

Energy Poverty Impact on Social Economics in Malaysia

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Abstract

Energy poverty presents a global challenge, impacting not only developing countries but also developed nations. The lack of access to energy in modern life gives rise to various problems, including environmental, health, education, and economic issues. However, the current measurement of energy poverty mostly relies on data analysis with different indicators for each method. In this paper, we propose a new approach on energy poverty evaluation that is capable of evaluating time series-based causal relationships between each indicator and understanding the significance of their influence on each other. This method enables policymakers to have a clear view of the weight of the relationship between indicators which has less significance in other energy poverty evaluation work. We utilize the autoregressive distributed lag (ARDL) approach and vector error correction model (VECM) for our analysis. The results show that short run cointegration exists in the ARDL bound test, which is further confirmed by the stability test. The results show that all indicators show a high level of significance in all cases except for EDU. A 1% increase in the current period of EC leads to a 0.287% increase in future EC, with other variables being held constant. CO₂, GDP, and HE had a positive impact on EC, with coefficients of 0.2896%, 0.7748%, and 0.7296%, respectively. Overall, the findings demonstrate a significant bidirectional influence of energy consumption on all indicators, except for education in the case of Malaysia.

1. Introduction

Energy poverty is a serious issue that affects the environment, human health, and economic growth on a global scale. [1]. The lack of accessible, dependable, and modern energy sources, which are necessary to meet fundamental modern human requirements can be classified as energy poverty. Requirements such as home lighting, vehicle fuel and energy for cooking. Around 800 million people worldwide do not have access to power, says the World Energy Outlook report. Aside from that, 2800 million people still rely on conventional energy sources such solid fuel for their everyday cooking and heating. [1].

Energy poverty also cause significant health consequences, especially for women and children [2]. Women and girls are particularly impacted by energy poverty because they frequently spend hours every day gathering firewood or other fuels for cooking and heating. Respiratory illnesses including pneumonia and chronic obstructive pulmonary disease which are major sources of morbidity and mortality in underdeveloped nations are frequently brought on by indoor air pollution from the burning of solid fuels [3-5]. Additionally, relying on conventional energy sources causes environmental deterioration and climate change, which exacerbates the effects of natural disasters and harsh weather conditions [6].

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Lack of access to electricity also affects education and economic opportunities, as students are unable to study after dark, and businesses are unable to operate efficiently. Energy poverty impedes economic development by limiting access to modern energy services that are required for income-generating firms, education, and healthcare [7]. This can perpetuate the cycle of poverty and hinder progress towards achieving sustainable development goals.

Hence, energy policy is highly important to play the role of understanding the relationship and need in terms of social economics of country societies. To address energy poverty, a multi-disciplinary approach is required that considers technological, economic, and social factors. Sustainable energy solutions, such as solar and wind power, can provide affordable and reliable energy services, while energy efficiency measures can reduce energy consumption and costs. Policy and regulatory frameworks that promote investment in sustainable energy and address energy access disparities are also essential. Addressing energy poverty is critical for improving human well-being and achieving sustainable development.

Energy poverty is issued in multiple methods depending on the research goal. Energy accessibility is one of the indicators widely used by researchers on elaboration on energy poverty. Rural areas are mostly out of the nation power grid system where facilities such as lighting system cannot aid the local to continue any social or economic matter after dark. Indonesia which consists of 16000 islands with different sizes and populations facing great challenge on fully grid connected whole country [8]. Affordability of energy also part of the energy poverty indicator where people still insist of apply solid fuel such as wood, charcoal and biomass combustion to deal with daily cooking or warning needs [9]. Research found the phenomenon is related to the price of clean fuel where expenditure is not sufficient for allocation [10].

Multidimensional energy poverty (MEP) is also one of the indicator widely used in evaluating energy poverty. MEP refers to a situation where households or communities experience energy poverty across multiple dimensions, such as access, cost, reliability, and quality of energy services. As indicators, Oihana Aristondo and Eneritz Onaindia advocated the ability to keep the home appropriately warm, utility bill arrears, and the presence of a leaking roof, damp walls, or rotten windows [11]. Cooking fuel, interior pollution, energy access, home appliances, entertainment, education, and telecommunication were suggested as indicators by Tabitha Atieno Olang et al [12].

Another method that similar to MEP is multidimensional household energy poverty (MEPI). The Multidimensional Energy Poverty Index (MEPI) is used to evaluate energy poverty based on the concept of energy deprivation, by considering various dimensions such as access, affordability, reliability, and quality of energy services. This index delivers a single statistic that provides a complete picture of national household energy poverty [13]. However, it has a limitation in that it only focuses on energy poverty within the household context and does not account for energy use for productive activities or beyond the household.

The Compound Energy Poverty Indicator (CEPI) is another tool for measuring energy poverty, which is defined as a lack of access to appropriate and cheap energy services. The indicator is also useful in a wide range of settings, from households to countries [14-16]. MEP, MEPI and CEPI have similar characteristics which is highly dependent on the survey and number of the data collected.

International Energy Agency (IEA) applies another analysis method named Energy Development Index (EDI) which uses energy development assessment for a country [17-18]. EDI is based under the Human development index (HDI) by changing the indicator to energy related indicators.

However, MEP nor MEPI is not a time series-based data analysis where limited on proving the existing of energy poverty. Literature overall shows that poverty issue has a high possibility on turn over with the energy poverty eradication. Clean energy such as renewable energy give another alternative on proceed with the humankind development without sacrificing our mother earth.

Literatures study mostly show energy poverty evaluation in different perspectives and conclude with static data collection. However, there is no significant study on the relationship between indicator used in time-based evaluation. Hence, this paper aims to propose ARDL model which can provide a time series-based fact on the cointegration relationship between each possible indicator which can aid energy policy maker on understanding the trend flows. Malaysia data is selected to apply proposed model on understanding the causal relationship between social economics determinants for ease energy policy planning.

Malaysia data adopted in this paper is obtain from World Development Indicator. The period from the year 2005 to year 2014 is due to the availability of the data set. Five variables adopted in the proposed model are CO₂ emissions (metric tons per capita), GDP per capita (constant 2010 US\$), government expenditure on education, total (% of GDP) and health expenditure, total (% of GDP). The data chosen is dependent on its availability in the existing data bank. Hence the selected parameter or indicator for the proposed model is limited. The model proposed aims to study the causal relationship between energy with local social economy and civilization level. Overall model analysis conducted as show in flowchart Figure 1.

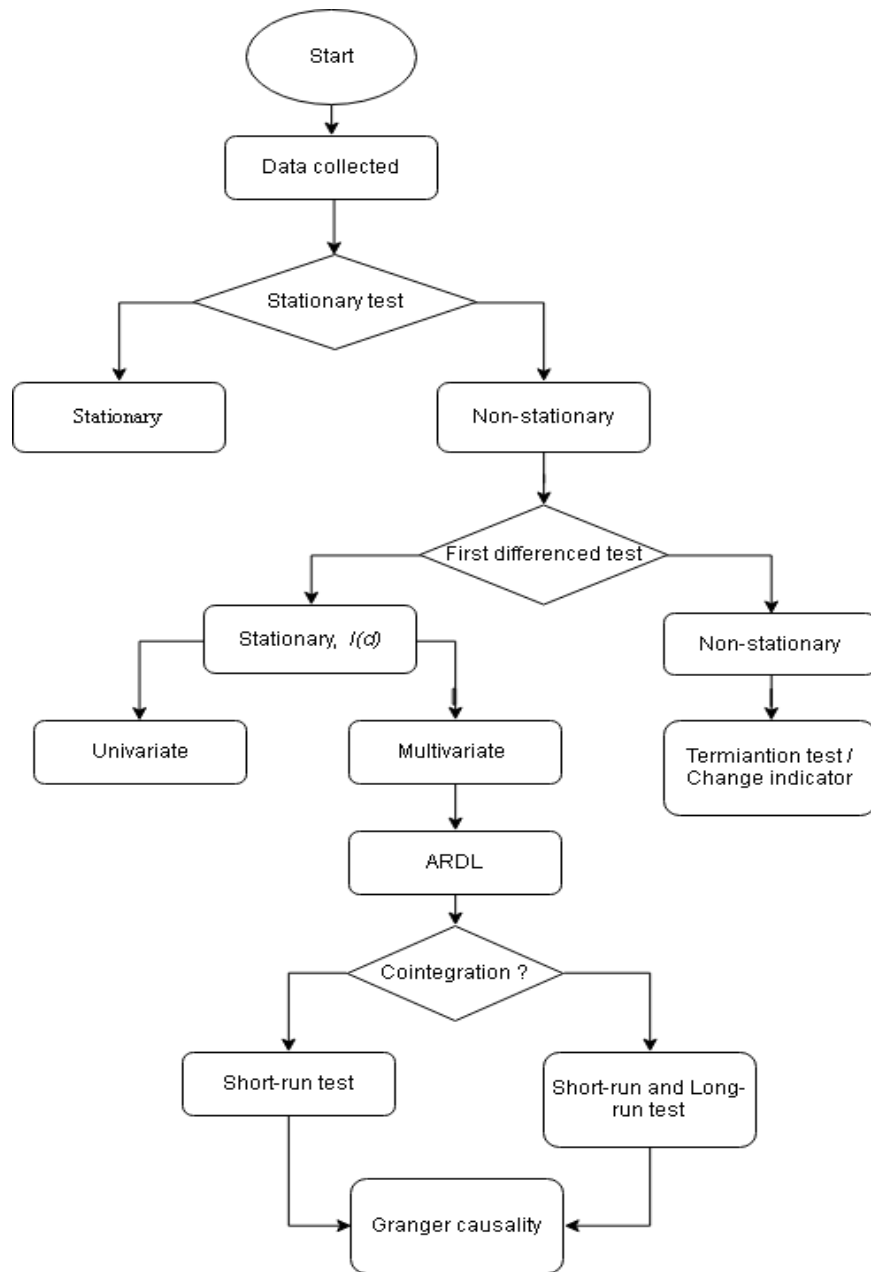


Fig. 1 Flowchart ARDL

2. Proposed Model

The proposed model is based in Autoregressive distributed lag (ARDL) approach which is one of the standards least square regressions that include lag of both dependent variables and descriptive variables as regressions. This method has been widely used to determine the co-integration relationship between variables.

ARDL co-integration method can ignore unit root test which is the only method among others [19-21]. Besides that, this method can accommodate up to a 1st order of variable and stay robust if long run relationship underlying variable detected throughout Wald test. However, ARDL may face model crash on the 2nd order of variable.

The basic formula for ARDL regression model is as shown in Eq. (1)

$$y_t = \beta_0 + \beta_1 y_{t-1} + \dots + \beta_p y_{t-p} + \alpha_0 x_t + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \dots + \alpha_q x_{t-q} + \varepsilon_t \tag{1}$$

Where ε_t is a random disturbance ARDL model can be definite by as autoregressive and distributed lag. Autoregression makes sense that y_t is lagged values of its value and distribution lag shown the successive lags of an explanatory variable which present in the equation as x . Sometimes, the current value of x_t itself is excluded

from the distributed lag part of the model's structure. ARDL next step is bounded test which is used to validate the long run relationship.

To investigate the existence of long run and short run causal relationships, severe steps need to be taken to ensure the reliability of the result. ARDL approach method have high advantages on small data size and ease on granger cointegration estimations. Data set apply in form of natural logarithm to induce stationarity in the variance-covariance matrix. Besides that, the quarterly data method applies to increase the data points set.

Unit root test is adopted to test stationarities of the time series data set. Stationary data is a series with a constant mean and variance over time, while non-stationary data is a series that exhibits trends or changes in the mean and/or variance over time [22-23]. Stationary time series are easier to model and forecast accurately. Augmented Dickey-fuller test (ADF) and Philips and Perron test (PP) is most used among researcher to test the stationarities of time series data.

The data set reaches stationary in first differential proceed with the ARDL approach and VECM model. The proposed model framework is as shown in Eq. (2)

$$y_t = \beta_0 + \beta_1 \ln(ec) + \beta_2 \ln(co) + \beta_3 \ln(gdp) + \beta_4 \ln(he) + \beta_5 \ln(edu) + \varepsilon_t \tag{2}$$

- Where, *ec* represent energy use (kg of oil equivalent per capita)
- co* represent carbon dioxide emissions (metric tons per capita)
- gdp* represent gross domestic product per capita (constant 2010 US\$)
- edu* represent government expenditure on education, total (% of GDP)
- he* represent health expenditure, total (% of GDP)

Overall ARDL bound test and VECM method model is proposed as shown in Eq. (3)

$$\begin{aligned} \Delta \ln(ec) = & \beta_0 + \sum_{i=1}^n \delta_1 \Delta \ln(ec)_{t-i} + \sum_{i=1}^n \delta_2 \Delta \ln(co)_{t-i} + \sum_{i=1}^n \delta_3 \Delta \ln(gdp)_{t-i} \\ & + \sum_{i=1}^n \delta_4 \Delta \ln(he)_{t-i} + \sum_{i=1}^n \delta_5 \Delta \ln(edu)_{t-i} + \beta_1 (ec)_{t-i} + \beta_2 (co)_{t-i} \\ & + \beta_3 (gdp)_{t-i} + \beta_4 (he)_{t-i} + \beta_5 (edu)_{t-i} + \varepsilon_t \end{aligned} \tag{3}$$

3. Results

3.1 Unit Root Test

Table 1 shows the results of the ADF test, indicating that all variables in the dataset were non-stationary at the level stage for both conditions. However, after taking the first differences, all variables demonstrated evidence of reaching stationarity under the intercept condition. Additionally, under the trend and intercept condition, all variables were found to be stationary at a significance level of 1%. These findings collectively suggest that the dataset is appropriate for conducting further ARDL analysis, as all variables were initially non-stationary at the level stage but achieved stationarity after differencing.

Table 1 ADF test

Variable	Intercept		Trend and intercept	
	Level	First differences	Level	First differences
CO ₂	-0.7544	-5.1504***	-2.7258	-5.0365***
EC	-1.4214	-4.8331***	-2.0809	-4.7332***
EDU	-1.3750	-6.3753***	-1.7945	-6.2662***
GDP	-0.5133	-3.7664***	-2.9256	-3.7182**
HE	0.8499	-5.2286***	-3.1925	-5.2064***

Based on the PP test results presented in Table 2 shows that none of the variables in the dataset were stationary at the level stage for both conditions. However, after applying first differences, the intercept condition demonstrated evidence of achieving stationarity for all variables at a significance level of 1%. Similarly, under the trend and intercept condition, all variables were found to be stationary at a significance level of 1%. These findings collectively suggest that all variables in the Malaysia dataset remain non-stationary at the level stage but attain stationarity after first differencing. As a result, the dataset is deemed suitable for further ARDL analysis.

Table 2 PP test

Variable	Intercept		Trend and intercept	
	Level	First differences	Level	First differences
CO ₂	-1.0608	-5.1364***	-3.0861	-5.0183***
EC	-1.2704	-4.8726***	-2.1860	-4.7801***
EDU	-2.0929	-4.4122***	-2.6263	-4.3442***
GDP	-0.3413	-3.8861***	-1.9359	-3.8428**
HE	-1.6678	-6.1610***	-3.5529**	-6.1113***

The process of determining the suitable lag length criteria involved using the Akaike Information Criteria (AIC) to identify the best model, as illustrated in Figure 2. After analysing the 20 best models generated, result shows the optimal lag lengths for the model were 4, 4, 0, 4, and 4 for the respective variables.

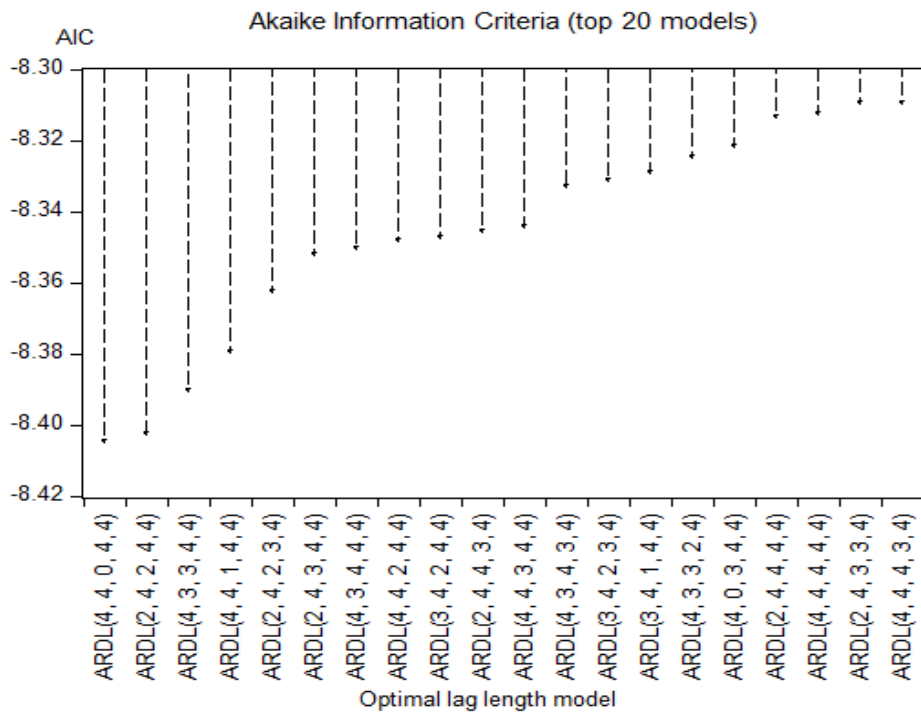


Fig. 2 Akaike information criteria

3.2 ARDL Bound Test

The ARDL bound test apply on the Malaysia data set, with EC variables as the dependent variable, show the existing of a long run relationship. Table 3 shows the outcomes of the long run relationship analysis with EC as the dependent variable. The result shows that CO₂, EDU, and GDP have a positive impact on EC, with coefficients of 0.1552, 0.0351, and 1.6959, respectively. However, HE has a negative impact on EC, with a coefficient of -0.7296. This shows that for every 1% increase in CO₂ will leads to a 0.1552% increase in EC. Serial correlation and heteroscedasticity tests were performed to further assess the model's stability. The results were highly significant, with probabilities of 0.2019 and 0.9949 respectively.

Table 3 Long run analysis

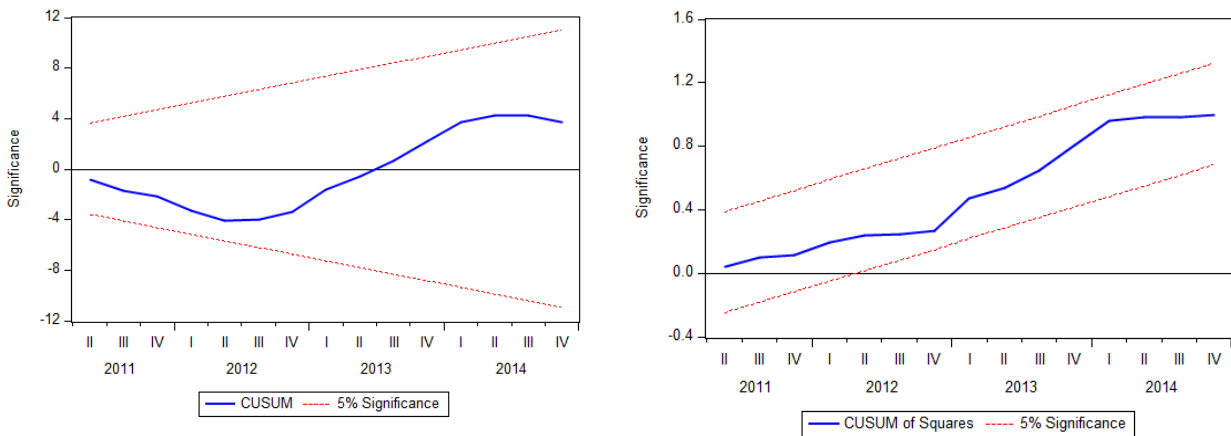
Variables	Coefficient	Std.error	T-statistic
CO ₂	0.1552	0.2803	0.5536
EDU	0.0351	0.1194	0.2941
GDP	1.6959	0.5356	3.1666
HE	-0.7296	0.4337	-1.6820
c	-0.9225	0.7196	-1.2818
EC = EC - (0.1552*CO + 0.0351*EDU + 1.6959*GDP - 0.7296*HE - 0.9225)			
Stability diagnostic	Serial correlation	Heteroscedasticity	
	1.814017 (0.2019)	0.286950 (0.9949)	

The results of the short run estimation using the ARDL approach are shown in Table 4. Except for EDU, the results demonstrate a high level of significance in all cases. The findings shows that a 1% increase in the current period of EC leads to a 0.287% increase in future EC, with other variables being held constant. Additionally, CO₂, GDP, and HE had a positive impact on EC, with coefficients of 0.2896%, 0.7748%, and 0.7296%, respectively, while EDU was found to be no significant in the short run estimation. Furthermore, at a 1% significance level, the error correction coefficient was negative and statistically significant, with a value of -0.5572. This means that the short-run model was revised by 1% in the direction of the long-run equilibrium path.

Table 4 Short run analysis

Variables	Coefficient	Std.error	T-statistic
D(EC)	0.287466**	0.110398	2.603911
D(CO ₂)	0.289682**	0.133769	2.165533
D(EDU)	0.019570	0.063852	0.306484
D(GDP)	0.774768**	0.281867	2.748702
D(HE)	0.729622***	0.127023	5.743993
EC _{t-1}	-0.557172***	0.105161	-5.298287

The stability of the proposed more is further tested with CUSUM and CUSUMsq test show in Figure 3. Both result show bound between the critical region of 5% significance level. Hence, the more is stable and reliable.



(a)

(b)

Fig. 3 (a) CUSUM; (b) CUSUMsq

3.3 VECM Test

The VECM was utilized to investigate Granger causality relationships. Table 5 shows the result of the Granger causality test. Based on the short-run Granger causality, GDP was found to have a significant causal relationship towards EC and CO₂. Additionally, GDP, EC, and CO₂ were found to have significant causality towards HE. However, in terms of long-run Granger causality, all indicators exhibited significant bi-directional causality with each other, except for EDU. Figure 4 shows the relationships of short-run and long-run Granger causality. Dotted line arrow represents the short-run causality, and the normal arrow line represents the long-run Granger causality. The figure visually represents the significant causal links among the variables as determined by the Granger causality test.

Table 5 Granger causality test

Causality	Short run granger				Long run granger	
	D(EC)	D(CO ₂)	D(EDU)	D(GDP)	D(HE)	ECM
D(EC)	-	0.6389	0.9909	0.0282*	0.9542	0.0275*
D(CO ₂)	0.7753	-	0.2226	0.0071*	0.5626	0.0010*
D(EDU)	0.7919	0.5874	-	0.0788	0.4593	0.0550
D(GDP)	0.7428	0.9425	0.8922	-	0.5645	0.0000*
D(HE)	0.0058*	0.0462*	0.3564	0.0190*	-	0.0447*

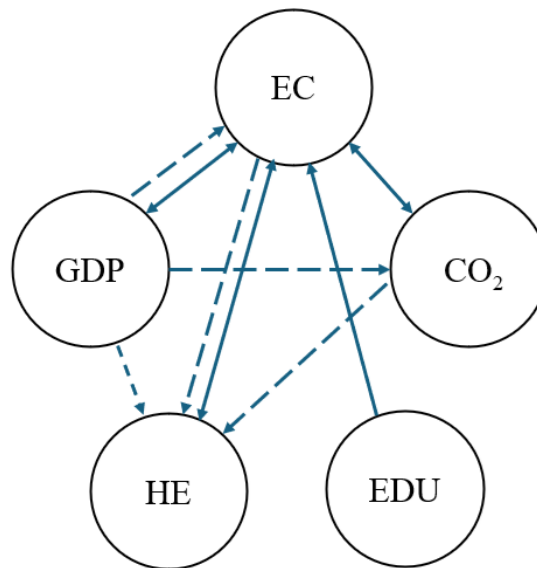


Fig. 4 Directional relationship (granger causality)

4. Conclusions

The study proposed an energy poverty indicators model using both the ARDL approach and VECM method. The ARDL analysis demonstrated the presence of more than one short-run cointegration between energy consumption and CO₂ emissions, GDP, health, and education, which were the selected indicators. The results from the short-run and long-run Granger causality relationships show a significant influence of energy consumption on all the aspects studied. Overall, the results indicate a strong interplay and mutual influence among the selected indicators. This phenomenon can be attributed to various factors, such as the maturity of energy services in Malaysia, government policies on renewable energy, and subsidies provided for electricity. The study's outcomes suggest that energy consumption plays a important role in shaping various aspects of the economy and society in Malaysia, affecting carbon dioxide emissions, GDP, health, and education. The findings highlight the importance of understanding and addressing energy poverty indicators to promote sustainable development and effective energy policies in the country.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper follows: **study conception, analysis and interpretation of results:** Ling Chin Wan; **draft manuscript preparation:** Kim Gaik Tay, Hui Hwang Goh. All authors reviewed the results and approved the final version of the manuscript.

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