Jejak Vol 18 (1) (2025): hlm 14-23 DOI: https://doi.org/10.15294/jejak.v18i1.8043

JEJAK

Journal of Economics and Policy

http://journal.unnes.ac.id/nju/index.php/jejak

A VECM Study on Impact of Electricity Consumption in ASEAN

Indah Susilowati[1], Tirsa Erfani Pujiastuti Sawo[2]✉, Nurrosyida Latifa Himma[3], Anna Uswatun Sholikhah[4]

[1,2,3,4]Faculty of Economics and Business, Diponegoro University, Semarang, Indonesia

Permalink/DOI: : https://doi.org/10.15294/jejak.v18i1.8043

Received: June 2024 ; Accepted: August 2024 ; Published: March 2025

Abstract

The objective of this study is to identify the long-term and short-term relationships between electricity consumption and employment, human welfare, and information and communication technology. The study uses panel data from ASEAN countries, covering 2015 to 2022. The sample consists of 8 countries with complete data for each variable within the specified period. Based on the results of testing using the Vector Error Correction Model, in the long term, electricity consumption has a significant positive relationship with employment and human welfare, which is proxied by the Human Development Index and Happiness Index. On the other hand, the relationship between electricity consumption and information and communication technology (ICT), proxied by the number of mobile cellular subscriptions, shows a significant negative result. In the short term, electricity consumption does not affect employment, human welfare, or information and communication technology. These results indicate that electricity consumption does not directly impact the improvement of human welfare but influences income levels directly through increased production processes and consumption of goods and services.

Key words : Electricity Consumption, HDI, HI, ICT, Work Force

How to Cite : Susilowati, I., *et al* (2025) A VECM Study on Impact of Electricity Consumption in ASEAN. JEJAK: Jurnal Ekonomi dan Kebijakan. 18(1). DOI: : https://doi.org/10.15294/jejak.v18i1.8043

✉ Corresponding author : Tirsa Erfani Pujiastuti Sawo
Address: Singosari, Semarang, Indonesia
E-mail: erfanitirsa@gmail.com

p-ISSN 1979-715X
e-ISSN 2460-5123

INTRODUCTION

Energy is one of the main factors driving economic growth (Cai et al., 2018). Previous studies have shown that energy use plays a crucial role in the economy, particularly in both developed and developing nations (Bejan et al., 2020; Hossain & Chen, 2020). Electricity, as a form of energy, plays a crucial role in supporting the economic sector. This is because the continuity of the economic system depends on the availability of electricity. In developed and developing countries, inadequate electricity supply can affect all aspects of economic development (Damena et al., 2022). Electricity plays a crucial role in economic activities, essential for both the creation and use of goods and services. Its importance is growing due to technological progress, population expansion, urban development, and heightened industrialization. (Suryanto et al., 2023).

Earlier studies have demonstrated that information and communication technology (ICT) significantly contributes to enhancing productivity, which affects economic growth (Shahiduzzaman & Alam, 2014). Other studies reveal that increased investment in ICT infrastructure results in higher electricity consumption (Zhang & Liu, 2015). In developing countries, ICT is rapidly adopted through the use of mobile phones and the internet, which significantly drives electricity demand (Naser et al., 2016; Saidi et al., 2017). This is because the operational performance of devices and data centers significantly requires electrical energy. Conversely, there is also research that states ICT reduces electricity consumption through energy efficiency and reduces energy needs in other sectors (Gelenbe & Caseau, 2015; Lee & Brahmasrene, 2014). In developing countries, ICT is rapidly adopted through the use of mobile phones and the internet, which significantly drives electricity demand (Naser et al., 2016; Saidi et al., 2017).

The consumption of electricity is vital for a country's economic and social development. Access to electricity improves various aspects of life, contributing to enhanced quality of life and societal well-being (Sarkodie & Adams, 2020). This statement is supported by previous research that mentions adequate electricity consumption also provides social, informational, and health benefits, underpinning the fulfillment of the basic needs of humans (Niu et al., 2016). The availability of electricity also affects the happiness levels of the community in 47 countries (Afia, 2019). Research by Suryanto et al. (2023) shows that electricity consumption impacts human well-being. The study also highlights the importance of understanding labor-related factors in comprehending the link between electricity consumption and human well-being. Aslan (2014) states that the consumption of electricity has a positive correlation with labor in Turkey. This aligns with the economic growth hypothesis mentioned above, suggesting that electricity influences production activities as a complement to labor and capital.

Over the past twenty years, numerous countries have experienced a rise in the need for electrical power., including those within the ASEAN (Association of Southeast Asian Nations) region. The increase in electrical energy demand has occurred alongside developments in industrialization, urbanization, and living standards. Higher developments in these areas positively impact electricity consumption. A significant increase in electricity consumption indicates production activities that undoubtedly engage both investors and employees (Makholm, 2022). Furthermore, the progress of industrial nations is consistently bolstered by access to electricity and typically exhibits greater well-being compared to agrarian nations (Pata, 2018). Figure 1 shows the trend of increasing electricity consumption from 8 ASEAN countries compared to GDP growth over the past 8 years.

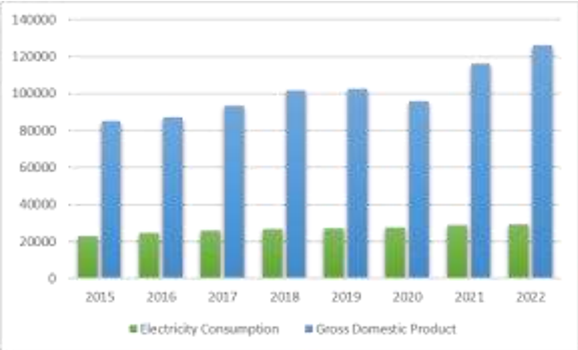


Figure 1. Electricity Consumption and GDP ASEAN 2015-2022

The correlation between electricity consumption and economic growth remains inconclusive. While numerous studies have explored the connection between electricity usage and economic development there are still few studies that examine the interplay between electricity consumption, human welfare, and technology. Addressing this research gap, the current study aims to provide empirical evidence on the long-term and short-term relationships between electricity consumption, human welfare, and technological advancement. This study examines eight ASEAN countries during the period 2015-2022. Thus, it is hoped that the results of this research can provide a deeper understanding of the complexity of the interaction between electricity consumption, technology, economic growth, and human welfare in ASEAN. A deep understanding of the relationship between electricity consumption, technology, and human welfare encourages governments to take more appropriate steps in increasing access to electricity, promoting technological innovation, and improving living standards in ASEAN. As a result, sustainable and inclusive economic growth is expected to be achieved throughout the ASEAN region.

RESEARCH METHODS

This study employs panel data spanning eight ASEAN countries from 2015 to 2022. The countries under examination are Indonesia, Thailand, Singapore, Malaysia, Philippines, Cambodia, Myanmar, and Vietnam. The study focuses on these 8 out of 11 ASEAN countries due to incomplete data availability for Laos, Brunei Darussalam, and Timor-Leste. The method employed in this research is the Vector Error Correction Model (VECM). VECM is utilized to analyze the relationship between electricity consumption, Index of Human Development (HDI), Index of Happiness (HI), labor force, and Information technology and communication (ICT) in both the short and long terms. This method is suitable for modeling the cause-effect relationships among these variables and considers long-term equilibrium.

The research conducted multiple examinations prior to constructing the vector error correction model. These examinations encompassed tests for stationarity, determination of optimal lag, VAR stability test, cointegration test, and analysis of Granger causality. Here is the Vector Error Correction Model equation:

$$\Delta y_t = \alpha e_{t-1} + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \ldots + \beta_2 \Delta y_{t-1+1} + \varepsilon_t \quad (1)$$

Where Δyt is the first difference of the dependent variable. Meanwhile, $\Delta yt\text{-}1$ is the first difference of the independent variable with a lag of 1.

$$\Delta EC_{it} = \alpha + \sum_{j=1} \beta_1 \Delta EC_{i,t-1} + \sum_{j=1} \beta_2 \Delta WF_{i,t-1} + \sum_{j=1} \beta_3 \Delta HDI_{i,t-1} + \sum_{j=1} \beta_4 HI_{i,t-1} + \sum_{j=1} \beta_5 \Delta MCS_{i,t-1}\ Ye_{it} + \varepsilon_t \quad (2)$$

$$\Delta WF_{it} = \alpha + \sum_{j=1} \beta_1 \Delta WF_{i,t-1} + \sum_{j=1} \beta_2 \Delta EC_{i,t-1} + \sum_{j=1} \beta_3 \Delta HDI_{i,t-1} + \sum_{j=1} \beta_4 HI_{i,t-1} + \sum_{j=1} \beta_5 \Delta MCS_{i,t-1} \ \Upsilon e_{it} + \varepsilon t \quad (3)$$

$$\Delta HDI_{it} = \alpha + \sum_{j=1} \beta_1 \Delta HDI_{i,t-1} + \sum_{j=1} \beta_2 \Delta EC_{i,t-1} + \sum_{j=1} \beta_3 \Delta WF_{i,t-1} + \sum_{j=1} \beta_4 HI_{i,t-1} + \sum_{j=1} \beta_5 \Delta MCS_{i,t-1} \ \Upsilon e_{it} + \varepsilon t \quad (4)$$

$$\Delta HI_{it} = \alpha + \sum_{j=1} \beta_1 \Delta HI_{i,t-1} + \sum_{j=1} \beta_2 \Delta EC_{i,t-1} + \sum_{j=1} \beta_3 \Delta WF_{i,t-1} + \sum_{j=1} \beta_4 HDI_{i,t-1} + \sum_{j=1} \beta_5 \Delta MCS_{i,t-1} \ \Upsilon e_{it} + \varepsilon t \quad (5)$$

$$\Delta MCS_{it} = \alpha + \sum_{j=1} \beta_1 \Delta MCS_{i,t-1} + \sum_{j=1} \beta_2 \Delta EC_{i,t-1} + \sum_{j=1} \beta_3 \Delta WF_{i,t-1} + \sum_{j=1} \beta_4 HDI_{i,t-1} + \sum_{j=1} \beta_5 \Delta HI_{i,t-1} \ \Upsilon e_{it} + \varepsilon t \quad (6)$$

Unit root tests on these variables are conducted to ensure that the data used in the analysis does not suffer from spurious regression issues. Additionally, the study also performs panel cointegration analysis to understand the long-term relationship between these variables.

Table 1. Operational Definition of Variables

Variable	Definition	Source
Electricity consumption (EC)	The amount of electricity used by a country or region within a specific time period, typically measured in kilowatt-hours (kWh).	Statistical Review of World Energy
Work Force (WF)	The total number of employed individuals and those actively seeking employment within a country or region, typically expressed as a percentage of the total working-age population.	World Bank
Human Development Index (HDI)	An index that measures a country's ability to achieve basic aspects of human development: these include health (life expectancy at born), education (average years of school and expected years of schooling), and the living standard (GDP per capita).	United Nations Development Programme
Happiness Index (HI)	An index that measures the subjective well-being or happiness of individuals within a country or region, often based on surveys or self-reported assessments of life satisfaction and positive emotions.	World Happiness Report
Technology (MCS)	The subscription to mobile phones is a common subscription for mobile phone services.	World Bank

RESULTS AND DISCUSSION

This study utilizes data from 8 countries in the Southeast Asia region. The data is processed using a Panel Vector Error Correction Model (PVECM) to obtain estimation results. Prior to this, the data will undergo a series of tests such as stationarity test, optimal lag test, and cointegration test to assess its distribution properties.

Table 2. Panel Unit Root Test – First Difference

Variable	t-statistic	Prob.
EC	-7.721202	0.0000
WF	-7.860016	0.0000
HDI	-8.078106	0.0000
HI	-8.644396	0.0000
MCS	-7.443363	0.0000

Source: processed data

Based on Table 2, The panel unit root test results in this paper show that all of the five variables are first difference stationary. This conclusion is drawn from the probability values of each variable being less than α = 5%.

Table 3. Optimal Lag Test

Lag	LR	FPE	AIC	SC	HQ
0	NA	1.05e-10	-8.78	-8.60	-8.71
1	323.08*	5.56e-13*	-14.03*	-12.97*	-13.62*
2	21.99	8.36e-13	-13.64	-11.70	-12.88
3	27.31	1.08e-12	-13.43	-10.61	-12.33
4	16.69	1.79e-12	-13.02	-9.32	-11.57
5	21.12	2.59e-12	-12.8	-8.23	-11.0

Source: processed data

This study employs a lag length ranging from 0 to 5. Table 3 shows the results of optimal lag test, lag 1 is selected as the optimal lag according to the LR, FPE, and AIC criteria. Therefore, the model used in this study is the Panel Vector Error Correction Model (PVECM) with lag 1, denoted as PVECM(1).

Table 4. Cointegration Panels

Cointegration	t-statistic	Prob.
	69.81889	0.0000

Source: processed data

Based on the results of cointegration test in Table 4, it is observed that the variables in this paper are cointegrated with a probability of 0.00, which is less than the alpha of 5%. This result indicates that the five variables have a long-term direct relationship with each other, thus allowing them to be analyzed using a Vector Error Correction Model (VECM).

Table 5 and Table 6 present the estimation results of the Panel Vector Error Correction Model (PVECM). Table 5 reports the long-term estimation results, while Table 6 reports the short-term estimation results. The VECM estimation in this study uses a lag of 1 with a significance level of 0.05 and a critical T-value of 2.000298.

Table 5. Panel Vector Error Correction Model (PVECM)- Long Term

Variable	t-statistic	Coefficient	Prob.
D(EC(-1))	1.000000		
D(WF(-1))	[-7.95381]	-44.10623	Sig.
D(HDI(-1))	[-7.42970]	-7.470059	Sig.
D(HI(-1))	[-2.84023]	-3.714856	Sig.
D(MCS(-1))	[7.83975]	2.410706	Sig.
C	-0.008792		

Source: processed data

Table 6. Panel Vector Error Correction Model (PVECM)- Short Term

Variable	t-statistic	t-tabel	Prob.
D(WF(-1))	0.82338	2.000298	No
D(HDI(-1))	0.59996	2.000298	No
D(HI(-1))	0.70761	2.000298	No
D(MCS(-1))	0.72697	2.000298	No

Source: processed data

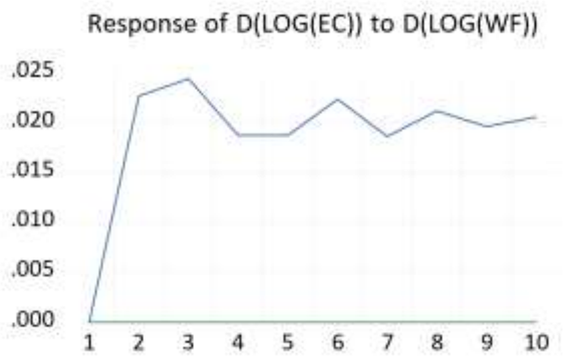
The long-term equation from the results in Table 5 can be expressed as follows.

$$EC_{t-1} = -0.008 + 44.10WF_{t-1} + 7.47HDI_{t-1} + 3.71HI_{t-1} - 2.41MCS_{t-1} \quad (7)$$

Based on Table 5, in the long term, electricity consumption (EC) shows a positive and significant relationship with WF, HDI, and HI. An increase in electricity consumption can enhance the labor force, Human Development Index (HDI), and Happiness Index (HI) of society. These results align with the study by Suryanto et al. (2023), which found that in the long term, electricity consumption has a significant relationship with HDI and the labor force, but does not directly impact the quality of life. Other studies have shown that increased electricity consumption provides better access to basic services and infrastructure, thereby promoting quality of life and human development (Afia, 2019; Suryanto et al., 2022). Meanwhile, the variable MCS exhibits a negative and significant long-term relationship with electricity consumption. ICT is approximated using MCS, as mobile phone batteries require less energy compared to other ICT proxies. These findings align with research (Gelenbe & Caseau, 2015) indicating that electricity use efficiency improves alongside advancements in ICT integrated with smart technologies. This suggests that despite an increase in ICT device usage, electricity consumption efficiency per device also increases. In contrast, other studies with significant positive results include other proxies such as internet usage and ICT infrastructure (Chimbo, 2020; Naser et al., 2016; Saidi et al., 2017). These studies demonstrate that electricity consumption and ICT have a significant positive relationship through the provision of infrastructure and other electronic devices, thereby increasing electricity demand.

Based on the short-term equation, it was found that WF, HDI, HI, and MCS do not affect EC. Suryanto et al. (2023) showed similar results, indicating that these factors do not directly influence electricity consumption levels in the short term. Wang et al. (2018) state that in the short term, electricity consumption affects income levels but does not influence human quality of life. However, in the long term, high electricity consumption will promote a better HDI in countries with already high income levels. This differs from the findings of Zheng & Wang (2022), who suggest that in the short term, electricity energy does impact HDI.

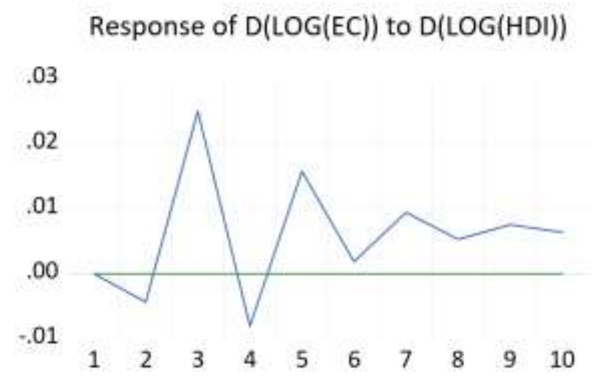
Every shock on each variable caused by shocks on other variables will have impacts both in the present and in the future. The illustration of shocks between variables can be seen through impulse response graphs.



Source: processed data

Figure 2. Impulse Responses of EC to WF

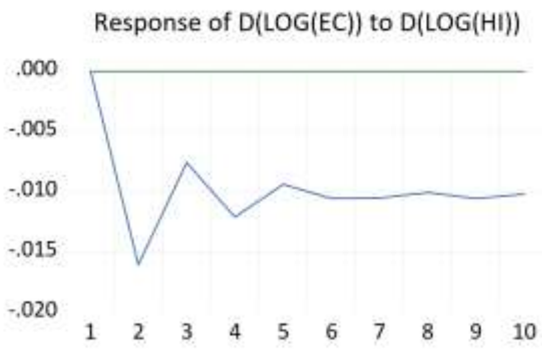
Figure 2 is the response of EC to shocks caused by the WF variable showing a positive relationship. This can be interpreted that an increase in the level of EC will increase the level of WF as well.



Source: processed data

Figure 3. Impulse Responses of EC to HDI

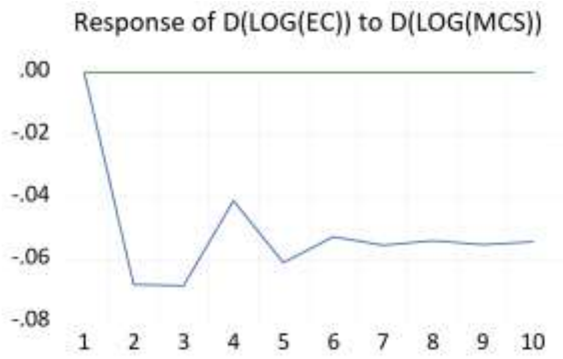
The response of the EC to shocks caused by HDI as shown in Figure 3 shows an average positive but fluctuating relationship. The negative response is shown by the EC to the HDI variable in periods 2 and 4. In general, if there is a shock from the HDI value, the EC will respond positively.



Source: processed data

Figure 4. Impulse Responses of EC to HI

Figure 4 shows the negative response of the EC to shocks generated by the HI variable from period 1 to period 10. The shocks in period 2 are responded weakly. In general, if there is a shock to the value of HI, the EC will respond negatively.



Source: processed data

Figure 5. Impulse Responses of EC to MCS

The negative response of the EC variable to shocks generated by the MCS variable is shown in Figure 5. The negative shocks occur in period 1 to period 10. The shocks weaken in periods 2 and 3. In general, if there is a shock from the MCS value, the EC will respond negatively.

Table 7. Variance Decomposition

Variance Decomposition of D(EC): Period	*S.E.*	*D(EC)*	*D(WF)*	*D(HDI)*	*D(HI)*	*D(MCS)*
1	0.534326	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.598215	98.48526	0.142962	0.005229	0.071986	1.294565
3	0.715256	97.77432	0.215999	0.126205	0.061583	1.821897
4	0.789283	97.81100	0.233613	0.114121	0.074002	1.767262
5	0.868213	97.60605	0.239563	0.127233	0.072903	1.954255
6	0.934982	97.54699	0.263546	0.110116	0.075623	2.003725
7	0.999976	97.49335	0.264909	0.105077	0.077200	2.059459
8	1.059725	97.45662	0.275753	0.096037	0.077761	2.093829
9	1.116811	97.42057	0.279068	0.091050	0.078964	2.130353
10	1.170927	97.39672	0.284697	0.085769	0.079436	2.153378

Source: processed data

The impact of shocks due to the variable itself and other variables can also be seen in Table 7. The Variance Decomposition or Forecast Error Variance Decomposition (FEVD) test is used to determine how the variance of a variable is determined by its own contribution and the contribution of other variables (Suryanto et al., 2023).

Based on Table 7, in the first period, the fluctuation of EC value is influenced by the contribution of EC itself by 100%. Then in the next period, it is known that the contribution of EC begins to be explained by other variables such as WF, HDI, HI and MCS. The contribution of other variables began to appear in the 2nd to 10th period. Until the 10th period, the variable that has the largest contribution to EC is EC itself with an average contribution of 97%, followed by MCS contribution of 1.7%, WF contribution of 0.22%, HDI contribution of 0.09%, and HI contribution of 0.05%. Over the 10 periods, EC provided the largest average contribution per period, but its contribution continued to decrease over the 10 periods. In contrast to the WF, HDI, HI, and MCS variables whose contributions increased over the 10 periods.

CONCLUSION

This research examines how electricity usage, workforce dynamics, human well-being, and information and communication technology (ICT) interrelate across ASEAN countries. The VECM is applied to analyze the data, revealing both enduring and immediate connections among these factors. In the long term, an increase in electricity consumption can enhance the labor force, Human Development Index (HDI), and Happiness Index of society. However, the results indicate a different direction between electricity consumption and ICT proxied by mobile cellular subscriptions. This implies that increased electricity does not affect the increase in mobile cellular subscriptions in the long term.

In the short term, variables such as labor force, human welfare (proxied by HDI and Happiness Index), and ICT do not directly influence electricity consumption. Human welfare, proxied through HDI and Happiness Index, is only influenced by its own values in the previous period. This suggests that in the short term, electricity consumption does not directly affect quality of life but does affect income levels. Electricity consumption can directly impact income levels because electricity is a crucial input for various economic activities. The availability of electricity promotes increased business and industrial productivity, thereby increasing income in a relatively shorter period compared to changes in quality of life, which are more complex and require longer timeframes.

The research findings indicate that electricity consumption has a direct impact on increasing income and productivity; therefore, governments in ASEAN countries need to implement policies that ensure sustainable electricity availability. Electricity consumption can drive the performance of productive economic sectors. Additionally, the quality of human well-being improvements is supported by access to electricity. Although electricity consumption does not directly influence the increase in mobile phone subscriptions in the long term, it is important to enhance the infrastructure and efficiency of ICT usage. Governments can develop policies to encourage the integration of more energy-efficient smart technologies to optimize electricity usage in the ICT sector.

Further research is needed to identify the relationship between electricity consumption and information and communication technology (ICT) integrated with smart technologies. This supports the need for implementing policies that enhance electricity consumption efficiency and its impact on societal well-being.

REFERENCES

Afia, N. Ben. (2019). The Relationship Between Energy Consumption, Economic Growth and Happiness. In Journal of Economic Development (Vol. 41, Issue 3).

Aslan, A. (2014). Electricity consumption, labor force and GDP in Turkey: Evidence from multivariate granger causality. Energy Sources, Part B: Economics, Planning and Policy, 9(2), 174–182. https://doi.org/10.1080/15567241003699470

Bejan, A., Errera, M. R., & Gunes, U. (2020). Energy theory of periodic economic growth. International Journal of Energy Research, 44(7), 5231–5242. https://doi.org/10.1002/er.5267

Cai, Y., Sam, C. Y., & Chang, T. (2018). Nexus between clean energy consumption, economic growth and CO2 emissions. Journal of Cleaner Production, 182, 1001–1011. https://doi.org/10.1016/j.jclepro.2018.02.035

Chimbo, B. (2020). Information and communication technology and electricity consumption in transitional economies. International Journal of Energy Economics and Policy, 10(3), 296–302. https://doi.org/10.32479/ijeep.8143

Damena, G., Sera, L., & Malatu, N. T. (2022). Impact of Electricity Consumption on Ethiopian Economic Growth: an Empirical Analysis. In Journal of International Trade, Logistics and Law (Vol. 8).

Gelenbe, E., & Caseau, Y. (2015). The impact of information technology on energy consumption and carbon emissions. Ubiquity, 2015(June), 1–15. https://doi.org/10.1145/2755977

Hossain, M. A., & Chen, S. (2020). Decoupling of energy-related CO2 emissions from economic growth: a case study of Bangladesh. Environmental Science and Pollution Research, 27(17), 20844–20860. https://doi.org/10.1007/s11356-020-08541-6

Lee, J. W., & Brahmasrene, T. (2014). ICT, CO2 Emissions and Economic Growth: Evidence from a Panel of ASEAN. Global Economic Review, 43(2), 93–109. https://doi.org/10.1080/1226508X.2014.917803

Makholm, J. D. (2022). The renewable energy supply chain problem: A new geography of power supply and new species of electricity transmission. Electricity Journal, 35(2). https://doi.org/10.1016/j.tej.2022.107079

Naser, M., Afzal, I., & Gow, J. (2016). International Journal of Energy Economics and Policy Electricity Consumption and Information and Communication Technology in the Next Eleven Emerging Economies. International Journal of Energy Economics and Policy, 3. http:www.econjournals.com

Niu, S., Jia, Y., Ye, L., Dai, R., & Li, N. (2016). Does electricity consumption improve residential living status in less developed regions? An empirical analysis using the quantile regression approach. Energy, 95, 550–560. https://doi.org/10.1016/j.energy.2015.12.029

Ouedraogo, N. S. (2013). Energy consumption and human development: Evidence from a panel cointegration and error correction model. Energy, 63, 28–41. https://doi.org/10.1016/j.energy.2013.09.067

Pata, U. K. (2018). Renewable energy consumption, urbanization, financial development, income and CO2 emissions in Turkey: Testing EKC hypothesis with structural breaks. Journal of Cleaner Production, 187, 770–779. https://doi.org/10.1016/j.jclepro.2018.03.236

Saidi, K., Toumi, H., & Zaidi, S. (2017). Impact of Information Communication Technology and Economic Growth on the Electricity Consumption: Empirical Evidence from 67 Countries. Journal of the Knowledge Economy, 8(3), 789–803._https://doi.org/10.1007/s13132-015-0276-1

Sarkodie, S. A., & Adams, S. (2020). Electricity access, human development index, governance and income inequality in Sub-Saharan Africa. Energy Reports, 6, 455–466. https://doi.org/10.1016/j.egyr.2020.02.009

Shahiduzzaman, M., & Alam, K. (2014). Information technology and its changing roles to economic growth and productivity in Australia. Telecommunications Policy, 38(2), 125–135. https://doi.org/10.1016/j.telpol.2013.07.003

Suryanto, S., Gravitiani, E., Diswandi, D., & Arintoko, A. (2023). The Impact of Electricity Consumption to Human Development Index in Asian Countries: Analysis Panel Vector Error Correction Model. International Journal of Energy Economics and Policy, 13(2), 240–246. https://doi.org/10.32479/ijeep.13947

Suryanto, S.-, Trinugroho, I., & Susilowati, F. (2022). Simultaneous Analysis: The Effect of Electricity Consumption on Human Development Index in ASEAN 5. JEJAK, 15(2), 234–243. https://doi.org/10.15294/jejak.v15i2.37743

Wang, Z., Danish, Zhang, B., & Wang, B. (2018). Renewable energy consumption, economic growth and human development index in Pakistan: Evidence form simultaneous equation model. *Journal of Cleaner Production*, *184*, 1081–1090. https://doi.org/10.1016/j.jclepro.2018.02.260

Zhang, C., & Liu, C. (2015). The impact of ICT industry on CO2 emissions: A regional analysis in China. In Renewable and Sustainable Energy Reviews (Vol. 44, pp. 12–19). Elsevier Ltd. https://doi.org/10.1016/j.rser.2014.12.011

Zheng, J., & Wang, X. (2022). Impacts on human development index due to combinations of renewables and ICTs—New evidence from 26 countries. *Renewable Energy*, *191*, 330–344. https://doi.org/10.1016/j.renene.2022.04.033