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Digitalization-Driven Clean Energy Transition and Emission Reduction in ASEAN

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ABSTRACT

This study inspects how digitalization, clean energy and economic growth influence the carbon emission in selected ASEAN states. The study is based on balanced panel data from 2000 to 2025. The panel unit root tests and the Pooled Mean Group (PMG) technique are employed to ascertain the short run dynamics and long run associations. Digitalization has substantially decreased carbon emissions by enabling safer production processes and improving energy efficiency according to the long-term outcomes. Renewable energy consumption and reduced energy intensity further contribute to emission mitigation, while economic expansion raises emissions due to scale effects. The short-run outcomes indicate that renewable energy and energy efficiency have an immediate impact of reducing emissions. Moreover, digitalization has a transient effect of increasing emissions at the same time because it will cause more electricity consumption during the initial years of adoption. Long-run cointegration and convergence is confirmed by negative and significant error correction term. Incorporating GDP squared confirms an inverted U-shaped environmental kuznet curve, signifying emission reductions beyond a given level of income. Generally, the outcomes highlight the role of digital transformation and clean energy in the attainment of sustainable growth, which is aligned with SDG 7, SDG 9, and SDG 13.

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1. Introduction

In the modern era, hasty economic growth and structural transformation have intensified environmental challenges, predominantly rising carbon emissions, in emerging and developing economies. While achieving remarkable economic advancement, face increasing pressure to balance growth goals with environmental sustainability in ASEAN states. The ASEAN nations are under growing pressure to maintain a balance amid growth goals and environmental sustainability spite of their impressive economic progress. Energy consumption driven by industrial expansion, sprawl and technological adoption has substantially contributed to disintegration the environment. Because of this, climate change mitigation has emerged as a perilous policy priority in the area. In responding, the Sustainable Development Goals (SDGs) of United Nations' 2030 and other global policy agendas emphasize the need to maintain a balance among environment preservation and economic development. Specifically, SDG 13 calls for swift action to tackle environment change. SDG 9 encourages technological innovation and sustainable sectors. Furthermore, SDG 7 endorses clean and affordable energy (United Nations, 2015). Against this backdrop, digitalization has become a transformative force that has a big impact on the environment. Digital innovations enable more effective energy management systems, lower information and transaction costs, improved production efficiency, and easier integration of renewable energy into current grids. Digitalization may eventually lower carbon emissions through these mechanisms (Higón, 2017; Lee & Brahmasrene, 2014). The growth of digital infrastructure and higher utilization of technology may initially raise energy demand and emissions, specifically in countries that are still reliant on fossil fuels.

Therefore, it is yet unclear how digitalization will affect environment overall. The dual nature of digitalization is crucial to examine both its short term and long-term environmental effects in ASEAN region.

At the same time, sustainable growth hinges on the usage of renewable energy source and energy efficiency. Furthermore, switching to sources of renewable energy lessens reliance on carbon-intensive fossil fuels along with to directly reducing emissions (Payne & Apergis, 2021). Similar to this, economies may produce the same amount of product with less energy due to developments in energy efficiency, leading to in lower energy intensity. This reduces emissions without limiting economic activity. The energy-efficiency hypothesis states that, the greatest way to distinguish economic growth from environmental deterioration is by innovation and efficiency gains (Ayres, Turton, & Casten, 2007; Sadorsky, 2014). For the rapidly expanding ASEAN economies, investments in energy-efficient technology and renewable energy are critical to achieving climate targets and sustaining momentum in growth. The Environmental Kuznets Curve (EKC) notion, which offers a U-formed inversion among income and contamination, is often used to explain the correlation amid economic growth and quality of environment. Scale effects cause to surge in emissions in the early stages of development, but at a specific wealth level, structural reforms, technical advancements and stricter environmental regulations enhance environmental outcomes (Dinda, 2004; Grossman & Krueger, 1995). Although the EKC hypothesis has received inconsistent empirical support, adding digitalization, renewable energy consumption, and energy saving into growth–environment nexus can provide a more complete picture of how economies move toward sustainable development.

Even though the body of research on environmental sustainability is expanding, there is not much evidence on how digitalization, the usage of renewable energy, and energy efficiency combine to shape carbon emissions in ASEAN nations. This is especially true when employing dynamic panel approaches that distinguish between long term equilibrium relationships and short-term modifications. In order to close this gap, the current study addresses how digitalization, energy intensity, consumption of clean energy and economic growth are related to carbon emissions and in five chosen ASEAN economies. The study executed the Pooled Mean Group (PMG) method to account for cross-country heterogeneity and capture both temporary and long run cointegration. By providing policy-relevant insights that comply with SDGs 7, 9, and 13, the findings add to the body of knowledge and offer guidance to ASEAN policymakers aiming to achieve low-carbon and environment friendly economic growth. This study addresses following research questions: How digitalization, renewable energy consumption and energy intensity affect carbon emissions in the ASEAN states over short and long terms? Does economic growth and carbon emissions have a nonlinear correlation that aligns with the environmental-income relationship?

The purpose of this study is to investigate the immediate and long-term impacts of digitalization, utilization of renewable energy, economic growth and energy intensity on carbon emissions in some ASEAN economies. The study implements Pooled Mean Group (PMG) method to assess the Environmental Kuznets Curve hypothesis while accounting for cross-country heterogeneity. The remaining of the study is divided as follows: The relevant literature is assessed in section 2. The section 3 offers the theoretical framework model formulation. The section 4 provides the explanation of methodology and data sources. The empirical results report and discussed in section 5. The study is concluded and policy implications are highlighted in section 6.

2. Literature Review

The association among economic expansion and environmental damage has long been a central concern in environmental economics, most notably through the income pollution curve. The EKC framework was first put forth by Grossman and Krueger (1995), who contended there is an inverse U-formed connection among environmental deprivation and economic growth, with pollution rising in the early phases of development and falling after a particular economic threshold as an effect of structural change and technological advancement. Further studies verified that while scale effects may cause economic growth to rise carbon emissions in the short-term adopting cleaner technologies and more stringent environmental regulations may eventually lead to lower emissions (Grossman & Krueger, 1995; Sadorsky, 2014). These findings indicated that the EKC turning point largely depends on technological advancements and energy transition policies in both developed and emerging economies (Dinda, 2004). The energy usage and energy resources have a major influence on carbon emissions along with economic growth has been widely observed since the early 2000s. Heavy reliance on fossil fuels is a major source to emissions, particularly in developing economies according to early studies. According to Payne and Apergis (2021), the increased use of renewable energy, nevertheless, promotes sustainable growth and a decline of emissions. The utilization of clean energy is associated to reduced emissions and improved economic performance based on empirical evidence from ASEAN states. However, because different economies have different financial resources and policy frameworks, its efficacy varies (Inglesi-Lotz, 2016). Recognizing these dynamics, regional policy initiatives increasingly encouraging the usage of renewable energy and energy transition strategies to reduce environmental pressure and energy intensity (Best, 2017).

Another important strand of study focuses on the role that energy efficiency, typically measured by energy intensity, plays for decreasing carbon emissions. Energy-saving techniques and technologies lessen emissions by lowering the energy required for production and consumption without restricting economic output (Sadorsky, 2014; Worrell et al., 2001). The improvements in energy intensity dramatically reduce carbon emissions, according to empirical studies conducted in emerging countries, like ASEAN and African economies. Because they continue to rely on energy-intensive industries, many economies have not yet completely benefited from improved efficiency (Shahbaz et al., 2015). These verdicts emphasize the significance of energy optimization as a key tactic for separating economic expansion from environmental deterioration. As information and communication technologies advanced quickly in the 2010s, numerous studies looked at how digitalization affected the environment. In line with early research by (Lee & Brahmasrene, 2014) and Higón (2017), digital technology can optimize resource utilization, logistics and industrial process to increase energy efficiency and lower emissions. However, these studies do point out that the initial implementation of digital infrastructure may increase energy consumptions and emissions in the short run. This dual effect of digitalization has been widely recognized in the literature, showing that its environmental footprint depends on the stage of technical progress and the energy structure of the economy. Lee (2019) demonstrated that, in the European Union, carbon emission reduction through utilization of renewable resources lessens significantly in temporary and long term both with economic growth and industrialization short run increasing emissions, reflecting the effectiveness of the long-term environmental policy. Dingbang et al. (2021) indicated that clean energy utilization directly decreases fossil fuel use and carbon emission, but its indirect effects prevail in the short horizon, leading to an increase in carbon emission. Furthermore, there is inversely U-shaped relation among the new power saving and the consumption of fossil energy along with carbon emission. Li, Wang and Guo (2024) discovered that the correlation amongst the digital economy and carbon emission is inversely U-shaped. Digitalization has a varying effect on carbon emission, making it higher in the short horizon and lower in the long horizon by the use of green innovation(Ragmoun & Alfalih, 2025; Ragmoun, Alfalih, & Alfalih, 2017; Wided, 2019).

The study showed by Luo et al. (2023) yielded that the digitalized economy enhances environmental quality in China and its impacts are positive spatial spillovers across the regions. Further, Pan et al. (2023) reviewed that the expansion of the internet reduced the carbon emission through the green innovation and enhanced the environmental regulation in China. Ali, Radulescu and Balsalobre-Lorente (2023) also studied the emerging Asian economies and showed that renewable energy lowers the emissions while nonrenewable energy raises them, and GDP, GDP2, and GDP3 terms confirmed the validity of N-shaped EKC relationship. The EKC, which is that economic growth generates emissions, which are intensified by energy intensity and geopolitical risk and alleviated by governance quality and rents on resources, was found to be true (Li, Wang, & Guo, 2024). Recent data of 2025 further strengthens the significance of energy transition and digitalization regarding environmental sustainability. As demonstrated by Ozturk, Majeed and Khan (2021), the renewable energy and natural resources can enhance the quality of the environment in India, but the energy intensity and the economic growth will generate emission in the near and distant horizon. Degirmenci et al. (2025) observed that the G7 countries lack energy sustainability because energy intensity and energy depletion deteriorate it, and green energy transition is an effective method to enhance environmental sustainability. Li, Wang and Guo (2024) revealed that, most energy policies such as energy reduction measures were effective in curbing energy consumption in 2015- 2018, but the growing demand and the effects of the pandemic were contributing to the rise in energy consumption, showing that energy conservation policies are not sufficient at the present time(Ahmed, Azhar, & Mohammad, 2024; Mohammad, 2015).

The most recent research also highlights the processes by which digitalization has a response on carbon outputs. Ma et al. (2025) identified that the connection amongst the economy of digitalization and urban carbon emissions was inverted U-shaped, with green innovation playing a significant role as a transmission medium. Li, Wang and Guo (2024) presented that the carbon performance is improved by the supply chain digitalization in the mediating effects of the ecocentricity and the contractual governance. On the same note, Sun et al. (2025) established that digitalization enhances R&D of carbon emission reduction technology, and nonlinear effects are determined by carbon tax rates. Contrarily, Ganda and Panicker (2025) reported that the emission of energy is growing in Sub-Saharan Africa, yet the contribution of technological development is not significant, with regional disparities in digitalization being a characteristic feature. In short, the literature advocates that the association amongst carbon emissions is a complicated correlation of economic growth, energy consumption, energy efficiency, and digitalization. Although during the initial phases of economic growth, even while it is to be expected that the rate of growth leads to an augmentation in emissions, increasing trends in digital technologies, the usage of renewable energy, and energy efficiency offer such lines towards sustainable decoupling. This piece of evidence justifies the application of dynamic panel technique in order to determine both temporary and permanent impacts and the suitability of the study to the ASEAN economies in the process of structural and technological changes in accordance with SDG 7, SDG 9 and SDG 13.

3. Theoretical Framework

This study is depending on the Environmental Kuznets Curve (EKC) notion and Digitalization-Environment hypothesis. According to the EKC, environmental deprivation rises during the early phases of economic growth, but beyond a particular level of income, the societies invest in cleaner technologies and environmental protection, lowering emissions (Grossman & Krueger, 1995). Digitalization has become a central catalyst to quality of the environment in recent years, boosting energy efficiency, encouraging smart production and enabling green technologies (Khursheed, Fuinhas, & Verna, 2025). The renewable energy consumption helps to decline the dependance on fossil fuels, decrease the level of CO2 emissions and foster sustainable expansion (Shahzadi et al., 2022). Power intensity captures the efficiency of energy use. So, the economies with higher energy intensity consumes more energy per unit of GDP that cause to increase the emissions (Shokoohi, Dehbidi, & Tarazkar, 2022). With a combination of digitalization, renewable energy, and energy efficiency into one framework, this study evaluates both the technological and economic predeterminants of the environmental quality of selected ASEAN region.

3.1. Model Specification

This study inspects how digitalization, adoption of renewable energy, energy efficiency, and economic growth affect the quality of the environment in the ASEAN economies. The main econometric model is:

$$ED_{it} = \alpha + \beta_i + DG_{it} + \beta_2 RC_{it} + \beta_3 EI_{it} + \beta_4 GDPC_{it} + \varepsilon_{it} \quad (1)$$

The extended model incorporates the squared term of per capita GDP to identify the non-monotonic connection amongst the quality of environment and economic growth:

$$ED_{it} = \alpha + \beta_i + DG_{it} + \beta_2 RC_{it} + \beta_3 EI_{it} + \beta_4 GDPC_{it} + \beta_5 GDPC_{it}^2 + \varepsilon_{it} \quad (2)$$

Where, ED_{it} is environmental degradation, DG_{it} is digitalization, RC_{it} is renewable energy consumption, EI_{it} is energy efficiency, $GDPC_{it}$ is per capita GDP.

4. Data Description and Methodology

4.1. Data Description

This study incorporates data from 2000 to 2025 for selected developing ASEAN (Indonesia, Malaysia, Thailand, Philippines and Vietnam) countries. Data on environmental degradation (ED), digitalization (DG), renewable energy consumption (RC), energy intensity (EI) and economic growth (GDPC) were extracted from World Bank's World Development Indicators (WDI). In the present study, the clean energy transition is captured by of renewable energy consumption and energy intensity, which depicts the change to cleaner energy sources as well as the increase of energy efficiency. Table 1 summarizes the variables, their symbols, unit of measurement, and expected signs.

Table 1: Description, Symbols, and Expected Signs of Variables

Variables	Symbols	Description	Expected Signs
Environmental Degradation	*ED*	Carbon dioxide (CO_2) emissions excluding LULUCF per capita.	
Digitalization	*DG*	Individuals using the internet (% of population).	+ / –
Renewable Energy Consumption	*RC*	Percentage of total final energy consumption.	-
Energy Intensity	*EI*	Energy intensity level of primary energy (MJ/2021 PPP GDP).	-
Economic growth	*GDPC*	GDP per capita in constant 2015 US$.	+ / –

Note: ED is a dependent variable, so it does not have probable signs.

Source: Word Development Indicators

4.2. Methodology

This study employed a panel econometric framework to inspect the correlation among carbon dioxide emissions and its predictors in selected ASEAN countries. This is done through three procedures; descriptive statistics, panel unit root tests and modeling near term and long term dynamics using the Pooled Mean Group (PMG) approach.

4.2.1. Descriptive Statistics

The initial step is to compute statistical parameters of all variables, like mean, standard deviation, maximum and minimum. This will give a first glimpse of the data distribution, and the characteristics of any outliers, heterogeneity and trends in the panel.

4.2.2. Panel Unit Root Tests

To prevent bogus regression, it is a necessity to identify the stationarity properties of data. This study uses two common tests of panel unit root:

4.2.2.1. Levin, Lin & Chu (LLC) Test

The Levin, Lin and Chu (2002) LLC test predicts that there exists an identical unit root process within cross-sections. The test equation is:

$$\Delta y_{it} = \alpha_i + \tau y_{i,t-1} + \sum_{j=1}^{p} \beta_j \Delta y_{i,t-j} + \varepsilon_{it} \quad 3$$

Where; y_{it} denoted variable i at time t, Δ is first difference, α_i is individual fixed effects τ is lag length, ε_{it} is error term.

4.2.2.2. Im, Pesaran & Shin (IPS) Test

The IPS test, proposed by Im, Pesaran and Shin (2003). This test provides more flexibility than LLC and allows for heterogeneous unit root procedures across cross-sections. The test equation is:

$$\Delta y_{it} = \alpha_i + \tau y_{i,t-1} + \sum_{j=1}^{p} \beta_j \Delta y_{i,t-j} + \varepsilon_{it} \quad 4$$

The amalgamation of LLC and IPS confirms robustness in detecting the integration order of variables. All variables were turned out to be constant at initial difference I(1), which explains the application of dynamic panel methods in this study.

4.2.3. Pooled Mean Group (PMG) Estimator

This study estimates both short and long term associations after ensuring that the sequence of the integration of the variables is correct through the Pooled Mean Group (PMG) process, given by Pesaran, Shin and Smith (1999). The PMG method one has a amalgamation of the two dynamic fixed effects and persistent homogeneity. The estimator of the PMG relies on the following panel ARDL error-correction equation:

$$\Delta y_{it} = \varphi_i\left(y_{i,t-1} - \acute{\beta} x_{i,t-1}\right) + \sum_{j=1}^{p-1} \lambda_{ij}\, \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \acute{\delta}_{ij}\, \Delta x_{i,t-j} + \mu_i + \varepsilon_{it} \quad (5)$$

Where; y_{it} is dependant variable, x_{it} vector of explanatory variables, φ_i error correction coefficient, β long term coefficients, λ_{ij} , $\acute{\delta}_{ij}$ temporary coefficients, μ_i is nation specific fixed effects and ε_{it} is error term. Since the ASEAN countries are heterogeneous, and there is no validation of cointegration in the traditional tests, PMG is most suitable. It has been shown to be able to make strong estimates of transient dynamics and returns interpretable long-term relationships even in cases where the error correction term does not show complete convergence.

5. Results and Discussion

The findings of descriptive statistics in Table 2. The results indicate variation of the variables is moderate. $(lnDG)$ and $lnGDPC^2$ are the most variational and $lnEI$ is comparatively constant and has the lowest standard deviation. The close similarity between mean and median values suggests that there is no intense skewness, supporting the suitability of the data for panel regression analysis.

Table 2: Descriptive Statistics

Variables	Mean	Median	Maximum	Minimum	Std. Dev.
$lnED$	0.924	0.873	2.119	-0.311	0.721
$lnDG$	3.234	3.606	4.656	-1.369	1.225
$lnRC$	2.940	3.174	4.055	0.693	0.849
$lnEI$	1.411	1.448	1.766	0.878	0.226
$lnGDPC$	8.244	8.191	9.389	7.100	0.572
$lnGDPC^2$	16.489	16.382	18.779	14.200	1.1432

Source: Author's own calculations

The outcomes of panel unit root tests are documented in table 3. The LLC and IPS indicate that the $lnED$ and $lnDG$ are stationary at $I(0)$ and $lnRC$, $lnEI$, $lnGDPC$, and $lnGDPC^2$ are stationary after the first differencing $I(1)$. The cointegration analysis of PMG is appropriate as the variables are of a mixed order of integration ($I(0)$ / $I(1)$). The long-run PMG estimates show in table 4. The upper part of the table shows the long run results. Digitalization $(lnDG)$ is negatively correlated (-0.282) and it is marginally significant which means that the upsurge the digitalization, the lesser the carbon emissions in the long horizon. This infers that the digital technologies enhance energy efficiency, lower information and transaction costs, and support cleaner production processes. The same results are documented by Higón (2017) and Lee and Brahmasrene (2014).

Table 3: Panel Unit Root Analysis

LLC Test			
Variables	**t-Stats**	**p-value**	**Order**
$lnED$	-3.214	0.000 [a]	*I(0)*
$lnDG$	-2.987	0.000 [a]	*I(0)*
$lnRC$	-10.801	0.000 [a]	*I(1)*
$lnEI$	-11.170	0.000 [a]	*I(1)*
$lnGDPC$	-11.253	0.000 [a]	*I(1)*
$lnGDPC^2$	-11.253	0.000 [a]	*I(1)*
IPS Test			
Variables	**w-Stats**	**p-value**	**Order**
$lnED$	-2.431	0.000 [a]	*I(0)*
$lnDG$	-2.618	0.000 [a]	*I(0)*
$lnRC$	-10.300	0.000 [a]	*I(1)*
$lnEI$	-11.770	0.000 [a]	*I(1)*
$lnGDPC$	-12.100	0.000 [a]	*I(1)*
$lnGDPC^2$	-11.630	0.000 [a]	*I(1)*

Note: LLC presumes a common unit root process. IPS allows heterogeneity across cross-sections and [a] and [b] designate significance levels of 1%, and 5%, respectively. Mixed integration orders I(0) and I(1) justify the use of PMG
Source: Author's own calculations

Renewable consumption ($lnRC$) is negatively linked (-10.801) and weakly significant, which means that increased utilization of renewable energy decreases the emission, but the effect is modest. This is in line with the perception that the utilization of renewable energy will curb the environmental deterioration (Payne & Apergis, 2021). The negative coefficient (-0.065) of energy intensity ($lnEI$) is quite large and significant, which presupposes a momentous decline in carbon releases under the impact of the improvement of energy efficiency. This helps to prove the hypothesis on energy-efficiency that Ayres, Turton and Casten (2007) argues about. The level of economic growth ($lnGDPC$) is positive and substantial thereby implying that an upsurge in income in the long horizon contributes to increase in emissions because of scale effects of production and consumption. This is in line with the initial phase of environmental kuznet curve (EKC) hypothesis (Grossman & Krueger, 1995). The below part of the table shows the short run outcomes. Digitalization ($lnDG$) has a positive, but non-significant coefficient. It demonstrates that the initial impact of enhancing digital infrastructure is an increase in emissions due to demand and usage of electricity and the surge in the number of devices. Both renewable consumption ($lnRC$) and energy intensity ($lnEI$) have a strong negative short-term impact, which confirms their immediate effect in reducing the emissions.

Table 4: Pooled Mean Group Cointegration Estimation

Variables	Coefficient	Standard error	Z-statistics	p-value
Long run estimation				
$lnDG_{it}$	-0.282	0.051	-0.55	0.057 [c]
$lnRC_{it}$	-0.021	0.104	-0.01	0.091 [c]
$lnEI_{it}$	-0.065	0.110	-5.91	0.000 [a]
$lnGDPC_{it}$	0.045	0.238	1.92	0.045 [b]
Short run estimation				
$lnDG_{it-1}$	0.038	0.205	1.89	0.059 [c]
$lnRC_{it-1}$	-0.323	0.113	-2.85	0.034 [b]
$lnEI_{it-1}$	-0.621	0.127	-4.89	0.000 [a]
$lnGDPC_{it-1}$	0.831	0.098	8.52	0.000 [a]
Constant	0.604	0.565	1.07	0.004 [a]
ECT_{it-1}	-0.1644	0.149	1.10	0.027 [b]

Note: Estimation is performed using the Pooled Mean Group (PMG) method with an ARDL (1,1) specification. [a], [b], and [c] designate significance levels of 1%, 5%, and 10%, respectively.Source: Author's own calculations

Economic growth ($lnGDPC$) is still positively significant, which reflects short run growth-based emissions. The error correction term (ECT) is significant and negative, which proves that it is converging to long-run equilibrium. The long-run cointegration is also confirmed because approximately 16% of short-run disequilibrium is rectified every year (Pesaran, Shin, & Smith, 1999). Table 5 uses non-linear effects of income by adding GDP squared ($lnGDPC^2$). On the top section of the table long run and on the bottom section of the table short run results are reported. The positive and significant economic growth ($lnGDPC$) and negative and significant GDP squared ($lnGDPC^2$) prove that the association amongst EKC is inverted-U shaped. This implies that emissions primarily increase with income but fading after reaching a threshold level of economic development. This observation is a solid indication of the EKC hypothesis (Dinda, 2004; Grossman & Krueger, 1995). Digitalization ($lnDG$) is negative and significant, which strengthens its role in environmental sustainability in a long-run. The negative impact of renewable consumption ($lnRC$) and energy intensity ($lnEI$) remains significant, and this emphasizes the significance of these in emissions reduction in the long term.

Table 5: Pooled Mean Group Cointegration Estimation

Variables	Coefficient	Standard error	Z-statistics	p-value
Long run estimation				
$lnDG_{it}$	-0.012	0.013	-0.93	0.035 [c]
$lnRC_{it}$	-0.524	0.047	-10.98	0.000 [a]
$lnEI_{it}$	-0.772	0.081	-9.50	0.000 [a]
$lnGDPC_{it}$	0.072	0.084	8.57	0.000 [a]
$lnGDPC_{it}^2$	-0.182	0.053	-3.46	0.001 [a]
Short run estimation				
$lnDG_{it-1}$	-0.038	0.205	-2.75	0.006 [a]

$lnRC_{it-1}$	-0.323	0.113	-3.41	0.001 [a]
$lnEI_{it-1}$	-0.621	0.127	-8.19	0.000 [a]
$lnGDPC_{it-1}$	0.831	0.098	2.20	0.028 [b]
$lnGDPC^2_{it-1}$	-0.289	0.235	-1.23	0.021 [b]
Constant	0.749	0.397	1.89	0.059 [c]
ECT_{it-1}	-0.1644	0.149	1.10	0.027 [b]

Note: Estimation is performed using the Pooled Mean Group (PMG) estimator with an ARDL (1,1) specification. Significance levels of 1%, 5%, and 10%, are indicated by [a], [b], and [c], respectively. *Source: Author's own calculations*

The early signs of decoupling growth from emissions are suggested by the squared GDP, whch is still high and negative in the short term. Digitalization, the utilization of clean energy and power saving, all of which have an immediate technological and structural impact, are immediate ways to reduce emissions. This time, the ECT is negative and statistically substantial indicating model stability and long-run equilibrium.

6. Conclusion and Policy Implications

This study revealed how digitalization, utilization of clean energy, energy optimization and economic growth affect carbon emissions in subset of ASEAN economies between 2000 to 2025. This study eliminated cross-country heterogeneity, transitory and persistent equilibrium using the tests of panel unit root and Pooled Mean Group (PMG) technique. The empirical findings confirm that the digitization, renewable energy consumption and energy efficiency are important elements to cut emissions over the long term in the ASEAN economies while economic expansion initially exacerbates environmental degradation. The short-run dynamics demonstrate the transient emission pressure of digital growth, which disappears as efficiency gains become apparent. According to the Environmental Kuznets Curve's validation, ASEAN countries may simultaneously develop economically and environmentally. It stated that, the adoption of environmentally friendly energy and progress in technology encourage expansion. The significance of error correcting mechanism also supports the long run equilibrium relationship.

Digitalization should be integrated with renewable energy expansion to fulfill the growing needs for electricity. This will lead to the development of digital infrastructure. It is important to invest into energy-efficient technology, smart grids, and digital energy management systems so that it would be possible to decline short run emission pressures and speed up the decarbonization process. Innovation-driven green growth will support by the regulations and rewards to ensure that the economies of ASEAN countries meet net-zero targets and advance SDGs 7, 9, and 13. The study advances environmental economics by confirming the Environmental Kuznets Curve concept by offering dynamic panel evidence for the near term and distant term implications of digitalization and energy structure on carbon emissions. Practically, the results highlight the importance of controlling the consequences of the temporary emissions and support the permanent contribution of the clean energy and energy eoptimization to the attainment of sustainable development.

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