a country does not necessarily reflect high digital literacy or the ability of workers to use digital Technology as a factor in production efficiency. This is seen from the results of this research study, which shows that although the Philippines has the smallest percentage of internet users compared to the other 3 countries, it shows that its internet users significantly affect labor productivity. English is the primary language in the Philippines. This has caused many foreign companies to recruit Philippine workers, especially in the field of call center services, making the Philippines a call center hub in the world. In 2021, the service sector contributed up to 61.05% of total Philippine GDP. Then it is quite rational if the number of internet users in the Philippines is able to reflect digital literacy that contributes to increasing labor productivity.

The individual influence shown by the digital literacy of workers in Malaysia and the Philippines shows that Technology can determine labor productivity. This study's results align with the endogenous growth theory proposed by (Romer, 1990), where Technology will become a production efficiency factor if workers have the skills to use Technology as a useful tool in increasing their productivity. Thus, the increasingly sophisticated technological developments can be optimally utilized in a country's economy. While the results of studies in Indonesia and Thailand, which show that internet user penetration does not significantly affect labor productivity, can be explained by the productivity paradox concept built by (Krueger, 1993; Triplett, 1999) in observing the early period of technology implementation in the business world, namely in the 1960s-1980s which concluded that one of the causes of the productivity lag paradox over technological developments is due to the implementation of information and communication technology not being accompanied by the readiness of human resources to use it as a production efficiency factor. In addition, it cannot be denied that implementing Technology requires high costs, and high costs in providing technological infrastructure will not increase productivity if the input is still greater than the output produced.

Some previous studies that support this study's results are those conducted by (Santoso et al., 2019), which state that digital literacy creates innovative workers and innovation correlates with productivity. According to (Markhaichuk & Panshin, 2018), indirectly, the influence of digitalization on labor productivity through digital competence is quite small but positive and significant. This explains that labor productivity will grow faster if accompanied by increased digital competence, and the influence of digitalization will be better. Residents' use of information and communication technology has the most positive and significant effect on labor productivity, among other digital literacy indicators. However, the use of information and communication technology will only affect labor productivity if an increase in internet users correlates positively with an increase in digital competence (Markhaichuk & Panshin, 2022). Meanwhile, according to (Metlyakhin et al., 2020), computerization with internet use will only significantly impact labor productivity if the workforce works in a field with a high level of automation. An example is workers who work as program developers or software engineers, and it is very possible for workers who work at companies that have implemented a digital business model where almost all divisions or departments at the company must be connected via an internet network.

## E. CONCLUSION

Based on the data analysis process that has been carried out, the results of this study conclude that current labor productivity is greatly influenced by labor productivity in previous years. The average length of schooling as a proxy used to see the results of education investment in emerging market countries in Southeast Asia does not significantly affect labor productivity. While internet user penetration significantly affects labor productivity only in 2 countries, namely Malaysia and the Philippines. This means that internet user penetration in Indonesia and Thailand still cannot reflect an increase in digital literacy as a production efficiency factor. However, the Wald test results show that education investment as proxied by the average length of schooling and digital literacy as proxied by the percentage of internet users together can significantly build labor productivity in all emerging market countries in Southeast Asia.

To take advantage of the demographic bonus possessed by Emerging Market countries in Southeast Asia, education equity needs to be one of the main priorities in development policies made by the government. The government must ensure that the allocation of government expenditure for education is effective to reach human resources who still live in remote villages. In addition to equitable access to education, quality standards must be continuously improved. Having national education quality standard indicators that can be implemented evenly will be a good foundation for the world of education. The policy of setting national education standards is useful for producing quality human resources who are able to remain relevant and meet competency standards according to the needs of a developing job market.

Seeing the significant influence of education and Technology together, the government needs to adopt more advanced Technology, especially for governments in Malaysia and the Philippines, because they already have human resources who are able to use Technology as a better production efficiency factor than human resources owned by Indonesia and Thailand. However, the development of technology implementation in the economies of Indonesia and Thailand needs to continue and be sustainable with the fulfillment of human resource competency standards so that both countries can have a capital-intensive economy as a good foundation for facing economic openness in the future.

**Appendix A. Additional Data**

Additional material related to this article can be found online at: https://drive.google.com/drive/folders/1badNTJ3UIPiI5tm8Ow_wZqQpk4LSNh_d?usp=drive_link.

## F. REFERENCES

Abidin, N. Z., Yussof, I., Ismail, R., & Karim, Z. A. (2018). The impact of human capital on total factor productivity growth in ASEAN+3 selected countries. *Jurnal Ekonomi Malaysia*, *52*(3), 57–74. https://doi.org/10.17576/JEM-2018-5203-5

Aji, R. H. S. (2020). Dampak Covid-19 pada Pendidikan di Indonesia: Sekolah, Keterampilan, dan Proses Pembelajaran. *SALAM: Jurnal Sosial Dan Budaya Syar-I*, *7*(5). https://doi.org/10.15408/sjsbs.v7i5.15314

Aji, R. H. S., Yussof, I., Saukani, M. N. M., & Baharin, R. (2020). Does Education Increase Labor Productivity? An Evidence From Indonesia During Reform Era. *Test Engineering and Management*, *82*(16193), 16193–16199.

Alfonzo, P. M., & Batson, J. (2014). Utilizing a Co-teaching model to enhance digital literacy instruction for doctoral students. *International Journal of Doctoral Studies*, *9*, 61–71. https://doi.org/10.28945/1973

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, *58*(2), 277–297. https://doi.org/10.2307/2297968

Arshad, M. N. M., & Malik, Z. A. (2015). Quality of human capital and labor productivity: A case of Malaysia. *International Journal of Economics, Management and Accounting*, *23*(1), 37–55.

Baharin, R., Aji, R. H. S., Yussof, I., & Saukani, N. M. (2020). Impact of human resource investment on labor productivity in Indonesia. *Iranian Journal of Management Studies*, *13*(1), 139–164. https://doi.org/10.22059/IJMS.2019.280284.673616

Baltagi, B. H. (2005). *Econometric Analysis of Panel Data* (Third Edit). John Wiley & Sons, Ltd.

Bawden, D. (2008). Origins and concepts of digital literacy. *Digital Literacies: Concepts, Policies and Practices*, 17–32. https://doi.org/10.1093/elt/ccr077

Becker, G. S. (1962a). Investment in Human Capital: A Theoretical Analysis. *Journal of Political Economy*, *70*(5, Part 2), 9–49. https://doi.org/10.1086/258724

Becker, G. S. (1962b). Investment in Human Capital: A Theoretical Analysis. *Journal of Political Economy*, *70*(5, Part 2), 9–49. https://doi.org/10.1086/258724

Bejaković, P., & Mrnjavac, Ž. (2020). The importance of digital literacy on the labour market. *Employee Relations*, *42*(4), 921–932. https://doi.org/10.1108/ER-07-2019-0274

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Brezis, E. S., & Brand, G. (2016). The Effects of Education on Labor Productivity : Differences between Tradable and Non-tradable Industries. *E-Journal Business*, *1*(9), 1–10.

Carlsson, M., Dahl, G. B., Öckert, B., & Rooth, D. O. (2015). The effect of schooling on cognitive skills. *Review of Economics and Statistics*, *97*(3), 533–547. https://doi.org/10.1162/REST_a_00501

Cetindamar, D., Abedin, B., & Shirahada, K. (2021). The Role of Employees in Digital Transformation: A Preliminary Study on How Employees’ Digital Literacy Impacts Use of Digital Technologies. *IEEE Transactions on Engineering Management*, 1–12. https://doi.org/10.1109/TEM.2021.3087724

Chalid, P. (2016). *Challenge of University Graduate on Tight Competition of Labor Market*.

Cobb, C. W., & Douglas, P. H. (1928). A Theory of Production. *The American Economic Review*, *18*(1), 139–165.

Cornish, J. (1851). On the word "raised" as used by the Americans. In *Notes and Queries* (Vols. s1-IV, Issue 92). https://doi.org/10.1093/nq/s1-IV.92.83-a

Dini, D., & Aji, R. H. S. (2022). Education Investment in Economic Growth Following Provinces in Indonesia in 2014-2020. *Pemikiran Dan Pengembangan Perbankan Syariah*, *8*(1), 163–180.

Ferschli, B., Rehm, M., Schnetzer, M., & Zilian, S. (2021). Digitalization, Industry Concentration, and Productivity in Germany. *Jahrbucher Fur Nationalokonomie Und Statistik*, *241*(5–6), 623–665. https://doi.org/10.1515/jbnst-2020-0058

Frank, R. H., & Bernanke, B. S. (2009). *Principle of Microeconomics* (Fourth). McGraw-Hill/Irwin.

Gudmundsson, T., Klyuev, V., Medina, L., Nandwa, B., Plotnikov, D., Schiffrer, F., & Yang, D. (2022). *Emerging Markets: Prospects and Challenges, WP/22/35, February 2022*.

Hartono, D. (2014). Memahami Pasar-Pasar Emerging (Understanding Markets). *Jurnal Ekonomi*, *16*(1), 87–109.

Hoang, N., Quoc, L. V., & Hoang, B. (2019). Effects of foreign direct investment and human capital on labour productivity: Evidence from Vietnam. *Journal of Asian Finance, Economics and Business*, *6*(3), 123–130. https://doi.org/10.13106/jafeb.2019.vol6.no3.123

Ichniowski, C., Shaw, K., & Prennushi, G. (1997). Effects of Human Resource Management Practices. *American Economic Review*, *87*(3), 291–313.

Ketteni, E., Mamuneas, T., & Stengos, T. (2011). The effect of information technology and human capital on economic growth. *Macroeconomic Dynamics*, *15*(5), 595–615. https://doi.org/10.1017/S1365100510000210

Knight, G., & Riesenberger, J. R. (2008). *International Business; Strategy, Management and New Realities*.

Krueger, A. B. (1993). How computers have changed the wage structure: Evidence from microdata, 1984–1989. *Quarterly Journal of Economics*, *108*(1), 33–60. https://doi.org/10.2307/2118494

Mahyus Ekananda. (2016). *Analisis Ekonometrika Data Panel Edisi 2: Teori Lengkap Dan Pembahasan Menyeluruh Bagi Peneliti Ekonomi, Bisnis, Dan Sosial.* (2nd ed.). Mitra Wacana Media.

Mankiw, N. G., Catherine, W., Charles, L., Shani, F., Jane, E. T., Carlos, M., Thomas, D., Alexander, K., Lukia, K., Tracey, K., Lisa, K., Julio, E., Robin, F., Diana, B., Kevin, K., Paul, R., & Sharon, P. (2016). Macroeconomics In R. F. Jane E.Tufis, Carlos Marin, Lukia Kliossis, Lisa Kinne, Julio Espin (Ed.), *A Macmillan Education Imprint New York* (Ninth Edit, Vol. 59). Worth Publishers A Macmillan Education Imprint.

Markhaichuk, M. (2018). *The Role of Digital Competence in the Impact of Digitalization on Labor Productivity*. *2016*, 6632–6641.

Markhaichuk, M., & Panshin, I. (2018). *The Role of Digital Competence in the Impact of Digitalization on Labor Productivity*. *2016*, 6632–6641.

Markhaichuk, M., & Panshin, I. (2022). The Impact of Digital Literacy on Labor Productivity in the Context of the Educational Environment Transformation. *Eurasian Journal of Educational Research*, *97*(97), 86–102. https://doi.org/10.14689/ejer.2022.97.05

Matthess, M., & Kunkel, S. (2020). Structural change and digitalization in developing countries: Conceptually linking the two transformations. *Technology in Society*, *63*, 101428. https://doi.org/10.1016/j.techsoc.2020.101428

Mendez, C. (2020). *Convergence Clubs in Labor Productivity and its Proximate Sources: Evidence from Developed and Developing Countries*. https://doi.org/10.1007/978-981-15-8629-3

Metlyakhin, A. I., Nikitina, N. A., Yarygina, L. V, & Orlova, E. O. (2020). Analysis of the Impact of Economy Digitalization on Labor Productivity in Russia. *Анализ Влияния Цифровизации Экономики На Производительность Труда В России*, *13*(2), 7–17. https://doi.org/10.18721/JE.13201

Nurjanah, E., Rusmana, A., & Yanto, A. (2017). Hubungan Literasi Digital dengan Kualitas Penggunaan E-Resources. *Lentera Pustaka: Jurnal Kajian Ilmu Perpustakaan, Informasi Dan Kearsipan*, *3*(2), 117. https://doi.org/10.14710/lenpust.v3i2.16737

Phelps, E. (1966). Models of Golden Rule of Progress and. *Res*, *33*(2), 133–145.

Puspasari, D. A., & Handayani, H. R. (2020). Analysis of Education, Health, and Wages Effect on Labor Productivity in Central Java Province. *Jurnal Dinamika Ekonomi Pembangunan*, *3*(1), 65–76.

Putriana, R., & Aji, R. H. S. (2022). Studi Atas Kemiskinan, Tingkat Partisipasi Angkatan Kerja, Rata-Rata Lama Sekolah Sebagai Penentu Pertumbuhan Ekonomi di Provinsi D.I Yogyakarta. *Pemikiran Dan Pengembangan Ekonomi Syariah*, *8*(1), 31–48.

Rachinger, M., Rauter, R., Müller, C., Vorraber, W., & Schirgi, E. (2019). Digitalization and its influence on business model innovation. *Journal of Manufacturing Technology Management*, *30*(8), 1143–1160. https://doi.org/10.1108/JMTM-01-2018-0020

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5), S71–S102. https://doi.org/10.3386/w3210

Santoso, H., Abdinagoro, S. B., & Arief, M. (2019). The role of digital literacy in supporting performance through innovative work behavior: The case of Indonesia's telecommunications industry. *International Journal of Technology*, *10*(8), 1558–1566. https://doi.org/10.14716/ijtech.v10i8.3432

Schultz, T. W. (1961). Invest in Human Capital. In *The American Economic Review* (Vol. 51, Issue No. 1, pp. 1–17).

Solow, R. M. (1956). A Contribution to the Theory of Economic Growth Author ( s ): Robert M . Solow Source. *The Quarterly Journal of Economics*, *70*(1), 65–94. http://www.jstor.org/stable/1884513

Todaro, M. P., & Smith, S. C. (2014). *Economic Development 12th Edition* (David Alexander (ed.); 12th ed.). Pearson.

Triplett, J. E. (1999). The Solow Productivity Paradox: What do Computers do to Productivity? *The Canadian Journal of Economics / Revue Canadienne d'Economique*, *32*(2), 309. https://doi.org/10.2307/136425

Wahyuni, R. N. T., & Monika, A. K. (2017). Pengaruh Pendidikan Terhadap Ketimpangan Pendapatan Tenaga Kerja Di Indonesia. *Jurnal Kependudukan Indonesia*, *11*(1), 15. https://doi.org/10.14203/jki.v11i1.63

Wang, Y., & Liu, S. (2016). Education, Human Capital and Economic Growth: Empirical Research on 55 Countries and Regions (1960-2009). *Theoretical Economics Letters*, *06*(02), 347–355. https://doi.org/10.4236/tel.2016.62039