

Panel Data Econometric Analysis of The Determinants of Carbon Emission Intensity: Integrating Digital Transformation, Structural Shift, and Macroeconomic Dynamics

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Abstract.

This study analyzes the relationship between digitalization, structural transformation, and carbon emission intensity in six ASEAN countries, namely Indonesia, Malaysia, Thailand, the Philippines, Vietnam, and Cambodia. The study uses annual panel data for the period 2004–2024, with the main estimation period covering 2010–2024. Carbon emission intensity is used as the dependent variable, while the number of internet users, industry value added, urban population, GDP per capita, international trade, and services sector value added are used as independent variables. All variables are transformed into natural logarithms so that the coefficients can be interpreted as elasticities. Estimation is conducted using the Fixed Effects Model with period fixed effects and Panel EGLS with period weights following model selection tests. The results show that digitalization, proxied by the number of internet users, has a positive but statistically insignificant relationship with carbon emission intensity. In contrast, industry value added, urban population, GDP per capita, and international trade have positive and significant relationships. Services sector value added has a negative and significant relationship with carbon emission intensity. These findings indicate that structural transformation toward the services sector is associated with lower emission intensity, while industrial expansion, urbanization, economic growth, and trade are associated with increased carbon emission intensity in the countries examined.

Keywords: carbon intensity; digitalization; structural transformation; trade and urbanization.

I. INTRODUCTION

Climate change and the increasing level of greenhouse gas emissions have become among the major challenges to sustainable economic development (IPCC, 2023). Rapid economic growth in developing countries is often accompanied by increases in energy consumption, industrialization, urbanization, and trade activities, which can intensify environmental pressure. The relationship between economic growth and environmental quality is not straightforward, as changes in the scale of economic activity, production structure, and technology can generate different environmental consequences (Grossman & Krueger, 1995; York et al., 2003; Dinda, 2004; Stern, 2004; Prawoto & Basuki, 2020).

In the context of ASEAN countries, this issue has become increasingly important because the region has experienced relatively rapid economic growth, urbanization, digitalization, and structural transformation. Empirical evidence from the ASEAN region indicates that the relationships among economic growth, energy consumption, trade, and emissions may vary according to country characteristics and economic structures (Ahmed et al., 2017; Munir et al., 2020). Increased economic activity may stimulate energy consumption and resource use, but at the same time, technological and economic structural changes may create opportunities to improve environmental efficiency. Grossman and Krueger (1995) explain that economic development can affect environmental quality through changes in the scale of economic activity, sectoral composition, and technological development, whereas Dinda (2004) and Stern (2004) discuss this relationship within the Environmental Kuznets Curve (EKC) framework.

Digitalization has become an important aspect of changes in the modern economic structure. The development of digital technologies can improve production efficiency, enhance information systems, reduce transaction costs, and enable more efficient resource use. However, digitalization also requires information technology infrastructure, data centers, communication networks, and electronic devices that consume energy. Therefore, digitalization may have different environmental consequences depending on a country's energy structure and economic characteristics (Xu et al., 2022; Lyu et al., 2023).

Several studies have found that the development of the digital economy is associated with lower carbon emission intensity through various mechanisms, including changes in industrial structure and improvements in economic efficiency (Dong et al., 2022; Lyu et al., 2023; Zhao et al., 2023; Zhang et al.,

2024). Lyu et al. (2023), for example, show that digital economy development in Chinese provinces is associated with lower carbon emission intensity, particularly through mechanisms of industrial structure optimization and resource allocation. Meanwhile, Zhao et al. (2023) find a negative long-run relationship between digital economy development and carbon emission intensity in Chinese provinces.

In addition to digitalization, structural transformation is an important factor in explaining changes in emission intensity. The shift in economic activity from goods-based and industrial sectors toward services can alter a country's energy consumption patterns and emission characteristics. Murshed et al. (2020) show that the development of value added in the services sector has implications for carbon emissions. Bashiri Dezfuli et al. (2025) show that structural transformation from goods-based to service-based economies has implications for carbon emissions, but the effect does not necessarily take the form of emission reductions. Using data from 23 OECD countries over 1990–2022, the study finds that Cost Disease in the services sector has a positive and significant relationship with CO₂ emissions. This finding indicates that the environmental effects of transformation toward the services sector depend on the productivity characteristics and structure of the service subsectors that develop. Findings on the relationship between industrial structure and emissions also indicate that changes in sectoral composition can constitute an important mechanism in the relationship between economic growth and the environment (Dong et al., 2020).

Urbanization can also affect carbon emission intensity through changes in energy consumption, transportation, infrastructure development, and consumption patterns. The concentration of population in urban areas can increase energy and transportation demand, but under certain conditions it can also generate efficiency through urban density and more effective infrastructure provision. Cross-country evidence indicates that the effect of urbanization on emissions may differ according to development levels and energy use (Poumanyvong & Kaneko, 2010; Zhu et al., 2012). In the ASEAN context, urbanization is also associated with changes in energy use and carbon emissions (Wang et al., 2016), while more recent research emphasizes the importance of urban development characteristics in determining environmental impacts (Luqman et al., 2023).

International trade is another factor that may affect environmental conditions. Antweiler et al. (2001) explain that the relationship between trade and the environment can operate through three main mechanisms, namely the scale effect, composition effect, and technique effect. This framework was subsequently developed in the trade and environment literature, which emphasizes that the effect of trade on environmental quality depends on production structure, income, technology, and environmental regulation (Copeland & Taylor, 2004; Frankel & Rose, 2005). Trade expansion may increase emissions if it expands the scale of carbon-intensive production activities, but trade can also facilitate the transfer of more efficient technologies and alter the composition of production. Empirical evidence from ASEAN countries also indicates linkages among trade, growth, and emission pressures (Ahmed et al., 2017; Munir et al., 2020).

Based on the foregoing discussion, this study analyzes the relationship between digitalization, structural transformation, urbanization, economic growth, and international trade and carbon emission intensity in six ASEAN countries, namely Indonesia, Malaysia, Thailand, the Philippines, Vietnam, and Cambodia.

This study is expected to contribute to the literature by integrating indicators of digitalization and structural transformation into a single empirical model to explain carbon emission intensity in ASEAN countries.

II. METHODS

2.1 Data and Sample

This study employs a quantitative approach using panel data for six ASEAN countries, namely Indonesia, Malaysia, Thailand, the Philippines, Vietnam, and Cambodia. The initial dataset covers the period 2004–2024, while the main model estimation uses the period 2010–2024, resulting in 90 observations, consisting of six countries over 15 years.

The use of panel data enables the study to combine cross-country (cross-section) and time (time series)

dimensions. This approach allows the analysis to accommodate heterogeneity across units while observing changes in variables over time (Baltagi, 2021; Wooldridge, 2010). In the panel econometrics literature, the development of panel models also includes instrumental variable and dynamic panel approaches to address potential endogeneity and dynamic characteristics in relationships among variables (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998). Although this study uses the Fixed Effects Model as the main model, this literature constitutes an important part of the development of panel-data estimation methodologies and provides a methodological foundation for selecting an estimation approach consistent with the characteristics of the data.

The dependent variable is carbon emission intensity (CO₂), while the independent variables consist of the number of internet users (IUI), industry value added (IVA), urban population (UP), GDP per capita (GDP), international trade (TRD), and services value added (SER). All variables are transformed into natural logarithmic form. The use of a log-log specification allows regression coefficients for continuous variables to be interpreted as elasticities, while taking into account the assumptions and specification of the model used (Wooldridge, 2010).

The research data are obtained from the World Development Indicators (WDI) published by the World Bank, with indicators covering carbon emission intensity, the number of internet users, industry value added, GDP per capita, urban population, international trade, and services value added (World Bank, 2026).

Table 1. Operational Definitions of Variables

Variable	Operational definition	Unit	Role
CO ₂	Carbon emission intensity	kg CO ₂ e per constant 2015 US\$ GDP	Dependent
IUI	Number of individual internet users	Number of individuals	Independent
IVA	Industry value added	Constant 2015 US\$	Independent
UP	Urban population	Urban population	Independent
GDP	GDP per capita	Constant 2015 US\$	Independent
TRD	International trade	Trade value	Independent
SER	Services value added	Constant 2015 US\$	Independent

2.2 Econometric Model

The empirical model of the study is formulated as:

$$\ln(\text{CO}_{2it}) = \alpha + \beta_1 \ln(\text{IUI}_{it}) + \beta_2 \ln(\text{IVA}_{it}) + \beta_3 \ln(\text{UP}_{it}) + \beta_4 \ln(\text{GDP}_{it}) + \beta_5 \ln(\text{TRD}_{it}) + \beta_6 \ln(\text{SER}_{it}) + \lambda_t + \varepsilon_{it}$$

In the equation, $\ln \text{CO}_{2it}$ = natural logarithm of the country's carbon emission intensity in year ; = constant; = digitalization coefficient; = natural logarithm of the number of internet users in the country in year ; = industry value-added coefficient; = natural logarithm of the country's industry value added in year ; = urban population coefficient; = natural logarithm of the country's urban population in year ; = GDP per capita coefficient; = natural logarithm of the country's GDP per capita in year ; = international trade coefficient; = natural logarithm of the country's international trade in year ; = services value-added coefficient; = natural logarithm of the country's services value added in year ; = country as the unit of observation; = research period 2010–2024; = period fixed effect; = error term. All variables are transformed into natural logarithms so that the coefficients can be interpreted as elasticities.

In panel-data estimation, the choice of estimator needs to consider the characteristics of the data, the possibility of individual heterogeneity, and the potential for simultaneous relationships or endogeneity among variables. Arellano and Bond (1991) developed the Generalized Method of Moments (GMM) approach for dynamic panel models by utilizing internal instruments, while Arellano and Bover (1995) developed a more general instrumental variable framework for error-components models. Subsequently, Blundell and Bond (1998) developed system GMM by incorporating additional moment conditions to improve estimation efficiency under certain conditions. This literature demonstrates the development of panel estimation methods that can be used when the model structure contains dynamics or potential endogeneity, whereas this study employs a fixed-effects specification to accommodate unobserved heterogeneity across observation periods.

2.3 Model Selection and Heteroskedasticity Correction

The estimations are compared using the CEM, FEM with period effects, and REM with period effects. The Chow test is used to compare the pooled model with the period fixed-effects model, while the Hausman test is used to compare period fixed effects and period random effects. The use of panel models and specification tests follows the econometric practices discussed in Wooldridge (2010) and Baltagi (2021). The heteroskedasticity test is conducted through an auxiliary regression of the log of squared residuals. When heteroskedasticity is indicated, the final estimation uses Panel EGLS with period weights to accommodate differences in variance across periods. In addition to heteroskedasticity testing, the panel-data literature also emphasizes the importance of considering cross-sectional dependence. Pesaran (2007) developed a test to detect cross-sectional correlation, while Driscoll and Kraay (1998) provide a covariance approach that is robust to heteroskedasticity, autocorrelation, and cross-sectional dependence. However, this study does not employ either of these approaches in the main estimation.

III. RESULTS AND DISCUSSION

3.1 Descriptive Statistics

Table 2. Descriptive Statistics

Variable	Mean	Median	Max	Min	Std. Dev.
CO2	0,628	0,634	1,075	0,272	0,206
IUI	$4,68 \times 10^9$	$3,46 \times 10^9$	$2,06 \times 10^{10}$	18.270.915	$4,26 \times 10^9$
IVA	$1,41 \times 10^{11}$	$1,22 \times 10^{11}$	$4,66 \times 10^{11}$	$4,41 \times 10^9$	$1,14 \times 10^{11}$
UP	49.872.333	33.382.876	167.000.000	3.063.021	45.913.091
GDP	4.520,97	3.485,16	11.883,79	1.155,85	2.838,35
TRD	$3,42 \times 10^{13}$	$3,77 \times 10^{13}$	$7,05 \times 10^{13}$	$1,84 \times 10^{12}$	$1,86 \times 10^{13}$
SER	$1,92 \times 10^{11}$	$1,81 \times 10^{11}$	$5,74 \times 10^{11}$	$6,85 \times 10^9$	$1,32 \times 10^{11}$

The descriptive statistics indicate substantial variation across countries. Carbon emission intensity has a mean value of 0.628, with a maximum value of 1.075 and a minimum value of 0.272. These differences indicate heterogeneity in the environmental characteristics of the countries included in the sample.

The number of internet users also shows substantial variation. This condition reflects differences in population size and levels of digital development across countries. Relatively large variation is also observed in industry value added, urban population, international trade, and the services sector.

3.2 Correlation and Indications of Multicollinearity

Table 3. Correlation Matrix

	CO2	IUI	IVA	UP	GDP	TRD	SER
CO2	1,0000	0,1239	0,1566	-0,0389	0,3942	0,6840	0,0624
IUI	0,1239	1,0000	0,7717	0,7580	-0,0278	0,4458	0,8158
IVA	0,1566	0,7717	1,0000	0,9488	0,1265	0,4997	0,9550
UP	-0,0389	0,7580	0,9488	1,0000	-0,1217	0,2711	0,9008
GDP	0,3942	-0,0278	0,1265	-0,1217	1,0000	0,5914	0,2206
TRD	0,6840	0,4458	0,4997	0,2711	0,5914	1,0000	0,5581
SER	0,0624	0,8158	0,9550	0,9008	0,2206	0,5581	1,0000

The correlation matrix indicates relatively high correlations among several independent variables. The correlation between IVA and SER reaches 0.9550, while the correlation between IVA and UP is 0.9488. The correlation between UP and SER is also relatively high, at 0.9008. This condition indicates potential multicollinearity that needs to be considered when interpreting the estimation results. Baltagi (2021) and Wooldridge (2010) emphasize the importance of considering relationships among explanatory variables in panel-data estimation, particularly when these variables represent interrelated economic dimensions.

3.3 Heteroskedasticity Test

Table 4. Heteroskedasticity Test Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG(IUI)	-0,502628	0,663736	-0,757272	0,4515
LOG(IVA)	0,560735	2,443148	0,229514	0,8191
LOG(UP)	0,115608	3,625143	0,031891	0,9747
LOG(GDP)	-1,278332	1,847952	-0,691756	0,4914

LOG(TRD)	1,649753	1,479419	1,115136	0,2687
LOG(SER)	-1,150027	2,116884	-0,543264	0,5887

The heteroskedasticity test produces an R-squared value of 0.350187, an Adjusted R-squared of 0.161835, an F-statistic of 1.859220, and a Prob(F-statistic) of 0.030537. The probability value indicates heteroskedasticity in the initial model. Therefore, the final estimation uses Panel EGLS with period weights to accommodate differences in error variance in the panel data.

3.4 Model Selection: Chow and Hausman Tests

Table 5. Model Selection Test Results

Test	Statistik	d.f.	Prob.	Decision
Chow: period fixed effects	F = 5,932733	(14,69)	0,0000	Supports period fixed effects
Hausman: period random effects	$\chi^2 = 40,748557$	6	0,0000	Rejects random effects; use period fixed effects

The Chow Test produces a probability of 0.0000, so the Common Effect model is rejected and the Fixed Effect model is selected. Subsequently, the Hausman Test produces a Chi-square value of 40.748557 with a probability of 0.0000. These results indicate that the Fixed Effect Model is more appropriate than the Random Effect Model. The selection of the Fixed Effect Model is also consistent with the panel-data approach, which considers specific characteristics of each observation unit that remain unchanged over time (Baltagi, 2021; Wooldridge, 2010).

3.5 Final Fixed Effects Model Estimation with Period Weights

Table 6. Fixed Effects Model Estimation Results with Period Fixed Effects

Variable	Coefficient	Std. Error	t-Statistic	Prob.	Conclusion
LOG(IUI)	0,029032	0,017609	1,648750	0,1037	Positive, insignificant
LOG(IVA)	0,136139	0,062664	2,172519	0,0333	Positive, significant
LOG(UP)	0,249217	0,089570	2,782377	0,0070	Positive, significant
LOG(GDP)	0,144860	0,044238	3,274546	0,0017	Positive, significant
LOG(TRD)	0,455356	0,039106	11,644210	0,0000	Positive, significant
LOG(SER)	-0,678244	0,051209	-13,244550	0,0000	Negative, significant
C	-5,663072	0,229252	-24,702440	0,0000	Significant
Model fit measure			Value		
Weighted R-squared			0,965658		
Adjusted R-squared			0,955703		
S.E. of regression			0,056653		
F-statistic			97,00899		
Prob(F-statistic)			0,000000		
Durbin-Watson			0,718000		
Unweighted R-squared			0,937930		

The estimation results indicate that the model is statistically significant overall. The F-statistic of 97.00899 with a probability of 0.000000 indicates that the independent variables jointly have a significant relationship with carbon emission intensity. The Adjusted R-squared value of 0.955703 indicates that approximately 95.57% of the variation in carbon emission intensity in the model can be explained by the independent variables and period effects, while the remainder is explained by factors outside the model.

3.6 Effect of Digitalization

The digitalization variable, proxied by the number of internet users, has a coefficient of 0.029032 with a probability of 0.1037. The coefficient is positive but not statistically significant at the 5% level. Thus, an increase in the number of internet users has not yet shown a significant relationship with carbon emission

intensity. This result indicates that increased internet penetration alone is not sufficient to generate statistically observable changes in carbon intensity.

Digitalization can improve production efficiency, reduce transaction costs, improve information efficiency, and optimize resource use. However, digitalization also requires information technology infrastructure, electronic devices, communication networks, and energy. Xu et al. (2022) show that digitalization can affect energy consumption through various mechanisms.

The results of this study differ in terms of statistical significance from several studies that find a relationship between digital economy development and carbon emission intensity (Dong et al., 2022; Lyu et al., 2023; Zhao et al., 2023; Zhang et al., 2024). These results can be compared with Wang et al. (2024), who show that the development of the digital economy industry and the structural characteristics of the digital economy are associated with carbon emission intensity. Differences in findings may be caused by differences in digitalization indicators, units of analysis, observation periods, and the economic characteristics of the countries studied. Such differences may be related to the digitalization proxy, country coverage, observation period, energy structure, and level of economic development. Accordingly, the use of the number of internet users as an indicator of digitalization should be understood as one dimension of digitalization rather than a representation of overall digital economy development.

3.7 Effect of Industry Value Added

Industry value added has a coefficient of 0.136139 with a probability of 0.0333. The result indicates a positive and significant relationship with carbon emission intensity. In the log-log model, a coefficient of 0.136139 indicates that a 1% increase in industry value added is associated with an approximately 0.136% increase in carbon emission intensity, holding other variables constant. This positive relationship may occur because industrial expansion increases production activity, energy use, transportation, and input consumption. If the energy used still originates from carbon-intensive sources, industrial expansion may increase environmental pressure (Basuki & Stioningrum, 2023).

This result can be explained through the scale effect, whereby an increase in the scale of economic activity increases resource use and environmental pressure (Grossman & Krueger, 1995; Antweiler et al., 2001). The literature on industrial structure also indicates that changes in production composition and industrial intensity can affect environmental pressure differently (Dong et al., 2020).

3.8 Effect of Urbanization

Urban population has a coefficient of 0.249217 with a probability of 0.0070, indicating a positive and significant relationship with carbon emission intensity. A 1% increase in urban population is associated with an approximately 0.249% increase in carbon emission intensity, holding other variables constant.

Urbanization can increase demand for transportation, housing, electricity, construction, and urban services. If urban development remains dependent on fossil-fuel-based transportation and energy-intensive infrastructure, urban population growth may increase emissions (Nisa et al., 2026)..

This finding is consistent with the literature concerning the relationship between urbanization and carbon emissions. Luqman et al. (2023) show that urbanization is an important factor that needs to be considered in explaining changes in CO₂ emissions. This finding is also consistent with Wang et al. (2018), who show that urbanization can be associated with increased CO₂ emissions through changes in energy use, economic activity, and urban infrastructure development.

3.9 Effect of GDP per Capita

GDP per capita has a coefficient of 0.144860 with a probability of 0.0017, indicating a positive and significant effect on carbon emission intensity. A 1% increase in GDP per capita is associated with an approximately 0.145% increase in carbon emission intensity, holding other variables constant. This positive relationship indicates that during the study period, increased economic activity continued to occur alongside higher carbon emission intensity. This may be related to the scale effect, whereby increased economic activity raises energy demand and resource use (Grossman & Krueger, 1995; Dinda, 2004). However, this result does not necessarily indicate an EKC pattern because a nonlinear relationship between income and environmental quality needs to be explicitly tested through an appropriate model specification (Stern, 2004).

Nevertheless, the result cannot be interpreted as evidence of the Environmental Kuznets Curve (EKC).

Grossman and Krueger (1995) examined the possibility of a nonlinear relationship between income and environmental indicators, whereas the model in this study includes GDP per capita only linearly in logarithmic form. Testing the EKC requires an additional specification incorporating a squared income term.

3.10 Effect of International Trade

International trade has a coefficient of 0.455356 with a probability of 0.0000. The result indicates a positive and significant relationship with carbon emission intensity. A 1% increase in international trade is associated with an approximately 0.455% increase in carbon emission intensity, holding other variables constant.

This relationship can be explained through the scale effect, composition effect, and technique effect (Antweiler et al., 2001). Increased trade can expand the scale of production, alter industrial composition, and affect production technology. The trade and environment literature emphasizes that these three mechanisms can operate simultaneously, so the direction of the relationship between trade and emissions depends on a country's economic and technological characteristics (Copeland & Taylor, 2004; Frankel & Rose, 2005). In the ASEAN context, the relationship between trade and emissions has also been identified in cross-country empirical research (Ahmed et al., 2017; Munir et al., 2020).

The positive result in this study indicates that, in the six observed ASEAN countries, increased international trade is associated with higher carbon emission intensity after accounting for other variables in the model. However, this finding does not mean that trade always produces negative environmental impacts because its effects depend on trade structure, industrial composition, technology, and energy sources.

3.11 Effect of Services Sector Value Added

Services sector value added has a coefficient of -0.678244 with a probability of 0.0000. The result indicates a negative and significant relationship with carbon emission intensity. A 1% increase in services sector value added is associated with an approximately 0.678% decrease in carbon emission intensity, holding other variables constant.

The result indicates that economic transformation toward the services sector is associated with lower carbon emission intensity. Murshed et al. (2020) show that the services sector has heterogeneous relationships with carbon emissions, while Bashiri Dezfuli et al. (2025) demonstrate the importance of structural transformation from goods-based economies toward service-based economies in explaining environmental change. Findings on industrial structure also indicate that changes in sectoral composition can be an important channel in determining environmental pressure (Dong et al., 2020).

Theoretically, changes in economic composition toward sectors that are relatively less energy- and material-intensive can reduce environmental pressure through the composition effect (Antweiler et al., 2001).

Nevertheless, the services sector is not entirely a low-carbon sector. Transport, logistics, tourism, and some energy-based services subsectors can still generate relatively high emissions. Therefore, the negative coefficient for the services sector in this study should be understood as the aggregate relationship between the services sector and carbon emission intensity.

3.12 Period-Specific Effects

Table 7. Period-Specific Effects

Year	Period Effect
2010	0.093754
2011	0.062491
2012	0.036157
2013	0.022547
2014	0.019833
2015	0.029686
2016	0.016028
2017	-0.033442
2018	-0.040604
2019	0.006928
2020	0.054011
2021	-0.056747

2022	-0.096573
2023	-0.047857
2024	-0.066212

Period effects are positive during 2010–2016, turn negative during 2017–2018, become positive again during 2019–2020, and then turn negative during 2021–2024. The lowest value occurs in 2022 (-0.096573), while 2020 shows a temporary increase to 0.054011. This pattern indicates that there are general changes across units that are not fully explained by the macroeconomic variables in the model. Because period effects are time-specific residual components, this study does not directly attribute these changes to technology, the pandemic, or specific policies without additional testing.

IV. CONCLUSION

This study analyzes the relationship between digitalization, structural transformation, urbanization, economic growth, and international trade and carbon emission intensity in six ASEAN countries. The estimation results show that the number of internet users, as a proxy for digitalization, has a positive but statistically insignificant relationship with carbon emission intensity. This finding indicates that increased internet penetration has not been sufficient to produce statistically observable changes in carbon intensity.

Industry value added, urban population, GDP per capita, and international trade have positive and significant relationships with carbon emission intensity. These results indicate that the expansion of industrial activity, urbanization, economic growth, and trade remains associated with increased carbon pressure. These relationships can be explained through the scale effect and changes in the composition of economic activity (Grossman & Krueger, 1995; Antweiler et al., 2001).

In contrast, services sector value added has a negative and significant relationship with carbon emission intensity. This result indicates that structural transformation toward a more service-based economy is associated with lower emission intensity, as also discussed in the literature on structural transformation and the environment (Murshed et al., 2020; Bashiri Dezfali et al., 2025).

The implications of the study indicate that low-carbon development strategies in ASEAN need to be implemented in an integrated manner through improvements in industrial efficiency, the development of sustainable urban infrastructure, the use of low-carbon technologies, and economic structural transformation. Findings from the digitalization literature indicate that digital technologies can provide efficiency benefits, but these benefits depend on how the technologies are used and on the characteristics of the energy system (Xu et al., 2022; Dong et al., 2022; Zhang et al., 2024). Digitalization should therefore be directed not only toward increasing connectivity but also toward the use of technologies capable of improving energy efficiency and reducing carbon intensity.

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