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An Application of Data Envelopment Analysis and Malmquist Productivity Index in the Development of Human Capital of ASEAN-5 countries

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Abstract

This work highlights the support of some indicators, which are assumed to be resources, namely mobile usage, internet usage, private credit, government education expenditure, and the export of high-technology products, for human capital development. To investigate the efficiency and productivity of creating human capital, the methods of Data Envelopment Analysis (DEA) and the Malmquist Productivity Index (MPI) are applied to the 2017 data, 2018 data, and 2020 data of the selected ASEAN-5 countries, namely Indonesia, the Philippines, Vietnam, Thailand, and Malaysia. It is discovered that, in a constant return to scale, Thailand and Malaysia nearly reach full technical efficiency in developing human capital, and the rest are fully efficient. When measured in terms of variable return to scale, only Thailand is inefficient and is in the stage of decreasing return to scale. The comparison between 2018 and 2020 shows that human capital creation productivity in 2020 in Vietnam, Thailand, and Malaysia improved compared to 2018 as a result of technological improvement. However, they are still less than Indonesia, the Philippines, and the target optimal efficiency level. Therefore, the recommendations are that the governments of Thailand and Malaysia should make more effort to utilize their inputs to support human capital development.

Keywords: Human capital, Data Envelopment Analysis, Malmquist Productivity Index, ASEAN-5 countries
JEL Classifications: E01, E22, E24, H75

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1. INTRODUCTION

In the realm of private business production units, the efficient utilization of a country's resource endowment is crucial for achieving desired outcomes. Traditionally, the Gross Domestic Product (GDP) has been widely employed as an indicator to measure the output derived from these resource endowments. Nonetheless, while GDP serves as a useful tool for assessing the quantity-based growth of nations, it falls short in capturing the multidimensional aspects of a country's development, such as the quality of its environment, society, community, and citizens. These qualitative dimensions can significantly impact a country's long-term growth trajectory.

Human capital is a crucial indicator often used to reflect the quality of citizens. It has been widely argued that human capital has the potential to not only improve the well-being of individuals but also contribute to the overall growth and development of a nation. The study of human capital has gained significant importance due to the belief that individuals possessing higher levels of human capital are more likely to efficiently perform various tasks and contribute to the production of desired goods and services. This, in turn, leads to a better quality of life for both citizens and the nation as a whole (Fan et al., 2016; Sheykhi, 2021). Human capital has emerged as a significant focal point for the Association of Southeast Asian Nations (ASEAN), established on August 8, 1967. Comprising ten member states, namely Indonesia, Malaysia, the Philippines, Singapore, Thailand, Brunei Darussalam, Vietnam, Lao PDR, Myanmar, and Cambodia, ASEAN aims to prioritize the development of human capital. However, to effectively attain this objective, the governments of these nations necessitate methodologies that enable the assessment of human capital promotion and resource utilization.

To assess efficiency, the Data Envelopment Analysis (DEA) is widely employed in various contexts. For instance, it has been utilized to evaluate the efficiency of nations in converting economic complexity into human development. In this case, an economic complexity index is used as an input, while a composite human development index serves as an output. This composite index is approximated by factors such as life expectancy at birth, mean years of schooling, unemployment rate, and sanitation rate (Ferraz et al., 2018). The DEA method has also been utilized to assess the technical efficiency of health systems and evaluate environmental efficiency in various domains. Within the healthcare sector, per-capita health expenditure is considered as an input, while health outcome indicators such as healthy life expectancy at birth and infant mortality per 1000 live births are regarded as outputs (Ahmed et al., 2019). Similarly, in the evaluation of environmental efficiency, inputs consist of energy consumption from coal, oil, gas, and the volume of vehicles, while outputs encompass measures such as GDP, CO2 emissions, and CH4 emissions (Wang et al., 2021).

Motivated by the significance of human capital as a key factor in the growth and development of countries as well as the need to improve the efficacy of governments in promoting human capital, this study thus aims to meet these objectives and expand the application of DEA at the macro level. Also, the well-known Malmquist Productivity Index will be used to identify an improvement in government productivity in promoting human capital. This work regards human capital as an output that the country needs to generate and some macro-level indexes, namely high-technology exports, mobile cellular subscriptions, private credit, government education expenditure, and individuals' internet usage, as inputs or resources. The objective of the country is to maximize the level of human capital within the limitations of its resources. An application objective of this work will be conducted using the data of the selected ASEAN-5 countries, and it will be managed in the following sequence: The next section will review some literature to gain a concept of human capital and an idea of indexes that are recognized as resources to be utilized for generating human capital. Then the concepts of Data Envelopment Analysis and the Malmquist Productivity Index will be presented. After that, the results of the analysis and policy recommendations will be discussed.

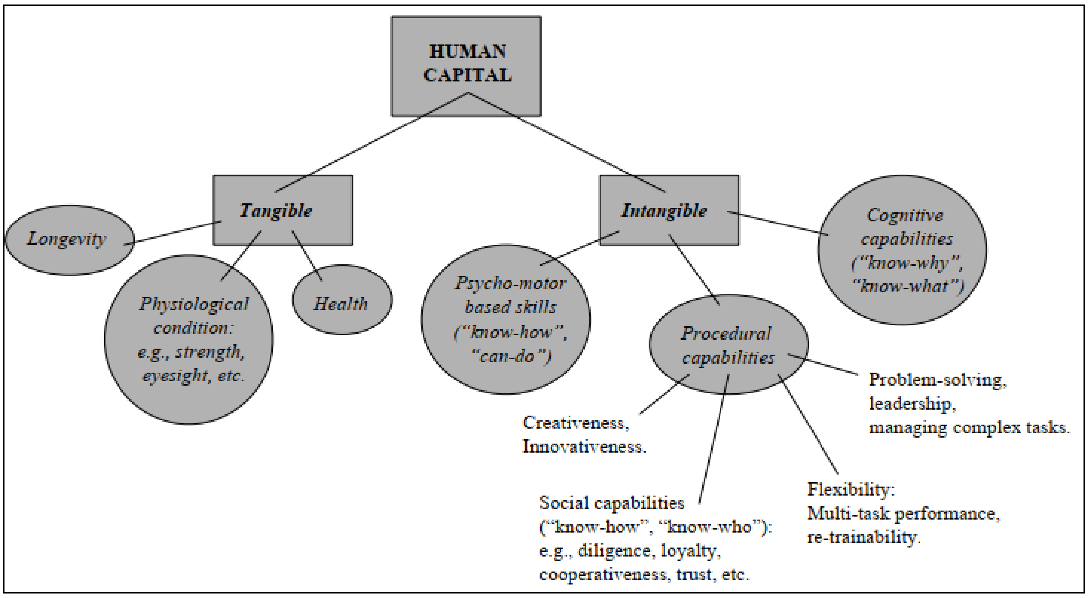
2. LITERATURE REVIEWS

This section will provide the definition and concept of human capital, as well as the empirical findings of a few studies. The following are the specifics of these topics.

2.1 The Concept of Human Capital

Human capital plays a vital role in driving economic growth and alleviating poverty. By accumulating human capital, individuals enhance their labor productivity, increase their chances of employment, and foster the development of innovative technologies. This form of capital is closely linked to education and contributes to a person's productivity and earnings over a significant period of time (Son, 2010). According to David (2001), human capital can be defined as the collection of enduring abilities that individuals acquire throughout their lives, which can be categorized into tangible and intangible components as illustrated in Figure 1.

Figure 1: Human Capital: A Taxonomy



Source: (David, 2001)

According to Figure 1, the tangible component is defined by three elements, i.e., 1) physiological attributes, e.g., stature, strength, stamina, eyesight, and hearing; 2) health status; and 3) longevity, which is the conditional expectation of the duration of the remaining lifespan. This part has to do with a person's performance and skills, which make up the intangible part of human capital. In the case of the intangible component, it is defined by three components: 1) psycho-motor-based skills; 2) cognitive capabilities; and 3) procedural capabilities, which are further defined by four subcomponents: 1) creativity and innovativeness; 2) problem-solving abilities, complex task management, and leadership; 3) flexibility, which is the ability to perform multi-task activities and absorb retraining; and 4) social capabilities, which are a set of personal qualities, e.g., diligence, loyalty, cooperativeness, and the capacity for discerning trust in other individuals, that are important in forming and maintaining social capital. To accumulate Tangible Human Capital Formation, it requires improvements in, e.g., nutritional status, stature, strength, health, and capability to learn. On the other hand, to accumulate intangible human capital, which involves the systematic accumulation of human knowledge, requires modes of learning that yield the needed knowledge of various kinds. Such knowledge includes "know what," or knowledge about workings; "know how," or knowledge about a variety of procedural capabilities, crafting skills, and problem-solving capacities; and "know who and where," or knowledge about where to find substantive "facts" and the identity of individuals who possess particular productive assets or the power to take certain actions. In fact, the accumulation of human capital can be conducted through a wide array of processes and is far from static. Furthermore, the knowledge to be accumulated may be in different forms, e.g., codified and tacit forms, which affect, e.g., the feasibility and costs of knowledge acquisition; the rates of return of intangible human capital formation; and the processes of knowledge production and transfer. It should be recognized that human capital is not a "free" and exogenous thing. It needs to be improved and thus involves both direct and indirect costs of investment, e.g., time spent to learn, money cost of learning, effort to learn, money spent to maintain health status, and satisfaction foregone.

2.2 The Discovery from Empirical Studies

The evidence of the associations between human capital and other variables under this study is as follows: Regarding the association between human capital and the export of high technology, indirect evidence can be found. A study on economic growth revealed a correlation between average education (a proxy for human capital) and exports, which support growth (Levin & Raut, 1997). Furthermore, it was discovered that human capital played a significant role in the performance of a country's high-tech industry (Tebaldi, 2011). Additionally, human capital was identified as an important variable influencing high-technology exports in developing countries (Mohsen et al., 2017). For the association between human capital and mobile cellular, it was discovered that mobile can make substantial contributions to capabilities and freedoms in economic and social spheres (Smith et al., 2011), and it is a pivotal tool for knowledge diffusion that supports sustainable and inclusive human development (Asongu et al., 2016). Also, it was found that the Internet and communication technology—the attributes of mobile cellular—are key aspects for the development of human capital (Sima et al., 2020). Regarding the association between human capital and private credit, it was discovered that domestic credit to the private sector, a component of financial development, was found to have a positive effect on human capital in emerging market economies (Kiliç & Özcan, 2018). Also, financial development can expand economic opportunities and income distribution, which are aspects of human capital development (Ross, 2021). In terms of the association between human capital and expenditure on education, it was discovered that public education expenditure has a positive influence on human resource development (Patel & Annapoorna, 2019). Furthermore, it was revealed that an increase in government education and health expenditure can positively and significantly impact primary and secondary school enrollment (Adewumi & Enebe, 2019). Also, an increase in state financial support in this area can reduce student debt and time to degree while inducing more collegiate and post-collegiate educational attainment (Chakrabarti et al., 2020). In the instance of the association between human capital and Internet usage, it was discovered that internet usage, innovation, and their interaction significantly and positively relate to human development (Ejemeyovwi et al., 2019). Also, broadband penetration (Djunaedi, 2021) and the strengths of virtual education, such as accessibility, flexibility, adaptability, and affordability (Saroj et al., 2022), can increase the coverage and formation of human capital.

3. METHODOLOGY

3.1 Data Envelopment Analysis

DEA (Ferraz et al., 2018; Ahmed et al., 2019; Wang et al., 2021) was developed by Charnes et al. (1978). This method aims to measure the productive efficiency of a set of decision-making units (DMUs) through the empirical construction of a piecewise linear frontier. It calculates technical efficiency by solving the nonlinear programming system of the DMUs. DEA is used to identify an efficiency frontier and the distance of each DMU to the frontier. One type of DEA model, developed by Charnes, Cooper, and Rhodes (CCR), assumes that production has constant returns to scale (CRS). On the other hand, the model proposed by Banker, Charnes, and Cooper (BCC) assumes that production has variable returns to scale (VRS), implying that an increase in the input will result in either an increase or a decrease in the output. The scale efficiency will indicate whether DMUs are operating at their optimal sizes or not. To understand the concept of DEA, let's define:

$$E_0 = \frac{\sum_{j=1}^{J} u_j y_{j0}}{\sum_{i=1}^{N} v_i x_{i0}} \tag{1}$$

where $0 \le E_0 \le 1$ is an efficiency score such that 1 imply maximum technical efficiency. The linear programming of output and input-oriented DEA based on Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) can be, respectively, represented as follows:

Constant returns to scale (CRS): Output oriented

$$\begin{aligned} & MAX \sum_{j=1}^{J} \mu_j y_j \\ & st. \\ & \sum_{i=1}^{N} {}_{i} x_i = 1 \\ & \sum_{j=1}^{J} \mu_j y_{jk} - \sum_{i=1}^{N} \upsilon_i x_{ik} \le 0, k = 1, \dots, K \\ & \mu_j, \upsilon_i \ge \varepsilon \end{aligned} \tag{2}$$

Variable returns to scale (VRS): Output oriented

$$
\begin{aligned}
& MAX\sum_{j=1}^{J}\upsilon_j y_j + w \\
& st. \\
& \sum_{i=1}^{N}\upsilon_i x_i = 1 \\
& \sum_{j=1}^{J}\mu_j y_{jk} - \sum_{i=1}^{N}\upsilon_i x_{ik} + w \le 0, k = 1,...,K \\
& \mu_j, \upsilon_i \ge \varepsilon
\end{aligned}
\tag{3}
$$

where x_i, $i = 1,2,...,N$, represents the amount of input i of K DMUs, y_i, $j = 1,2,...,J$, represents the amount of output j of K DMUs; x_{ik}, $k = 1,2,...,K$, represents the amount of input i of DMU k; y_{jk} represents the amount of output j of DMU k; $\upsilon_i = t\upsilon_i$ represents the weight of input i; $\mu_j = tu_j$ represents the weight of output j, being $t = \left(\sum_i \upsilon_i x_i\right)^{-1}$; w represents the scale factor. ε is a parameter to force the variables to be positive**.**

3.2 Malmquist Productivity Index

The Malmquist index is defined by the distance function. This function includes two kinds, i.e., the input distance function, which depicts the production technology that reduces the input vector for a given output vector, and the output distance function, which depicts the production technology that increases the output vector for a given input vector. To get an idea of the output distance function (Coelli et al., 1998; Zrelli et al., 2020), let's define

$$P^t\left(\mathbf{x^t}\right) = \left\{\mathbf{y^t} : \mathbf{x^t}\right\}, t = 1,...,T \tag{4}$$

where $P^t\left(x^t\right)$ is the output possibility set is, $\mathbf{y^t}$ is the set of output vector, $\mathbf{x^t}$ denote the set of input vector. Then we can define the distance function as follows:

$$D^t\left(x,y\right) = \min\left\{\lambda \in [0,1] : \frac{y}{\lambda} \in P^t\left(x\right)\right\} \tag{5}$$

where $D^t\left(x,y\right) \le 1$ and $\boldsymbol{\lambda}$ is weight.

This index can be used to measure total factor productivity (TFP) change between any particular two periods. In the case of output-oriented MPI, MPI is given by:

$$M_O^{t,t+1}\left(x^t, x^{t+1}, y^t, y^{t+1}\right) = \left[\frac{D_O^t\left(x^{t+1}, y^{t+1}\right)}{D_O^t\left(x^t, y^t\right)} \frac{D_O^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_O^{t+1}\left(x^t, y^t\right)}\right]^{\frac{1}{2}} \tag{6}$$

where $M_O^{t,t+1}\left(x^t, x^{t+1}, y^t, y^{t+1}\right) > 1$ indicates the productivity improvement as a result of technology change. The first ratio signifies the MPI in period t that expresses the efficiency change that measures the change of productivity from period t to period t + 1 using period t technology as a reference. It reflects an ability to utilize technology at a particular time. However, the second ratio represents MPI in period t+1, which measures productivity change from period t to time t+1 using time t + 1 technology as a reference. These two terms express MPI as a geometric mean.

By assuming constant returns-to-scale, we can calculate these four distance functions between period t and t + 1 as follows:

$$\left[D_O^t\left(y_t, x_t\right)\right]^{-1} = max\theta$$
$$Y_t\lambda \geq \theta y_{it}$$
$$x_{it} \geq X_t\lambda$$
$$\lambda \geq 0$$

$$\left[D_O^{t+1}\left(y_{t+1}, x_{t+1}\right)\right]^{-1} = max\theta$$
$$Y_{t+1}\lambda \geq \theta y_{i,t+1}$$
$$x_{i,t+1} \geq X_{t+1}\lambda$$
$$\lambda \geq 0$$

$$\left[D_O^t\left(y_{t+1}, x_{t+1}\right)\right]^{-1} = max\theta$$
$$Y_t\lambda \geq \theta y_{i,t+1}$$
$$x_{i,t+1} \geq X_t\lambda$$
$$\lambda \geq 0$$

$$\left[D_O^{t+1}\left(y_t, x_t\right)\right]^{-1} = max\theta$$
$$Y_{t+1}\lambda \geq \theta y_{it}$$
$$x_{it} \geq X_{t+1}\lambda$$
$$\lambda \geq 0$$

where y_{it} , $i = \left(1, ..., N\right)$, is the $M \times 1$ vector of output, x_{it} is the $K \times 1$ vector of input, Y_t is, is the $M \times N$ vector of output and, X_t is the $K \times N$ vector of input, λ is $N \times 1$ vector of weights, and θ is a scalar indicating the technical efficiency score.

The MPI is performed to evaluate the relative technical efficiency of each country in maximizing outcomes. This MPI can be evaluated with either the assumption of constant or variable returns to scale. However, a variable return to scale output□oriented model is assumed in the analysis of a cross□sectional study with heterogeneity in the characteristics of the studied units. Analytically, a DMU could be better than it was in the successive periods with an MPI score greater than unity, i.e., it is more efficient than in the previous periods. This means frontier productivity shifts outward, which may be a result of utilizing fewer inputs or technical progress within or emanating from outside the system. Conversely, a DMU could experience productivity regress when the MPI score is less than unity, i.e., it is less efficient than in the previous periods. This may be the result of an increase in inputs without a corresponding rise in output. Similarly, a DMU may experience productivity stagnation over a given time frame with a unit score of MPI (Shailender et al., 2021).

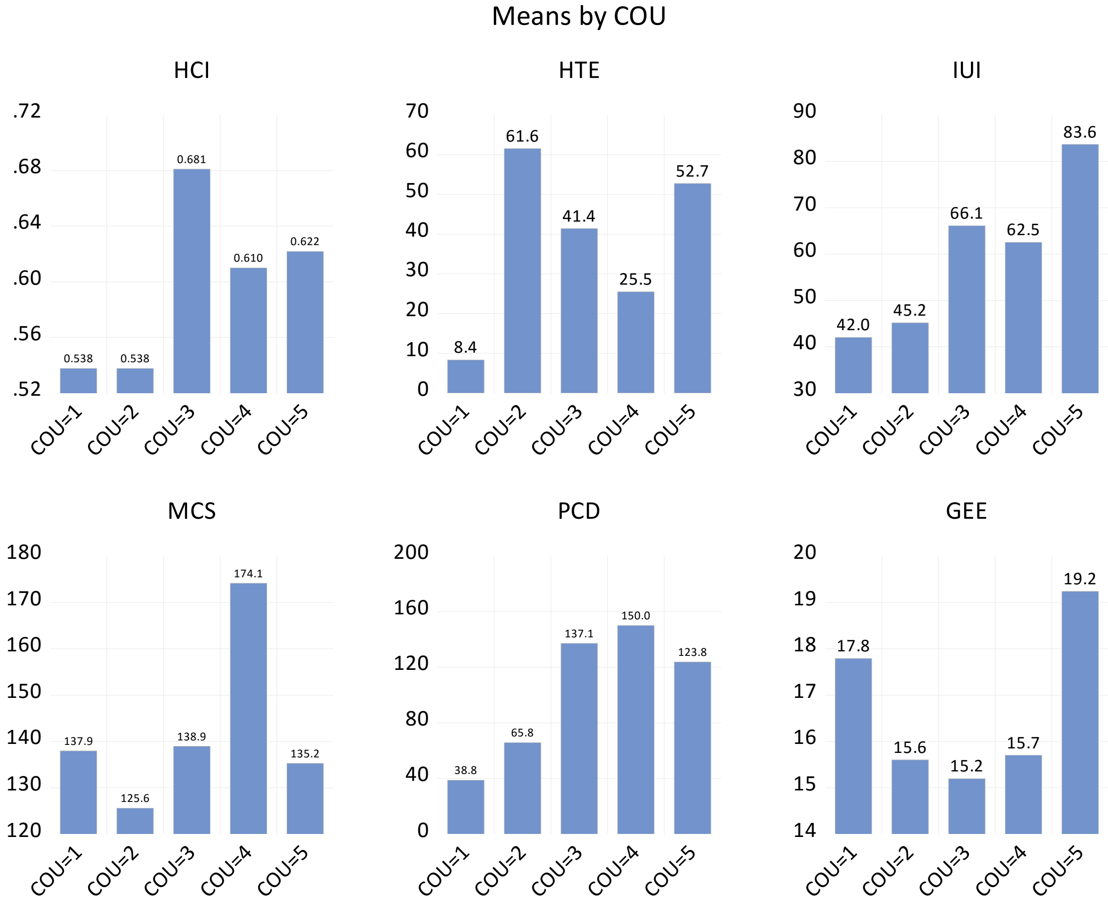
In this work, data for 2017, 2018, and 2020 from the ASEAN-5 countries with complete data for the target variables will be analyzed. The output orientation is chosen because governments need to utilize the resources in an efficient manner to be perceived as competitive countries in a competitive world environment (Wahyudi & Azizah, 2018). To conduct the analysis, data on the Human Capital Index (HCI), High-technology exports (HTE), Mobile cellular subscriptions (MCS), private credit (PCD), government expenditure on education (GEE), and individuals using the Internet (IUI) of the selected ASEAN-5 countries, namely Indonesia, the Philippines, Vietnam, Thailand, and Malaysia, in the years 2017, 2018, and 2020, the latest available data downloaded from the World Bank website, are utilized.

4. RESULTS

4.1 Reliability Test

Figure 2 depicts a fundamental characteristic of variables represented by the means of the years 2017, 2018, and 2020. For example, Vietnam has the highest mean for HCI, whereas the Philippines has the highest mean for HTE.

Figure 2: Variables' Mean Calues Across Countries



Note: 1 = Indonesia, 2 = the Philippines, 3 = Vietnam, 4 = Thailand, and 5 = Malaysia
Source: Authors' Presentation

The technical efficiency calculated based on the constant returns to scale (CRS) assumption for the year 2020 is shown in Table 1. It shows that Indonesia, the Philippines, and Vietnam perform efficiently on the frontier, while Thailand and

Malaysia perform inefficiently, as reflected by the scores of 0.925 and 0.943, respectively. As these technical efficiency scores are computed under the output-oriented approach, the inefficient countries can improve their HDI by trying to utilize the rest of the inputs shown in Table 2. To make improvements, inefficient countries can use the countries in their peers' columns as a benchmark.

Table 1: Countries' Technical Efficiency of CRS in 2020

Countries	TE_{CRS}	**peers**	
Indonesia	1.000		
Philippines	1.000		
Vietnam	1.000		
Thailand	0.925	Vietnam	Indonesia
Malaysia	0.943	Vietnam	Indonesia

Source: Authors' calculation

Table 2: Countries' Slacks of CRS in 2020

Countries	**Output Slacks**	**Input Slacks**				
		HTE	**MCS**	**PCD**	**GEE**	**IUI**
Indonesia	0	0	0	0	0	0
Philippines	0	0	0	0	0	0
Vietnam	0	0	0	0	0	0
Thailand	0	0	21.07	58.851	0	11.349
Malaysia	0	16.059	0	0	2.877	23.63

Source: Authors' calculation

The technical efficiency calculated based on the variable returns to scale (VRS) assumption for the year 2020 is shown in Table 3. It shows that Indonesia, the Philippines, Malaysia, and Vietnam perform efficiently on the boundary of the frontier, while only Thailand performs inefficiently, as reflected by the score of 0.972. Similarly, Thailand can increase its HCI by trying to utilize the rest of the inputs shown in Table 4. In the case of scale efficiency, it is shown that Thailand performs under decreasing returns to scale (DRS) and Malaysia performs under increasing returns to scale (IRS). This implies that Thailand has a relatively large size of operation compared with the optimal size, while Malaysia has a relatively small size of operation compared with the optimal size.

Table 3: Countries' Technical Efficiency of VRS in 2020

Countries	TE_{VRS}	**scale**	**Return to Scale**	**peers**	
Indonesia	1.000	1.000			
Philippines	1.000	1.000			
Vietnam	1.000	1.000			
Thailand	0.972	0.951	DRS	Vietnam	Indonesia
Malaysia	1.000	0.943	IRS		

Source: Authors' calculation

Table 4: Countries' Slacks of VRS in 2020

Countries	Output Slacks	Input Slacks				
		HTE	MCS	PCD	GEE	IUI
Indonesia	0	0	0	0	0	0
Philippines	0	0	0	0	0	0
Vietnam	0	0	0	0	0	0
Thailand	0	0	29.25	59.572	1.16	14.545
Malaysia	0	0	0	0	0	0

Source: Authors' calculation

The changes in TFP can be decomposed into technical efficiency changes and technological changes, as expressed in Tables 5 and 6. The technical efficiency change represents improvements in efficiency due to improved operations, management, and returns to scale which increase the ability to use the given inputs to produce a maximum level of output. This efficiency change index, with a value above 1, suggests that technical efficiency has improved. Technological change is a source of productivity change that shifts the production frontier. Technological change occurs due to improvements in the technology used in production and service processes. This index with a value above 1 will suggest technological progress, while a value less than 1 will suggest technological regress.

Table 5: Technical Change

Countries	2018	2020
Indonesia	1.001	1.105
Philippines	1.01	0.983
Vietnam	0.961	1.009
Thailand	1	1
Malaysia	1	1

Source: Authors' calculation

Table 6: Technological Change

Countries	2018	2020
Indonesia	1.008	0.898
Philippines	0.957	0.897
Vietnam	0.757	0.86
Thailand	0.805	0.844
Malaysia	0.711	0.831

Source: Authors' calculation

Table 7: Total Factor Productivity Change

Countries	2018	2020
Indonesia	1.008	0.992
Philippines	0.967	0.882
Vietnam	0.728	0.868
Thailand	0.805	0.844
Malaysia	0.711	0.831

Source: Authors' calculation

It is indicated in Table 7 that HCI creation productivity in 2020 in Vietnam, Thailand, and Malaysia are improved compared to 2018. The source of this productivity improvement can be traced back to technological improvements. However, they are still less than Indonesia and the Philippines and less than the target optimal efficiency level indicated by the value of 1.

Nonetheless, the TFPs of Indonesia and the Philippines fell in 2020 relative to 2018. The decline in TFP in Indonesia is a result of technological change, while the Philippines' TFP decline is the result of two factors: technical change and technological change.

5. POLICY RECOMMENDATION

Based on the input slacks, this research recommends that the governments of Thailand and Malaysia should prioritize efforts to enhance the knowledge and skills of their citizens. To achieve this objective, the following measures are suggested: 1) Facilitate the transfer of technological knowledge utilized in high-tech export products to the target workforce segment. This will enable individuals to stay updated with the latest advancements in technology and apply them effectively in their respective fields. 2) Foster the development and support of mobile applications that promote learning and knowledge enhancement among citizens and the workforce. By leveraging the power of mobile technology, individuals can conveniently access educational resources and improve their skills at their own pace. 3) Provide financial credit support to facilitate the development of citizen knowledge and skills. This will ensure that individuals have access to the necessary resources and opportunities to enhance their expertise and contribute effectively to the economy. 4) Streamline the process for accessing government-allocated education funds and optimize the quality of internet technology accessible to citizens. By simplifying the application process and improving the affordability and reliability of internet services, individuals can take advantage of online learning platforms, thus expanding their knowledge and boosting their skill set.

6. CONCLUSION

This work aims to present the idea of measuring efficiency and productivity in the public sphere at a macro level. The measuring techniques of Data Envelopment Analysis and Malmquist Productivity Index techniques are employed with the data of the human capital index (HCI), high-technology exports (HTE), mobile cellular subscriptions (MCS), private credit (PCD), government expenditure on education (GEE), and individual internet usage (IUI) of the selected ASEAN-5 countries, namely Indonesia, the Philippines, Vietnam, Thailand, and Malaysia, in the years 2017, 2018, and 2020, as downloaded from the World Bank website. The index that is assigned as the output is HCI, and the indexes that are assigned as the resources include HTE, MCS, PCD, GEE, and IUI. The results reveal that under the constant returns to scale assumption, in the year 2020, Indonesia, the Philippines, and Vietnam will perform efficiently on the boundary of the frontier, while Thailand and Malaysia will perform inefficiently in creating HCI. However, under the variable returns to scale assumption, only Thailand performs inefficiently in creating HCI. In terms of productivity, it was found that HCI creation productivity in 2020 in Vietnam, Thailand, and Malaysia improved compared to 2018 as a result of technological improvements. However, they are still less than Indonesia and the Philippines and less than the target optimal efficiency level. Thus, the recommendations are that the governments of Thailand and Malaysia should make more efforts to utilize the technology from their hi-tech export products, mobile application programmes, financial credit that citizens obtain, government education expenditure, and internet technology to support the human capital improvement of citizens, e.g., the improvement in knowledge and working skills of citizens.

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