International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(5), 158-168.

Digitalization, Net-Zero Strategies, and Sustainable Economic Growth in Vietnam

Nam Tuan Lai*, Thi Hoa Nguyen

Faculty of Management, Ho Chi Minh City University of Law, Vietnam. *Email: lntuan@hcmulaw.edu.vn

Received: 11 March 2025 **Accepted:** 24 June 2025 **DOI:** https://doi.org/10.32479/ijeep.19648

ABSTRACT

This study investigates the dynamic relationship between digitalization, economic sustainability, and Vietnam's pursuit of Net Zero emissions from 1975 to 2023, a period marked by rapid technological advancements. Employing econometric methods, including unit root tests, Johansen cointegration, and Granger causality, alongside robustness checks using Dynamic Factor Analysis (DFA) and Principal Component Analysis (PCA), the research explores the complex interlinkages between digital connectivity, economic sustainability indicators, and emissions. Findings reveal a statistically significant positive relationship between digitalization and emissions, acknowledging technology's dual role in both economic resilience and environmental impact. Trade intensity, private consumption, and primary sector activities, particularly energy-intensive agriculture and export-oriented industry are identified as significant drivers of CO_2 emissions. The analysis quantifies these effects and identifies time-related feedback mechanisms, providing insights into sustainability-oriented trade and industrial policies. PCA further confirms a negative correlation between sustainability scores and emissions. Policy recommendations emphasize renewable energy investments for ICT infrastructure, green technology promotion, digital literacy initiatives, and sustainable macroeconomic policies focused on resource optimization. These findings offer actionable strategies for Vietnam's Net Zero transition and provide valuable lessons for other emerging Asian economies facing similar challenges.

Keywords: Digitalization, Economic Sustainability, Net Zero Emissions
JEL Classifications: Q01, Q56, O33

1. INTRODUCTION

Vietnam's remarkable economic growth over the past two decades has positioned it as a dynamic force in Southeast Asia (Do, 2022; Coppola et al., 2024). However, this rapid development also faces significant challenges from climate change, digital transformation, and pollution, threatening sustainable development. Vietnam's commitment to net-zero emissions by 2050 (Do and Ta, 2022) aligns with global mitigation efforts. The historical link between economic growth and environmental degradation (Schandl et al., 2016; Awolusi, 2021; Zhang et al., 2022) facilitate a shift towards sustainable paradigms. Decoupling economic growth from environmental harm is crucial. Moreover, Anh and Da (2024) highlight digitalization's role in facilitating a low-carbon transition, presenting an opportunity for Vietnam to become a regional leader in sustainable development. This study examines the interplay between digitalization, sustainability, and CO_2 emissions in Vietnam, providing evidence-based insights for policy decisions.

The Environmental Kuznets Curve (EKC) suggests an inverted U-shaped relationship between economic growth and environmental degradation, where pollution initially rises, then declines with maturity (Dinda, 2004; Jalil and Rao, 2019). Digitalization's role in mitigating climate change is increasingly recognized. Further, Belkhir and Elmeligi (2018) emphasize ICT's mitigation potential, urging holistic approaches. Zhang et al. (2022) advocate prioritizing digitalization for low-carbon transitions via efficiency and monitoring. Che et al. (2024) highlight the importance of sustainable digital infrastructure for carbon reduction, underscoring its crucial role in environmental strategies. According to the International Energy Agency (IEA), as of 2022, Vietnam accounts for approximately 0.8% of global CO_2 emissions. This figure reflects the nation's rapidly expanding industrial and energy sectors.

For instance, Vietnam is among the top contributors to CO_2 emissions within Southeast Asia, ranking behind countries such as Indonesia and Thailand (Nguyen et al., 2024). This position is largely attributable to Vietnam's significant reliance on coal-fired power generation, coupled with its rapid industrialization and intensifying energy demands associated with economic growth. Consequently, a successful energy transition in Vietnam is not only crucial for achieving national sustainable development goals but also contributes significantly to regional and global climate change mitigation efforts. The complex relationship between sustainable economic growth, digitalization, and CO_2 emissions has been the subject of extensive empirical investigation over recent decades. However, the nature and direction of these relationships remain a topic of debate among scholars and policymakers, with varying perspectives on the potential for digitalization to act as a driver of both economic growth and environmental sustainability.

This study significantly contributes to the existing body of knowledge by empirically investigating the complicated relationships between digitalization, economic sustainability, and the pursuit of net-zero emissions within the specific context of Vietnam. By focusing on Vietnam's unique developmental progression, the research highlights the potential of digital transformation to serve as a key driver of both environmental and economic progress. Utilizing a comprehensive time-series dataset from the World Bank's World Development Indicators between 1975 and 2023, the study employs a robust econometric approach to generate novel insights into this critical nexus. A primary contribution of this study is its explicit focus on examining the potential decoupling effect of digitalization on the established relationship between economic growth and CO_2 emissions, particularly within the context of a developing economy. By addressing this relatively underexplored dimension, the research aims to elucidate how digital transformation can be strategically leveraged as a tool for progressing towards sustainable development goals. This focus distinguishes the study from previous research that often treats digitalization as a mere correlate or consequence of economic development, rather than a potential driver of decoupling.

Methodologically, this research employs a robust econometric framework, including unit root tests for stationarity, Johansen cointegration for long-run relationships, and Granger causality for directional impacts between digitalization, economic sustainability, and CO_2 emissions. It also examines the Environmental Kuznets Curve (EKC) hypothesis to explore potential non-linear relationships, assessing whether Vietnam's development aligns with EKC theory, moderated by digitalization. This comprehensive approach enhances the reliability and nuances of the findings, offering deeper insights into both long-run and short-run dynamics. Based on the empirical findings, this study proposes three strategic pathways for policymakers and relevant authorities. First, it emphasizes the necessity of strategically targeted investments in sustainable digital infrastructure to effectively support decarbonization efforts across various sectors. Second, it highlights the crucial importance of designing and implementing integrated policy frameworks that effectively align economic and environmental objectives, fostering synergistic outcomes. Third, it advocates for fostering innovation and promoting the adoption of advanced technologies to ensure that Vietnam's development pathway is not only economically robust but also environmentally sustainable and socially inclusive.

The remainder of this study is organized as follows. Section 2 presents a comprehensive literature review on the interrelationships between digitalization, economic growth, and environmental sustainability. Section 3 outlines the research methodology, including data sources, variable definitions, and econometric techniques employed. Section 4 presents and discusses empirical results, including robustness checks to ensure the validity of the findings. Finally, Section 5 concludes with a discussion of the key findings, policy implications, and directions for future research.

2. LITERATURE REVIEW

Global warming and climate change constitute paramount environmental challenges worldwide, dominating scientific and policy agendas for decades. Greenhouse gas (GHG) emissions, particularly CO_2, are widely recognized as the primary drivers of these phenomena (Alvarado and Toledo, 2017; Belkhir and Elmeligi, 2018; Do and Ta, 2022; Che et al., 2024; Coppola et al., 2024). Consequently, the interplay between climate change, digitalization, and sustainable economic growth has become a central focus of academic and policy discourse, reflecting the integrated aspects of these global issues. For instance, Alvarado and Toledo (2017) contribute to this discussion by examining the relationship between economic growth and environmental degradation, specifically highlighting the contribution of industrial activities in developing countries to climate change through CO_2 emissions. Their work establishes a crucial foundation for understanding the inherent environmental trade-offs associated with conventional economic growth models, a key consideration within broader discussions of sustainable development.

Furthering this line of perspective, Awolusi (2021) provides an in-depth analysis of the complex relationship between economic growth and socioeconomic sustainability within the BRICS economies, employing a Vector Error Correction Model (VECM). This study underscores a critical concern shared by economists and policymakers: the potential for environmental regulations and policies, while essential for achieving sustainability objectives, to impose constraints on production possibilities and potentially impede long-term economic growth. More recently, Che et al. (2024) explore the diverse impact of digital infrastructure on carbon emissions. They demonstrate that digitalization's potential to simultaneously drive economic growth and facilitate emissions reductions. This highlights digitalization's complex role in sustainable development. Within Asia's context of rapid industrialization and manufacturing-led growth, digitalization enhances productivity through automation and resource optimization (Dubois et al., 2019; Coppola et al., 2024). It also fosters innovation by lowering barriers to entry and creating new markets, crucial for Asia's transition to knowledge-based economies. Furthermore, it expands market access through e-commerce and global value chain integration, vital for export-oriented Asian economies. Digitalization promotes enhanced market access and connectivity by facilitating e-commerce, cross-border trade, and deeper integration into global value chains.

The Environmental Kuznets Curve (EKC) hypothesis posits an inverted U-shaped relationship between economic growth and environmental degradation (Kaika and Zervas, 2013; Jalil and Rao, 2019). For instance, Kaika and Zervas (2013) were among the early researchers to explore this theoretical framework, focusing specifically on the relationship between economic growth and CO_2 emissions. Their work suggests that while economic expansion initially correlates with increasing CO_2 emissions, a turning point is reached at a certain income threshold, beyond which further economic growth is associated with a decline in emissions. This turning point is often attributed to factors such as technological advancements, stricter environmental regulations, and shifts in societal preferences towards environmental quality. In the context of the EKC, economic growth is a central variable, as the hypothesis focuses on the changing relationship between economic output and environmental indicators. The inclusion of these factors allows for a more nuanced understanding of the factors contributing to environmental degradation within the context of economic development.

Building upon this foundational work, Jalil and Rao (2019) advanced EKC research by employing robust time-series econometrics, specifically utilizing stationarity tests, cointegration, and Granger causality. Notably, they revealed that causality between economic growth and CO_2 emissions varies with development stages, initially driven by growth, but then stabilizing with policy maturity. Consequently, this complex understanding of long-run equilibrium and causal direction significantly contributes to EKC literature. Similarly, Shahzad et al. (2021) further explored this dynamic in the Philippines using the ARDL model, which adeptly handles mixed integration orders. Therefore, this allowed for detailed analysis of both long-run and short-run impacts of economic activities on CO_2 emissions. In particular, their study highlighted the sectoral heterogeneity of these impacts, emphasizing the significant contributions of trade, private consumption, agriculture, and industry to greenhouse gas emissions. Ultimately, this underscores the need for sector-specific environmental policies within the broader EKC framework.

A critical review of the existing literature on CO_2 emissions reveals a substantial body of research investigating the relationships between CO_2 emissions and various macroeconomic variables, including economic growth, energy consumption, trade openness, and digitalization. However, to the best of my knowledge, a significant gap remains in the empirical literature concerning the integrated analysis of the interrelationships between digitalization, economic sustainability, and CO_2 emissions, particularly within the context of developing economies like Vietnam. While individual studies have explored pairwise relationships, a comprehensive investigation of their simultaneous interaction is lacking. This study addresses this gap using multiple econometric approaches, including cointegration, Granger causality, and error correction models, to capture complex dynamic interactions. This multifaceted methodology allows for identifying both long-run equilibrium and short-run adjustments, providing a comprehensive understanding of causal pathways. This rigorous framework generates evidence-based insights to inform policy strategies supporting Vietnam's 2050 net-zero commitment, offering actionable recommendations for leveraging digital technologies for concurrent economic and environmental objectives.

3. METHODOLOGY

3.1. Model Specification

This study examines the impact of digitalization on CO_2 emissions, recognizing the complex interplay between technological advancements, economic activity, and environmental outcomes. The Environmental Kuznets Curve (EKC) suggests that economic development initially leads to environmental degradation, but after reaching a certain income level, the trend reverses, resulting in improved environmental quality (Dina, 2004; Kaika and Zervas, 2013). While the traditional EKC focuses on income per capita, this study extends the framework to incorporate digitalization as a key driver influencing environmental quality. This aligns with the growing body of literature exploring the role of technology in both compounding and mitigating environmental problems (Belkhir and Elmelig, 2018; Che et al., 2024). The study also draws on the theory of induced technological change (Schandl et al., 2016; Zhang et al., 2022). These authors suggest that environmental pressures can incentivize technological innovation aimed at reducing pollution and improving resource efficiency. The statistical equation is as follows:

$$CO_{2t} = \alpha + \beta_1\, IPR_t + \beta_2\, MUR_t + \beta_3\, ES_t + \epsilon_t \tag{1}$$

Where

- CO_{2t}: Carbon dioxide emissions at time t.
- IPR_t: Individuals using the Internet (% of population) at time t
- MUR_t: Mobile cellular subscriptions (per 100 people) at time t
- ES_t: Economic Sustainability indicators at time t
- α: Intercept term.
- ϵ_t: *Error term*.

The analysis employs a combination of econometric techniques to examine the causal relationships and dynamic interactions among the variables. The Granger causality test is utilized to assess whether past values of Digital Transformation (DT) and Green Investment (GI) indicators significantly predict future values of Financial Stability indicators. To ensure the reliability of the results, the stationarity properties of the time series are examined using the Augmented Dickey-Fuller (ADF) test. Stationarity is a fundamental assumption in time series analysis, as it ensures that the statistical properties of the series remain constant over time (Mushtaq, 2011). Depending on the stationarity properties of the variables, either a Vector Autoregression (VAR) model or a Vector Error Correction Model (VECM) is employed. If the variables are stationary, a VAR model can be used to analyze the short-run dynamic relationships. However, if the variables become stationary after taking the first difference or integration of order I(1), it would indicate a long-run equilibrium relationship. Thus, a VECM model is more appropriate because it captures both short-run dynamics and long-run adjustments.

3.1.1. Unit root test

A unit root test is employed to determine the stationarity of a time series. A stationary time series has a constant mean, variance, and autocorrelation structure over time. In contrast, a non-stationary time series exhibits trends 1 or cycles that do not diminish over time. The Dickey-Fuller test is a commonly used unit root test. The null hypothesis of the test is that the time series is non-stationary, while the alternative hypothesis is that the time series is stationary. The test equation for the Dickey-Fuller test is generally as follows:

$$d(Y_t) = \alpha+\beta_t + \gamma Y_{t-1}+d(Y_t(-1))+\epsilon_t \quad (2)$$

3.1.2. Granger causality test

The correlation matrix provides a measure of linear association between variables, but it does not imply causation. To establish causal relationships, more sophisticated econometric techniques, such as Granger causality tests, are necessary. Granger causality tests examine whether past values of one variable can predict future values of another. However, these tests require stationary time series. To ensure stationarity, unit root tests are conducted. If a series is non-stationary, differencing can be applied to render it stationary. However, differencing may eliminate long-term relationships, limiting the scope of causal inferences. For non-stationary series exhibiting long-term equilibrium relationships, alternative models like the Autoregressive Distributed Lag (ARDL) model (Pesaran et al., 2001; Kripfganz and Schneider, 2016) can be employed.

3.1.3. Test for cointegration

The order of integration, denoted as I(d), classifies time series based on the number of differences required to achieve stationarity. A stationary time series, I(0), has a constant mean and variance over time, enabling standard statistical inference techniques. Non-stationary time series, typically denoted as I(1), exhibit trends or cycles. Cointegration occurs when two or more non-stationary time series share a long-run equilibrium relationship. The Johansen cointegration test employs a multivariate framework to determine the presence of long-run equilibrium relationships among a set of variables.

3.1.4. The error correction model (ECM)

In the Vector Autoregression (VAR) model, it is crucial that the variables are stationary because it ensures the reliability of the model. The VAR framework is suitable for analyzing multivariate time series data, allowing us to examine the impact of shocks to one variable on the others. However, stationarity is a crucial assumption for the validity of VAR models. If the variables are non-stationary, the VAR model may produce spurious regressions, leading to misleading conclusions.

$$\Delta y_t = \alpha+\beta\Delta x_t+\gamma(y_{t-1}-\theta x_{t-1})+\varepsilon_t \quad (3)$$

Where:

- Δ denotes the first difference operator.
- $y_{t-1}-\theta x_{t-1}$ is the error correction term, reflecting the long-term relationship.
- ε_t is the error term.

3.2. Data

This study examines how digitalization has influenced economic growth and environmental sustainability in Vietnam. Using annual data from the World Bank's World Development Indicators

Table 1: A summary of these variables and their measurements

Variables	Abbre.	Descriptions	Measurements
Internet penetration rate (% of population)	IPR	Percentage of the population with internet access, a key indicator of digital connectivity and economic development.	Digital transformation
Mobile usage rate	MUR	Number of mobile cellular subscriptions per 100 people, reflecting the level of mobile connectivity and its potential to drive economic growth and social development.	
Trade intensity (% of GDP)	TRA	The total value of a country's exports and imports of goods and services expressed as a percentage of its gross domestic product (GDP)	Economic sustainability
Primary sector output	AFF	The contribution of the agriculture, forestry, and fishing sectors to a country's gross domestic product (GDP).	
Population growth (Annual %)	PGR	The percentage increase in a country's population over a specific year compared to the previous year.	
Inflation, consumer prices (annual %)	CPI	The annual percentage change in the cost of a basket of goods and services typically consumed by households.	
Private consumption (% of GDP)	FCE	The total value of all goods and services consumed by households and government at the end of a specified period, expressed as a percentage of a country's gross domestic product (GDP).	
Export intensity	EGS	The total value of all goods and services produced in a country that are sold to other countries, expressed as a percentage of the country's Gross Domestic Product (GDP).	
Carbon dioxide (CO_2) emissions excluding LULUCF per capita	CO_2	The total amount of carbon dioxide emissions produced per person in a specific geographic area (such as a country) over a defined period, excluding emissions and removals associated with land use, land use change, and forestry (LULUCF)	Net zero emission

Source: World Bank Indicators

from 1975 to 2023, the research will analyze the relationship between these key factors. Table 1 summarizes these variables. Digitalization is measured using two key indicators: Individuals Using the Internet (% of Population) and Mobile Cellular Subscriptions. These metrics provide a comprehensive assessment of digital transformation encompassing access and inclusion. These metrics reflect the extent of information access, service utilization, and online participation, impacting economic activity. The study also incorporates several economic and environmental variables. Trade (% of GDP) reflects economic openness, while Agriculture, Forestry, and Fishing (% of GDP) represents the primary sector's importance. Population Growth (Annual %) captures demographic influences on resource consumption and economic dynamics. Inflation (Annual %) reflects price stability and influences economic behavior. Final Consumption Expenditure (% of GDP) provides insights into domestic demand. Finally, Carbon Dioxide (CO_2) Emissions per capita serves as the key environmental indicator, capturing the environmental impact of economic activities.

4. RESULT ANALYSIS

4.1. Descriptive Statistics and Unit root Tests

Table 2 displays descriptive statistics (mean, standard deviation, minimum, maximum) and ADF unit root test results for all variables, indicating first-order integration. All variables are transformed using natural logarithms for enhanced interpretability in subsequent econometric analyses. Internet Penetration Rate exhibits moderate variability (Mean = 4.618, SD = 0.562), indicating varying levels of internet access. Mobile Usage Rate shows lower variability, suggesting more consistent usage. Trade Intensity (% of GDP) displays significant variability, reflecting heterogeneity in trade across the economies. Primary Sector Output demonstrates moderate variability, capturing diverse reliance on agriculture. Population Growth exhibits relatively low variability, suggesting consistent demographic trends. Inflation shows minimal variability, indicating relatively stable inflation rates. Export Intensity reflects global market integration, while Carbon Dioxide Emissions per Capita (CO_2) serves as a key environmental indicator. These variations underscore diverse economic and social contexts, highlighting the importance of considering heterogeneity in further analyses.

Unit root tests, using the Augmented Dickey-Fuller (ADF) test, assess the stationarity of the variables. I(0) signifies stationarity at level (constant mean and variance), while I(1) indicates non-stationarity at level, requiring first differencing. Results reveal a mixed pattern: Internet Penetration Rate and Mobile Usage Rate are stationary at level, while Primary Sector Output, Population Growth, and CO_2 emissions become stationary after first differencing. This necessitates careful consideration of dynamic relationships, as non-stationary variables can lead to spurious regressions. Cointegration analysis is employed to examine long-run equilibrium relationships among these variables.

The selected variables are economically relevant because Internet Penetration Rate, Mobile Usage Rate, and Trade Intensity reflect technology and economic openness, while Primary Sector Output, Population Growth, and CO_2 emissions represent economic development and environmental impact. Exploring cointegration among these variables provides insights into the long-term interplay between economic growth, technology, and sustainability. If cointegration exists, it implies a long-run equilibrium, with short-term deviations corrected over time. This has significant implications for policy formulation and economic modeling, enabling better understanding of variable dynamics and informing policy decisions through models like VECM.

4.2. Johansen Test for Cointegration

Table 3 presents the optimal lag length selection for a Vector Autoregression (VAR) model, balancing model fit and complexity using various information criteria. These criteria, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Criterion (HQ), and Final Prediction Error (FPE), systematically evaluate different lag structures. Optimal lag selection is crucial. Under-parameterized models may fail to capture dynamic relationships, leading to biased estimates. Over-parameterized models risk overfitting, resulting in poor performance and inaccurate predictions. Evaluating multiple lags using these criteria identifies the most parsimonious model with adequate data fit, avoiding overfitting and improving generalization. The results indicate a lag order of three as the most suitable specification. While log-likelihood increases with additional lags, the improvement diminishes beyond lag three. Lag three exhibits the lowest AIC, indicating the best balance. BIC and HQ also support lag three, albeit less strongly. Lag zero shows the lowest log-likelihood and high AIC/BIC values, indicating poor fit. Lag four, while demonstrating a high log-likelihood, risks overfitting. Therefore, a VECM model with three lags for each endogenous variable (Internet Penetration Rate, Mobile Usage Rate, Trade Intensity, Primary Sector Output, Population Growth, Inflation rate, Private Consumption, Export Intensity, and CO2) is

Table 2: Descriptive statistics of variable and unit root test

Variable	Obs	Mean	Standard deviation (SD)	Min	Max	Order of integration	ADF test (P-value)
ln (IPR)	28	1.872	3.389	−8.948	4.364	I (1)	0.0000
ln (MUR)	32	15.731	3.654	6.685	18.764	I (1)	0.0206
ln (TRA)	37	4.618	0.562	2.942	5.229	I (1)	0.0000
ln (AFF)	38	3.051	0.411	2.467	3.835	I (1)	0.0000
ln (PGR)	50	0.372	0.418	−0.382	0.944	I (1)	0.0025
ln (CPI)	28	5.682	5.165	−1.710	23.115	I (1)	0.0000
ln (FCE)	28	4.264	0.070	4.154	4.416	I (1)	0.0072
ln (EGS)	37	3.827	0.735	1.373	4.542	I (1)	0.0000
ln (CO_2)	49	−0.276	0.866	−1.268	1.267	I (1)	0.0000

Source: Author's calculations

Table 3: Lag order selection for key variables

Lag	LL	LR	df	P	FPE	AIC	HQIC	SBIC
0	103.181	0.000	−8.190	−8.078	−7.745			
1	341.841	477.320	81	0.000	0.000	−21.899	−20.782	−17.456
2	2569.990	4456.300	81	0.000	1.1e-99*	−208.608	−206.485	−200.166
3	6216.420	7292.9*	81	0.000		−522.558*	−519.988*	−512.339*
4	6191.460	−49.921	81			−520.388	−517.817	−510.168

*Optimal lag

recommended. This specification captures dynamic relationships while minimizing overfitting. An intercept term accounts for constant mean effects. This chosen lag order is used for subsequent model estimation and cointegration analysis.

Table 4 presents the Johansen cointegration test results, examining long-run equilibrium relationships among non-stationary time series. This test determines if variables are cointegrated, indicating a long-term relationship despite individual non-stationarity. Rejecting the null hypothesis of no cointegration suggests one or more cointegrating relationships. The results provide strong evidence for multiple cointegrating relationships. The trace statistics significantly exceed critical values up to Rank 8, indicating at least eight cointegrating vectors. This suggests that the nine variables (Internet Penetration Rate, Mobile User Rate, Trade Intensity, Primary Sector Output, Population Growth, Inflation rate, Private Consumption, Export Intensity, and CO_2 emissions) are interconnected through long-term equilibrium relationships, reflecting underlying economic, social, and environmental forces.

The presence of multiple cointegrating relationships necessitates using econometric models that explicitly account for these relationships. Given this, a Vector Error Correction Model (VECM) is appropriate. VECMs incorporate cointegrating relationships, allowing investigation of both short-term dynamics and long-run equilibrium tendencies. Analyzing error correction terms within the VECM provides insights into the speed of adjustment to deviations from long-run equilibrium. This underscores the importance of considering these interconnections when formulating policies, as policies aimed at promoting digitalization, for example, may have significant consequences for other variables. Understanding these long-term relationships is crucial for developing effective and sustainable policies.

4.3. Error correction model (ECM)

The ECM provides insights into the short-run and long-run dynamics among the variables. Table 5 presents the results for ECM. Model fit is assessed using the Akaike Information Criterion (AIC), with lower values indicating a better fit, and the log-likelihood, with higher values suggesting better data fit. The determinant of the covariance matrix, Det(Sigma_ml), provides insights into model stability and potential multicollinearity. A very small determinant (-2.51×10^{-67}) may suggest potential issues with model specification or the presence of high multicollinearity. Individual VECM equations reveal dynamic relationships. The Root Mean Squared Error (RMSE = 0.0545) measures the average prediction error, and R-squared (0.902) indicates the proportion of variance explained. Statistical significance tests, such as Chi-squared tests, assess the overall model and individual coefficient significance. The significant coefficient (64.4196) strongly suggests a long-term equilibrium relationship among the variables, confirming the VECM's applicability.

Table 4: Johansen tests for cointegration (trace)

Hypothesized No. of CE (s)	Eigen value	Trace statistic	0.05 Critical value
None	.	.	192.89
At most 1	1.00000	.	156.00
At most 2	1.00000	.	124.24
At most 3	1.00000	.	94.15
At most 4	0.96208	.	68.52
At most 5	0.92503	.	47.21
At most 6	0.72702	.	29.68
At most 7	0.61494	.	15.41
At most 8*	0.44970	.	3.76
At most 9	0.17965	.	

*Selected rank

Cointegration results reveal long-run equilibrium relationships through cointegrating equations (_ce1 to _ce8). Coefficients within these equations indicate each variable's relative importance in determining this equilibrium. For example, a positive coefficient for Agriculture suggests that increased agricultural output positively contributes to the long-run equilibrium. The VECM results reveal dynamic interdependencies. Significant coefficients, particularly for Internet User and Mobile Phone variables, suggest strong dynamic relationships and significant impacts on respective dependent variables.

Multiple cointegrating relationships confirm long-run equilibrium relationships, highlighting the importance of considering these long-term dependencies when analyzing economic and social dynamics. Analyzing individual equation coefficients reveals significant relationships, such as the lagged effect of Mobile Subscriptions on current mobile usage, suggesting a positive feedback loop. Similarly, the lagged effect of CO_2 emissions on current CO_2 emissions indicates persistence in emissions over time. The cointegration analysis identifies significant long-run relationships through the estimated cointegrating equations, capturing long-term equilibrium tendencies and indicating that deviations will be corrected over time. The coefficients within these equations offer insights into the nature of these long-run relationships.

4.4. Granger Causality Test

Granger causality tests are employed to establish causal relationships between digitalization, economic sustainability, and CO_2 emissions (Engle and Granger, 1987; Shojaie and Fox, 2022).

Table 5: Error correction model

Variable	_ce1 lag 1.	_ce2 lag 1.	_ce3 lag 1.	_ce4 lag 1.	_ce5 lag 1.	_ce6 lag 1.	_ce7 lag 1.	_ce8 lag 1.	D (CO_2) lag
Coef.	0.0304	0.0889***	−0.1183***	−0.5133	1.1128	−0.0045	1.7566***	−1.3433**	−0.690***
Std. Err.	0.1891	0.0224	0.0277	0.3178	0.7504	0.0042	0.3796	0.5645	0.1241
Variable	**D (IPR) lag**	**D (MUR) lag**	**D (TRA) lag**	**D (AFF) lag**	**D (PGR) lag**	**D (CPI) lag**	**D (FCE) lag**	**D (EGS) lag**	**_cons**
Coef.	−0.0433***	0.1864***	−0.2984	0.1877	−0.4763	0.0057***	0.6586*	−0.6923	0.0014
Std. Err.	0.0147	0.044	0.5241	0.2596	0.487	0.0021	0.3793	0.5258	0.0156

***Significance at 0.001, **Significance at 0.01, *Significance at 0.05

Table 6: Granger causality test

Null hypothesis	F-statistic	Prob.	Direction
IPR does not Granger cause CO_2	6.2625	0.100	No
CO_2 does not Granger cause IPR	3.9588	0.266	
MUR does not Granger cause CO_2	0.18644	0.980	No
CO_2 does not Granger cause MUR	6.1535	0.104	
TRA does not Granger cause CO_2	24.815	0.000	Bidirectional
CO_2 does not Granger cause TRA	57.164	0.000	
AFF does not Granger cause CO_2	19.958	0.090	Unidirectional
CO_2 does not Granger cause AFF	0.81439	0.846	
PGR does not Granger cause CO_2	6.4767	0.091	No
CO_2 does not Granger cause PGR	2.545	0.467	
CPI does not Granger cause CO_2	2.5532	0.466	No
CO_2 does not Granger cause CPI	0.99185	0.803	
FCE does not Granger cause CO_2	3.3019	0.347	Unidirectional
CO_2 does not Granger cause FCE	11.911	0.008	
EGS does not Granger cause CO_2	27.667	0.000	Bidirectional
CO_2 does not Granger cause EGS	110.48	0.000	

Table 6 reveals diverse causal relationships. No causal relationship is found between Internet Penetration Rate (IPR) and CO_2 emissions (P = 0.100 and P = 0.266), aligning with studies arguing limited direct impact from digital infrastructure development, as internet usage primarily relates to communication and data sharing (Zhang et al., 2022; Che et al., 2024). These studies suggest digitalization's environmental value lies in enabling mechanisms for efficiency, innovation, and data-driven decision-making, indirectly benefiting sustainability. Similarly, no causality is found between Mobile Usage Rate (MUR) and CO_2 emissions (P = 0.980 and P = 0.104), suggesting mobile device adoption does not directly drive emissions. Belkhir and Elmeligi (2018) support this, noting mobile technology's relatively small environmental footprint compared to industrial and energy sectors. The authors highlight that emissions are primarily attributable to the supporting infrastructure, including data centers and network operations, rather than solely to the energy consumption of individual devices. Therefore, ICT sector emission reduction policies should focus on improving infrastructure energy efficiency, such as green data centers and renewable energy for network operations.

Bidirectional Granger causality (P = 0.000) between Trade Intensity (TRA) and CO_2 emissions highlights a strong mutual influence. Increased trade often drives higher emissions due to logistics and production, while emissions levels can affect trade policies (Mutascu, 2018; Kolcava et al., 2019). Mutascu (2018) finds that trade openness has both short- and long-term effects on CO_2 emissions. In the short term, increased trade is associated with higher emissions due to transportation and increased production activities. However, in the long term, the results suggest that trade can lead to emissions reductions through technological advancements and the adoption of cleaner practices. Kolcava et al. (2019) focus on environmental burden-shifting caused by trade liberalization. Their findings suggest that liberalized trade policies can lead to the relocation of polluting industries to countries with weaker environmental regulations, resulting in a phenomenon known as "pollution havens."

Unidirectional causality is observed from Primary Sector Output (AFF) to CO_2 emissions (P = 0.090), but not vice versa (P = 0.846), suggesting that activities like agriculture, forestry, and fishing drive emissions through land use changes and resource consumption (Smith et al., 2014; Kanianska, 2016). Smith et al. (2014) highlight the substantial impact of agriculture, forestry, and other land use (AFOLU) sectors on environmental degradation, particularly through greenhouse gas emissions, deforestation, and land-use changes. These activities result in soil erosion, biodiversity loss, and pollution, further harming the environment and reducing ecosystem services (Kanianska, 2016). No causality is found between Population Growth (PGR) and CO_2 emissions (P = 0.091 and P = 0.467), contrasting with some studies (Schandl et al., 2016; Khan et al., 2021). This may reflect effective policies or moderating factors. Similarly, no causal relationship is found between Inflation (CPI) and CO_2 emissions (P = 0.466 and P = 0.803), aligning with findings by Djedaiet (2023) that inflation's effects on environmental quality are varied.

A unidirectional relationship exists between Private Consumption (FCE) and CO_2 emissions (P = 0.347 and P = 0.008), suggesting higher consumption drives emissions (Ivanova et al., 2016; Dubois et al., 2019). Bidirectional causality between Export Intensity (EGS) and CO_2 emissions (P = 0.000) emphasizes their interdependence (Alvarado and Toledo, 2017; Iqbal et al., 2021). Kolk (2016) examines the environmental challenges tied to global trade, highlighting the urgent need for sustainability integration. Fan et al. (2021) examines the intricate interplay between international trade and carbon emissions intensity within the framework of global value chains.

The absence of direct causality between digitalization metrics and CO_2 emissions suggests indirect environmental benefits, such as optimized energy usage and green innovations (Liu and De Giovanni, 2019). Belkhir and Elmeligi (2018) argue that internet penetration's direct contribution to environmental degradation is minimal compared to traditional industries, positioning the internet as an enabler of more sustainable practices. Policy efforts should focus on decoupling economic activities from emissions, fostering sustainable practices, and leveraging digital tools for efficiency and environmental management.

4.5. Robustness Test

4.5.1. Dynamic factor analysis (DFA)

Dynamic factor analysis (DFA) enhances the robustness of Johansen cointegration, VECM, and Granger causality analyses by uncovering latent factors driving variable co-movements. In Table 7, DFA offers a common factor representation, capturing shared dynamics and aligning with cointegration analysis for identifying long-term relationships (West and Wong, 2014). It also contributes to noise reduction by filtering idiosyncratic fluctuations, ensuring identified relationships are not spurious (Lam and Yao, 2012). Finally, DFA provides model consistency checks; comparing extracted factors with cointegration vectors and causal relationships strengthens confidence in the conclusions (Shahzad et al., 2021). Thus, DFA provides a more holistic and robust understanding of complex interactions, enhancing the rigor and reliability of econometric analysis.

Table 7 reveals statistically significant positive contributions to CO_2 emissions from several key variables: internet penetration, mobile phone usage, trade intensity, primary sector output, inflation, private consumption, and export intensity. These findings underscore the complex interplay of modernization, diverse economic activities, and demographic influences on environmental outcomes, offering a more nuanced perspective than single-factor explanations.The estimated coefficients highlight specific relationships. Internet penetration (1.7799) and, notably, mobile phone usage (16.6747) display strong positive associations with emissions. This contrasts with the Granger causality analysis, which found no significant causal links between digitalization and CO_2 emissions. This discrepancy is consistent with existing literature emphasizing the energy intensity of ICT infrastructure, including data centers and device manufacturing. While Granger causality assesses temporal precedence, DFA measures the overall contribution of factors, suggesting digitalization's impact is likely indirect, gradual, and systemic. The unusually high coefficient for mobile phone usage necessitates further investigation for potential multicollinearity, model misspecification, or data quality issues.

Significant positive coefficients for trade intensity (4.8859) and private consumption (4.2587), corroborated by both DFA and Granger causality, reinforce the link between globalization, consumption, and environmental impacts, likely due to trade logistics and increased production. Similarly, primary sector output (2.8756) and export intensity (4.1640), also supported by Granger causality, reflect the environmental footprint of these activities. Inflation (5.7722) also exhibits a significant positive coefficient, suggesting a link between macroeconomic instability and emissions, potentially due to increased resource use during economic volatility. Population growth (0.0446), while showing a positive coefficient, is statistically insignificant, suggesting a weak direct impact within this model. Variance estimates reveal the dynamic nature of ICT-related emissions (internet penetration: 11.2503; mobile usage: 6.3818) and the volatile influence of inflation (26.4529). The model's convergence, indicated by improving log-likelihood values, supports the estimates' reliability. However, earlier non-concavity issues highlight optimization challenges in such complex frameworks, suggesting potential local optima. The integration of Granger causality and DFA provides a robust methodological framework, identifying both potential causal relationships and underlying latent factors driving emissions, informing targeted policy interventions for achieving net-zero targets.

4.5.2. Principal component analysis (PCA)

In Table 8, Principal component analysis (PCA) reduces dimensionality and addresses multicollinearity by transforming correlated variables into uncorrelated components, serving as a robustness check for econometric models like Johansen cointegration, Granger causality, and VECM (Awolusi, 2021). In this study, PCA generated principal component scores for Digitalization (pc_Digitalization), comprising Internet Penetration Rate and Mobile User Rate, capturing digital adoption and connectivity. The KMO value of 0.5000 suggests marginal suitability for factor analysis. The principal component scores for Economic Sustainability (pc_Sustainability) include Trade Intensity, Primary Sector Output, Population Growth Rate, Inflation Rate, Private and Government Consumption, and Export Intensity, integrating factors related to economic sustainability and demographic-economic dynamics. The overall KMO value of 0.6546 indicates mediocre suitability for factor analysis (Pořízka et al., 2018), suggesting some limitations due to heterogeneity in inter-variable correlations, potentially hindering the extraction of fully meaningful and interpretable factors.

Granger causality analysis and Principal Component Analysis (PCA) regression offer complementary perspectives on the relationships between digitalization, economic sustainability, and carbon emissions. Granger causality examines temporal precedence

Table 7: Dynamic-factor model result

Variable	var (e.CO_2)	var (e.IPR)	var (e.MUR)	var (e.TRA)	var (e.AFF)	var (e.PGR)	var (e.CPI)	var (e.FCE)	var (e.EGS)
Coefficient	0.337***	11.25***	6.382***	0.0364***	0.0732***	0.0252***	26.45***	0.00419***	0.0492***
Std. Error	(0.0917)	(3.062)	(1.737)	(0.00989)	(0.0199)	(0.00687)	(7.200)	(0.00114)	(0.0134)

Log likelihood = −187.71367. Standard errors in parentheses. ***P<0.01, **P<0.05, *P<0.1

Table 8: PCA results

Variables	pc_Digitalization	pc_Sustainability	Constant	Obs.	R^2
Independent variable (CO_2)	0.110**	−0.202***	0.393***	27	0.915
	(0.0517)	(0.0283)	(0.0337)		

Robust standard errors in parentheses. ***P<0.01, **P<0.05, *P<0.1

and potential causal links within time series data, using lagged variables to infer directional influence. However, it is limited in capturing aggregated or latent variable effects and is sensitive to lag length and confounding factors. PCA regression, conversely, analyzes aggregated relationships by reducing data dimensionality through uncorrelated principal components, effectively addressing multicollinearity. Examining the relationship between these components and the dependent variable allows PCA regression to quantify the overall influence of the original variables, providing a more comprehensive understanding of aggregated effects.

This methodological distinction explains why digitalization may not exhibit direct causality in Granger analysis yet shows a statistically significant positive impact on emissions in PCA regression. The absence of Granger causality suggests that digitalization's influence on emissions is likely indirect, systemic, or mediated through unobserved factors. PCA, however, captures the broader impact of digital factors. The positive coefficient of the digitalization principal component (pc_Digitalization) suggests that while digitalization may improve certain efficiencies, it also contributes to emissions, potentially due to the substantial energy consumption of digital infrastructure, including data centers, network equipment, and electronic device manufacturing—aspects often missed by Granger analysis. Granger analysis reveals bidirectional causality between trade intensity and CO_2 emissions, indicating a dynamic feedback loop where trade influences emissions, which subsequently affects trade policies and patterns. Unidirectional causality from agricultural, forestry, and fishery (AFF) output to emissions highlights sector-specific environmental impacts. Bidirectional causality between private consumption and emissions underscores the complex interplay between consumption patterns and environmental pressures. While Granger causality elucidates these dynamic relationships, PCA regression quantifies the aggregated impact of sustainability. The strong negative coefficient of the sustainability principal component (pc_Sustainability) on CO_2 emissions indicates that increased sustainability measures significantly reduce emissions. Specifically, a one-unit increase in pc_Sustainability is associated with a 0.2021-unit decrease in CO_2 emissions ($P < 0.001$), demonstrating the substantial potential of sustainability initiatives.

These combined insights suggest several policy strategies. Trade policies should be aligned with emission reduction targets through mechanisms such as carbon pricing and eco-certification schemes. Sectoral interventions should prioritize the sustainable transformation of the primary sector through sustainable agricultural and forest management practices and investments in low-emission technologies. Crucially, policymakers should prioritize investments that enhance pc_Sustainability, including promoting renewable energy, improving energy efficiency, and encouraging sustainable consumption and production patterns, to effectively mitigate carbon emissions and achieve long-term environmental sustainability.

5. CONCLUSION

This study examines the sophisticated interplay between digitalization, economic sustainability, and Vietnam's progress towards achieving Net Zero emissions between 1975 and 2023. To investigate these dynamic interactions, the study employs econometric techniques, including Unit root tests, Johansen cointegration analysis, and Granger causality testing. Robustness checks utilizing Dynamic Factor Analysis (DFA) and Principal Component Analysis (PCA) further support the findings of a statistically significant positive relationship between digitalization and emissions reduction. The relationship between digitalization and economic sustainability is complicated. Both Granger causality and DFA identify key economic drivers of emissions, including trade intensity, private consumption, and primary sector activities. While both methodologies converge on the significance of private consumption, they offer distinct perspectives. While Granger causality testing establishes the presence of causal relationships, Dynamic Factor Analysis (DFA) provides a quantitative assessment of the magnitude and direction of these effects.

The analysis suggests that energy-intensive agricultural practices and export-oriented industrial production significantly contribute to emissions in economies reliant on these sectors. PCA further reveals a statistically significant negative correlation between sustainability component scores and CO_2 emissions, providing crucial quantitative insights for policymakers. These findings underscore the imperative of integrating digitalization and sustainability considerations into policy frameworks aimed at achieving both economic stability and sustainable growth.

Key mechanisms driving CO_2 emissions in Vietnam include trade intensity, private consumption, and primary sector contributions, particularly energy-intensive agriculture and export-oriented industry. This is especially relevant given trade's role in Asian emerging markets' economic stability. Both Granger causality and DFA highlight private consumption's central role, with Granger causality revealing temporal dynamics and feedback loops, and DFA quantifying the magnitude of these effects. Understanding trade and industrial activity's contribution to emissions enables policymakers to formulate sustainability-informed trade policies, mitigating economic risks while promoting sustainable growth. PCA emphasizes a significant negative relationship between sustainability component scores and CO_2 emissions, providing quantitative evidence for prioritizing resource allocation and assessing sustainability interventions. The integrated methodological approach—Granger causality for temporal dynamics and PCA for quantitative assessment of aggregated impacts, especially sustainability—facilitates the development of more targeted and effective policy strategies. This is particularly relevant for Vietnam's Net Zero target and offers broader implications for other emerging Asian economies facing similar development and environmental challenges. Analyzing digitalization's role highlights the importance of strategically leveraging technological advancements not only to mitigate economic shocks but also to drive sustainable development.

Informed by Granger causality and DFA analysis, policy recommendations emphasize the need for investments in renewable energy for data centers and Information and

Communication Technology (ICT) infrastructure to minimize the digital economy's carbon footprint. Promoting green innovation in ICT manufacturing and recycling, coupled with enhancing digital literacy for sustainable technology use, is also crucial. Addressing inflationary pressures and promoting economic stability requires macroeconomic policies that minimize resource inefficiencies, promote energy efficiency, reduce waste, and invest in sustainable infrastructure. Fostering investments in green sectors, such as renewable energy, green transportation, and sustainable agriculture, can contribute to stabilizing economic growth while reducing emissions. While this study offers valuable insights, it is subject to limitations. The use of aggregate data may mask firm- or sector-level heterogeneity. Future research should explore these relationships at a more granular level, incorporating firm-level data and sector-specific analyses. Furthermore, other factors, such as technological diffusion rates, policy implementation effectiveness, and socio-cultural factors, may influence these dynamics. Future research could investigate these complex interactions using more sophisticated modeling techniques and incorporating additional control variables.

REFERENCES

Alvarado, R., Toledo, E. (2017), Environmental degradation and economic growth: Evidence for a developing country. Environment, Development and Sustainability, 19, 1205-1218.

Anh, H.H., Da, H.T. (2024), System dynamics analysis of Vietnam's energy-related carbon emissions: Towards a net zero future. International Journal of Sustainable Energy Planning and Management, 42, 8327.

Awolusi, O.D. (2021), Economic growth and socioeconomic sustainability in BRICS countries: A vector error correction modeling approach. Journal of Economics and Behavioral Studies, 13(3 (J)), 1-23.

Belkhir, L., Elmeligi, A. (2018), Assessing ICT global emissions footprint: Trends to 2040 and recommendations. Journal of Cleaner Production, 177, 448-463.

Che, S., Wen, L., Wang, J. (2024), Global insights on the impact of digital infrastructure on carbon emissions: A multidimensional analysis. Journal of Environmental Management, 368, 122144.

Coppola, A., Dray, S.S.J., Wai-Poi, M.G., Winkler, D.E. (2024), Vietnam 2045: Trading Up in a Changing World-pathways to a High-income Future. Washington, DC: World Bank Group.

Dinda, S. (2004), Environmental Kuznets curve hypothesis: A survey. Ecological Economics, 49(4), 431-455.

Djedaiet, A. (2023), Does environmental quality react asymmetrically to unemployment and inflation rates? African OPEC countries' perspective. Environmental Science and Pollution Research, 30(46), 102418-102427.

Do, T.N., Ta, D.T. (2022), Vietnam's Environmental Policy: A 30-Year Critical Review. [ZCEAP Working Paper].

Do, T.T. (2022), Vietnam's growing agency in the twenty-first century. The Pacific Review, 35(2), 319-341.

Dubois, G., Sovacool, B., Aall, C., Nilsson, M., Barbier, C., Herrmann, A., Sauerborn, R. (2019), It starts at home? Climate policies targeting household consumption and behavioral decisions are key to low-carbon futures. Energy Research and Social Science, 52, 144-158.

Engle, R.F., Granger, C.W. (1987), Co-integration and error correction: Representation, estimation, and testing. Econometrica: Journal of the Econometric Society, 55, 251-276.

Fan, J.L., Zhang, X., Wang, J.D., Wang, Q. (2021), Measuring the impacts of international trade on carbon emissions intensity: A global value chain perspective. Emerging Markets Finance and Trade, 57(4), 972-988.

International Energy Agency. (n.d.), Vietnam - Countries and Regions. Available from: https://www.iea.org/countries/viet-nam/emissions [Last accessed on 2025 Jan 25].

Iqbal, N., Abbasi, K.R., Shinwari, R., Guangcai, W., Ahmad, M., Tang, K. (2021), Does exports diversification and environmental innovation achieve carbon neutrality target of OECD economies?. Journal of Environmental Management, 291, 112648.

Ivanova, D., Stadler, K., Steen-Olsen, K., Wood, R., Vita, G., Tukker, A., Hertwich, E.G. (2016), Environmental impact assessment of household consumption. Journal of Industrial Ecology, 20(3), 526-536.

Jalil, A., Rao, N.H. (2019), Time series analysis (stationarity, cointegration, and causality). In: Environmental Kuznets curve (EKC). United States: Academic Press, p85-99.

Kaika, D., Zervas, E. (2013), The Environmental Kuznets Curve (EKC) theory-Part A: Concept, causes and the CO_2 emissions case. Energy Policy, 62, 1392-1402.

Kanianska, R. (2016), Agriculture and its impact on land-use, environment, and ecosystem services. Landscape Ecology-The Influences of Land Use and Anthropogenic Impacts of Landscape Creation. London: IntechOpen, p1-26.

Khan, I., Hou, F., Le, H.P. (2021), The impact of natural resources, energy consumption, and population growth on environmental quality: Fresh evidence from the United States of America. Science of the Total Environment, 754, 142222.

Kolcava, D., Nguyen, Q., Bernauer, T. (2019), Does trade liberalization lead to environmental burden shifting in the global economy?. Ecological Economics, 163, 98-112.

Kolk, A. (2016), The social responsibility of international business: From ethics and the environment to CSR and sustainable development. Journal of World Business, 51(1), 23-34.

Kripfganz, S., Schneider, D.C. (2016), ARDL: STATA module to estimate autoregressive distributed lag models. Chicago: STATA Conference, p1-20.

Lam, C., Yao, Q. (2012), Factor modeling for high-dimensional time series: Inference for the number of factors. The Annals of Statistics, 2012, 694-726.

Liu, B., De Giovanni, P. (2019). Green process innovation through Industry 4.0 technologies and supply chain coordination. Annals of Operations Research, 1-36. doi: 10.1007/s10479-019-03498-3

Mushtaq, R. (2011), Augmented Dickey Fuller Test. [SSRN Electronic Journal].

Mutascu, M. (2018), A time-frequency analysis of trade openness and CO_2 emissions in France. Energy Policy, 115, 443-455.

Nguyen, M.P., Ponomarenko, T., Nguyen, N. (2024), Energy transition in Vietnam: A strategic analysis and forecast. Sustainability, 16(5), 1969.

Pesaran, M.H., Shin, Y., Smith, R.J. (2001), Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), 289-326.

Pořízka, P., Klus, J., Képeš, E., Prochazka, D., Hahn, D.W., Kaiser, J. (2018), On the utilization of principal component analysis in laser-induced breakdown spectroscopy data analysis, a review. Spectrochimica Acta Part B: Atomic Spectroscopy, 148, 65-82.

Schandl, H., Hatfield-Dodds, S., Wiedmann, T., Geschke, A., Cai, Y., West, J., Owen, A. (2016), Decoupling global environmental pressure and economic growth: Scenarios for energy use, materials use and carbon emissions. Journal of Cleaner Production, 132, 45-56.

Shahzad, U., Schneider, N., Jebli, M.B. (2021), How coal and geothermal energies interact with industrial development and carbon emissions? An autoregressive distributed lags approach to the Philippines. Resources Policy, 74, 102342.

Shojaie, A., Fox, E.B. (2022), Granger causality: A review and recent advances. Annual Review of Statistics and Its Application, 9(1), 289-319.

Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E.A., Bolwig, S. (2014), Agriculture, forestry and other land use (AFOLU). In: Climate Change 2014: Mitigation of climate change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, UK: Cambridge University Press, p811-922.

West, K.D., Wong, K.F. (2014), A factor model for co-movements of commodity prices. Journal of International Money and Finance, 42, 289-309.

Zhang, J., Lyu, Y., Li, Y., Geng, Y. (2022), Digital economy: An innovation driving factor for low-carbon development. Environmental Impact Assessment Review, 96, 106821.