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DETERMINANTS OF DIGITAL ECONOMY DEVELOPMENT IN SOUTHEAST ASIA: IMPLICATIONS FOR VIETNAM

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ABSTRACT

This study examines the key determinants of digital economy development in Southeast Asia and draws policy implications for Vietnam. Based on endogenous growth theory, human capital theory, and institutional theory, the research employs panel data from Southeast Asian countries and applies advanced econometric techniques, including unit root tests, cointegration analysis, and Driscoll-Kraay estimations. The findings indicate that education is the most influential factor driving digital economy growth. Governance quality, however, exhibits a negative association with digital development, suggesting that traditional governance effectiveness may not align with the institutional flexibility required for digital transformation. Additionally, CO_2 emissions are positively associated with digital development, implying that digitalization may currently function as an adaptive response to structural and environmental pressures. These results provide important empirical evidence and practical policy recommendations for Vietnam in promoting sustainable and innovation-driven digital growth.

Keywords: Digital economy, Southeast Asian countries, Driscoll-Kraay panel estimation.

1. INTRODUCTION

Southeast Asia is recognized as one of the world's most dynamic and fastest-growing regions, with a population of over 660 million and a young demographic structure well-adapted to digital technology. In the context of the Fourth Industrial Revolution, countries in the region are accelerating digital transformation and positioning the digital economy as a key driver of productivity growth and national competitiveness [1]. According to the World Bank, Southeast Asia's digital economy is expanding at an unprecedented pace. The signs of digital transformation in the region are clear: from impressive "unicorn" technology companies to entrepreneurs and small businesses that are innovating and using technology to grow. Forecasts indicate that Southeast Asia's digital economy will continue to grow strongly, reflecting the region's strong long-term potential [2]. The Google–Temasek–Bain report (2022) forecasts that the size of Southeast Asia's digital economy will exceed US$300 billion by 2025 and could reach US$1 trillion GMV by 2030, showing the region's rapid expansion and great potential. With an internet penetration rate of 75.6% and over 400 million users, Southeast Asia is becoming a vast digital market, except for a few countries such as Laos, Myanmar and Timor-Leste [3].

Despite this rapid expansion, there are still significant disparities among ASEAN countries in terms of digital readiness, governance capacity, human resources, attracting foreign investment and environmental sustainability. Digitalization affects almost every aspect of economic and social life, from production and consumption to service provision and value creation [4]. Therefore, developing flexible and well-coordinated policy frameworks is essential to maximize digital opportunities while minimizing associated risks [5].

Due to the uneven development of the digital economy in Southeast Asian countries, identifying the key determinants of digital economic growth is becoming increasingly important. Understanding these drivers provides essential evidence for policymakers to design effective interventions and ensure sustainable digital transformation [2]. Accordingly, this study develops an empirical model to examine the impact of governance efficiency, economic scale, educational attainment, foreign direct investment, and environmental factors on the digital economy in selected ASEAN countries during the period 2003–2023. The findings are expected to contribute to policy development to promote effective and sustainable digital economic development in the region.

2. LITERATURE REVIEW

2.1. Theoretical Framework and Literature Review

2.1.1. Theoretical Framework

Endogenous growth theory [6, 7] provides the central theoretical foundation for this study. This theory posits that long-term economic growth is driven by intrinsic factors, particularly human capital and knowledge accumulation. In the context of the digital economy, this mechanism is reflected in the role of human resource quality including educational attainment, digital skills, and technological adaptability in transforming digital technology into sustainable economic growth. Accordingly, the Education Index is used as a representative indicator of a country's structural readiness to participate in and develop the digital economy.

Human capital theory [8] complements this view by conceptualizing labor as an investable form of capital accumulated through education, training, and experience. In digital transformation processes, technology only creates economic value when the workforce possesses the necessary capabilities to use it effectively. Therefore, digital human capital acts as an absorption capacity that determines the efficiency with which IT investment is translated into output at both the enterprise and macroeconomic levels.

Technology diffusion theory [9] explains why identical digital technologies produce different outcomes between countries. The speed and extent of diffusion depend on technological characteristics, communication channels, institutional conditions, and user differences. This framework supports the inclusion of access to and adoption of technology as central determinants of digital economic development.

Institutional theory [10] emphasizes that legal systems, legal frameworks, and governance structures significantly shape the dynamics for innovation and technology investment. A transparent policy environment, intellectual property protection, data governance, and competitive market conditions encourage entrepreneurship and digital innovation. Conversely, poor institutional quality can reduce the returns from digital investment and potentially increase inequality in the digital transformation process.

Network economic theory [11] emphasizes the importance of network effects, whereby the value of digital platforms increases as users participate. This perspective explains why the scale, connectivity, and integration of the ecosystem are decisive for the effectiveness of the digital economy and why countries that achieve significant volumes of digital adoption differ significantly from those that do not.

2.1.2. Literature Review

Macro-level studies on the digital economy, notably those by the OECD, UNCTAD, and the World Bank, have played a crucial role in building the conceptual framework and identifying the fundamental pillars of the digital economy. Instead of approaching the digital economy as a single industry or variable, these studies unanimously view it as the result of a multidimensional combination of structural factors, including digital infrastructure, human resources, institutions, and the level of technology adoption.

According to the OECD (2014, 2020), the digital economy is formed from the interaction between digital infrastructure, digital skills, the institutional environment, and the level of adoption of technology. It emphasizes the simultaneous role of policy, infrastructure, people, and access to technology, especially in the context of developing countries [12, 13]. The World Bank, through the framework of the Digital Economy for Africa (DE4A), has systematized the digital economy into four main pillars: institutions, infrastructure, skills, and innovation – technology application [14].

Most previous related documents have not truly synthesized and presented the factors affecting the digital economy comprehensively, but only assessed each factor individually, such as:

Digital governance: Empirical evidence consistently shows that the quality of governance influences the adoption of ICT and digital development. Using the Global Governance Index (WGI), Gold et al. [15] found that government efficiency promotes ICT adoption in 15 African countries, while the quality of regulations can have negative impacts related to the burden of compliance. Adeleye et al. [16] showed that the quality of institutions positively affects both ICT adoption and inclusive growth. More broadly, Acemoglu et al. [17] and Rodrik et al. [18] identify institutions as the fundamental determinant of long-term growth and resource allocation efficiency. The World Bank [2] further warns that digitalization under weak institutional conditions can exacerbate inequality. Despite this evidence, governance variables are often considered control variables rather than conceptualized as core pillars of digital economic development within an integrated empirical framework.

Digital human capital: The relationship between skills and digital growth is widely supported in literature. Autor et al. [19] demonstrate that technological change is skill oriented. Niebel [20] found that the impact of IT growth is weaker in developing economies due to limited absorption capacity. Benhabib and Spiegel [21] also pointed out that differences in human capital explain the heterogeneous growth outcomes among countries with comparable levels of technology investment. However, many studies rely on indirect educational indicators and treat human capital primarily as a moderating variable. Systematically quantifying digital human capital as an independent structural determinant remains relatively underdeveloped.

FDI is chosen because it is a crucial resource that helps countries access new technologies, modern management skills, and global production networks. Studies suggest that FDI creates a spillover effect of technology and promotes domestic innovation. Including FDI in the model benefits the assessment of the ability to leverage international capital for digital economic development, while also determining the extent to which capital flows contribute to the transformation and modernization of the economy. Research results show that FDI has a positive impact on the digital economy, but at a modest level, implying that only high-quality FDI projects with technology transfer and linkages with domestic businesses will produce real results. The basis for selecting FDI is based on: Endogenous growth theory. Studies on the effectiveness of technology spillovers from multinational corporations to the domestic economy. FDI is widely recognized as the comprehensive transfer of capital, technology, managerial expertise, and global networks [22]. The spillover effects operate through forward and backward linkages, spillover effects, and the movement of skilled labor. However, in studies of the digital economy, FDI is often combined as macroeconomic control rather than being explicitly modeled as a structural contributor to the formation of the digital ecosystem.

The GDP variable was chosen because it reflects a nation's level of economic development, its financial capacity, and its ability to invest in digital infrastructure, technology, education, and innovation. Previous studies have shown that high-income countries generally have stronger technological development capabilities and higher readiness. Including GDP in the model is beneficial in assessing whether economic growth materials truly contribute to the digital economy, and it helps analyze the relationship between the scale of the underlying economy and the digital transformation process. Research results show that GDP has a positive impact on the digital economy when the economy grows extensively, heavily reliant on resources and cheap labor. This implies a shift in the growth model towards innovation and digitalization. The theoretical basis of this variant stem from economic growth theory and studies on the global digital divide, suggesting that economic development determines a nation's ability to access and absorb digital technology. Economic development level: Per capita income has consistently been identified as a strong predictor of cross-border digital adoption [23, 24]. International organizations also emphasize that the level of development shapes the capacity to invest in digital infrastructure and innovation [3, 4, 25]. However, the two-way relationship between digitalization and economic development has not been fully studied.

The CO_2 variable was chosen to reflect the relationship between digital economic development and the environment. In the context of digital transformation and sustainable development, appropriate digital technologies have the potential to support a green economy while simultaneously increasing energy consumption and carbon emissions. The benefit of including the CO_2 variable in this study is that it helps assess whether the value of the digital economy is accompanied by robust hardware development and supports the development of green digital transformation policies. The study shows that CO_2 emissions are closely linked to the digital economy, reflecting the reality that current digitalization is still associated with high energy consumption. This provides a basis for policies promoting green technologies and renewable energy in the digital economy. The basis for choosing this variable is based on: Studies on the economic environment. The Kuznets curve theory of the environment. Studies on green growth and sustainable transformation. The environment and the digital economy: Research on the environmental Kuznets curve shows that economies capable of decoupled growth from carbon emissions tend to possess stronger technological capabilities and innovation systems [26]. However, carbon emissions are often included as macroeconomic controls. Their potential role as structural drivers or constraints in the development of the digital economy has not been systematically integrated into empirical modeling frameworks.

Based on the theoretical and empirical insights considered above, this study conceptualizes the development of the digital economy as a multidimensional outcome shaped by institutional quality, digital human capital, FDI, economic development level, and environmental performance. Unlike most existing literature, these determinants are considered simultaneously within a unified empirical framework to assess their relative contributions in the context of Southeast Asian economies. The authors' identification of research variables is based on the four pillars of the digital economy concept, where the variables are the source of shaping.

2.2. Empirical Study

This study empirically verifies the determinants of digital economic development in Southeast Asian countries during the period 2003–2023 using macroeconomic panel data compiled from World Development Indicators (WDI). Based on endogenous growth theory, human capital theory, and institutional economics, the study analyzes and evaluates the role of economic development, digital human capital, foreign direct investment, government efficiency, and environmental conditions in shaping digital transformation outcomes. The empirical model estimates the long-term relationship between digital economic development and its structural dynamics, while also considering interdependence between countries and dynamic panel characteristics. The variables selected for measurement are based on the four pillars of the United Nations Conference on Trade and Development's concept of the digital economy.

2.3. Research model

Based on a review of existing research and the information gathered, the authors propose the following research model:

$$DE_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 EI_{it} + \beta_3 FDI_{it} + \beta_4 GE_{it} + \beta_5 CO_{2it} + \varepsilon_{it}$$

In the model, i represents the country (i= 0,1,2, 3..., N) respectively, which are the countries in Southeast Asia including Vietnam, Cambodia, Thailand, Malaysia, Singapore, Indonesia, Philippines. And t represents the number of years of study (t = 2003, 2004, ..., 2023).

DE represents the level of digital economic development, GDP represents economic growth, EI represents the education index, FDI represents foreign direct investment, GE represents the effectiveness of government operations, and CO_2 represents the level of environmental pollution. β_0 is the constant of the research model, β_1, β_2, β_3, β_4, β_5 are the slope coefficients of the variables GDP, EI, FDI, GE, CO_2 respectively. When the coefficients $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are less than 0, it means that the variables create an inverse relationship with the dependent variable DE, meaning that the independent variable has a negative impact on the digital economy by reducing the level of digital economic development and vice versa. ε here is considered a random error because, in addition to the 5 independent variables, there are other variables not mentioned in the research model. The study also intends to use a second-generation regression method (which can solve the cross-correlation problem) such as the Driscoll-Kraay Estimator Regression Model to estimate the model.

3. METHODOLOGY

The authors used the following econometric methods in this study:

3.1. Cross-Dependence Testing

In panel data analysis, cross-sectional dependence refers to the phenomenon where cross-sectional units in a data sample are not independent of each other but interact with each other, often stemming from unobservable factors or common shocks affecting multiple units simultaneously. Ignoring this phenomenon can distort the standard error, leading to inefficient estimates and inaccurate statistical conclusions.

To control and assess the existence of cross-sectional dependence, the study applies common testing methods in panel data analysis, including:

LM Test (Breusch and Pagan, 1980)

The LM test is based on residuals from the regression model and is calculated using the following formula:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij}^2$$

T: Number of time periods.

N: Number of cross-sectional units.

ρ_{ij}*:* The correlation coefficient between the residuals of units i and j.

CD test (Pesaran, 2004)

$$CD = \sqrt{\frac{2T}{N\,(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij}$$

T: Number of time periods.

N: Number of cross-sectional units.

ρ_{ij} The correlation coefficient between the residuals of units i and j.

This study applies the cross-dependency tests of Breusch and Pagan (1980) and Pesaran (2004) to detect the existence of dependent relationships between cross-units in panel data. Performing these tests helps assess the goodness of fit of model assumptions, thereby providing a basis for selecting appropriate estimation methods and improving the reliability of the analysis results. Cross-dependency testing is particularly important in economic studies at the national or regional level, where common shocks and economic linkages can simultaneously affect multiple units.

3.2. Stationarity Testing

In panel data analysis, stationarity testing of variables is a crucial step before estimating a model to avoid spurious regression. First-generation unit root tests such as Levin, Lin, and Chu (LLC), Im, Pesaran, and Shin (IPS), Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) are widely used; however, these tests assume that cross-units in the data sample are independent of each other.

In practice, panel data at the national or regional level often exhibit cross-dependencies between units, making first-generation unit root tests potentially inefficient and inaccurate. To overcome this limitation, second-generation unit root tests have been developed to allow for the existence of cross-dependencies in the data.

Specifically, the study uses the Cross-sectionally Augmented IPS (CIPS) test, built from Pesaran's (2007) CADF statistic, to check stationarity at the table-wide level in the context of cross-dependencies. This method not only effectively handles cross-dependencies but also ensures robustness in the context of heterogeneity between cross-units.

CADF test (Cross-sectional Augmented Dickey-Fuller test)

The CADF test is a second-generation unit root test method designed to handle cross-dependencies in panel data. The formula for the CADF test is expressed as follows:

$$\Delta y_{it} = \alpha_i + \beta_i Y_{i,t-1} + \gamma_i Y_{t-j} + \sum_{j=1}^{\rho} \delta_{ij}\, \Delta y_{i,t-j} + \sum_{j=0}^{\rho} \theta_{ij}\, \Delta y_{t-j} + \varepsilon_{it}$$

Δy_{it}: First difference of the dependent variable for unit i at time t.

α_i : Individual intercept (fixed effects).

$Y_{i,t-1}$: First lag of the level variable.

$\sum_{j=1}^{\rho} \delta_{ij}\, \Delta y_{i,t-j}$: First lag of the level variable.

$\sum_{j=0}^{\rho} \theta_{ij}\, \Delta y_{t-j}$: Cross-sectional averages of lags and differences to account for common factors.

ε_{it}: Stochastic error term.

CIPS Test (Cross-sectionally Augmented IPS Test)

The CIPS statistics are calculated by averaging the t-statistics from the CADF tests across all units:

$$\text{CIPS} = \frac{1}{N}\sum_{i=1}^{N} t_i^{CADF}$$

Where:

t_i^{CADF}: is the t-statistic of the CADF test for the cross-unit i.

N: is the number of cross-sectional units in the sample.

The use of the CIPS test in this study helps ensure that the stationarity test results are reliable and robust, even when cross-dependence and heterogeneity exist between the cross-units.

3.3. Cointegration Test

To assess long-term equilibrium relationships, the study employs the Westerlund (2007) cointegration test. Unlike traditional tests, this method is based on the structural dynamics of the Error Correction Model (ECM), effectively handling cross-sectional dependence and autocorrelation.

Westerlund's system of statistical tests comprises four categories, divided into two main groups:

Group Statistics G_t, G_aThe null hypothesis (H_0) states that there is no cointegration for any of the units. The alternative hypothesis (H_2) assumes that cointegration exists for at least one cross-sectional unit.

Panel Statistics (P_t, P_a) These statistics test a similar null hypothesis H_0. However, the alternative hypothesis (H_1) asserts the existence of a cointegrating relationship for the entire panel (indicating homogeneity).

Combining both sets of statistics ensures comprehensiveness and enhances the reliability of conclusions regarding the existence of long-run equilibrium relationships among the research variables. These statistics are computed based on the Error Correction Model (ECM), which is specified as follows:

$$\Delta Y_{it} = \theta_i + \delta_i d_t + \alpha_i Y_{i,t-1} + \tau_i X_{i,t-1} + \sum_{j=1}^{\rho} \alpha_{ij}\Delta Y_{i,t-j} \sum_{j=1}^{\rho} \gamma_{ij}\, \Delta X_{i,t-j} + u_{it}$$

Variable definitions for Equation (7):

Y_{it}: The dependent variable for cross-sectional unit i at time t.

X_{it}: A vector of independent variables.

Δ: The first-difference operator.

$i = 1,2, \ldots, N$ represents the cross-sectional units.

$t = 1,2, \ldots, T$ represents the time series.

θ_i: The individual intercept (fixed effect) for each cross-sectional unit.

d_t: The time trend or time dummy variable.

α_i: The error correction coefficient, reflecting the speed of adjustment of Y_{it} back to the long-run equilibrium state following short-term shocks.

α_{ij} and γ_{ij}: The short-run dynamic coefficients.

u_{it}: The stochastic error term (residual).

3.4. Regression Estimation

In panel data analysis, the Driscoll-Kraay (D-K) regression method, proposed by Driscoll and Kraay (1998), is widely utilized to estimate the relationship between independent and dependent variables within complex panel data structures. The primary strength of this approach lies in its ability to provide robust standard errors, which simultaneously control temporal autocorrelation, heteroskedasticity, and cross-sectional dependence among units. Consequently, the Driscoll-Kraay method enhances the reliability of statistical tests and ensures the robustness of estimation results in empirical studies using panel data.

The panel regression model using the Driscoll-Kraay estimator is specified as follows:

$$Y_{it} = \alpha_i + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \cdots + \beta_k X_{k,it} + \varepsilon_{it}$$

Y_{it} : The dependent variable for cross-sectional unit i at time t.

$X_{1,it}, X_{2,it}, \ldots, X_{k,it}$: The vector of independent variables in the model.

α_i : The individual fixed effect, reflecting unobserved characteristics of each unit i that remain constant over time.

$\beta_1, \beta_2, \ldots, \beta_k$: The regression coefficients, measuring the magnitude and direction of the impact of independent variables on the dependent variable.

ε_{it} : The stochastic error term, reflecting unobserved factors that vary over time.

4. RESULTS

Table 1. Summary Statistics Table

	Average value	Median value	Greatest value	Smallest value	Standard deviation	Deviation	Sharpness	Sample size
lnDE	3.276	3.751	4.581	-1.344	1.350	-1.640	5.370	147
lnGDP	8.486	8.181	11.126	6.578	1.146	0.990	3.164	147
lnEI	-0.456	-0.442	-0.136	-0.902	0.187	-0.479	2.854	147
lnFDI	1.345	1.251	3.553	-2.870	1.031	-0.140	4.060	147
lnGE	-0.034	0.089	4.446	-3.990	1.626	0.054	3.182	147
lnCO_2	0.881	0.849	2.368	-1.700	1.004	-0.377	2.439	147

Descriptive statistics show a clear difference in macroeconomic indicators and levels of digitization among ASEAN countries. The dependent variable Digital Economic Development Level (lnDE) tends to be concentrated at a high threshold (median 3.751). However, the presence of a small group of low-level countries has pulled the mean down to 3.276, creating a left-skewed distribution with a large sharpness (5.370). Similarly, economic growth (GDP) exhibits a disparity in scale, with most of the study sample being developing economies, while a few dominant nations have led the mean (8.486) above the median. Conversely, the Education Index (lnEI) is the most stable variable with a low standard deviation (0.187), reflecting relative uniformity of human resources in the region. Regarding resources, foreign direct investment (lnFDI) and government efficiency (lnGE), these factors exhibit high heterogeneity with large ranges of variation, demonstrating differences in capital attraction strategies and institutional governance capacity among countries. Finally, CO_2 emissions (lnCO_2) maintain moderate fluctuation and are less extreme than other economic variables. Overall, except for education, the remaining factors reflect a multi-speed development picture, creating an urgent need to manage the unique characteristics of each nation in subsequent econometric estimations.

Table 2. Correlation matrix of variables

	lnDE	lnGDP	lnEI	lnFDI	lnGE	$lnCO_2$
lnDE	1.000 -					
lnGDP	0.640*** (0.000)	1.000 -				
lnEI	0.746*** (0.000)	0.856*** (0.000)	1.000 -			
lnFDI	0.174** (0.034)	0.474*** (0.000)	0.163** (0.048)	1.000 -		
lnGE	-0.097 (0.241)	0.050 (0.546)	-0.047 (0.569)	0.265*** (0.001)	1.000 -	
$lnCO_2$	0.756*** (0.000)	0.879*** (0.000)	0.858*** (0.000)	0.242*** (0.003)	0.022 (0.789)	1.000 -

*Note: ***, **, and * designate statistical significance at the 1%, 5%, and 10% levels, respectively.*

The correlation matrix provides information on the linear relationship between the variables in the research model, including the level of digital economic development (lnDE), economic size (lnGDP), education index (lnEI), foreign direct investment (lnFDI), government performance (lnGE), and CO_2 emissions ($lnCO_2$).

The results show that lnDE has a strong and statistically significant positive correlation with lnGDP (0.640*), lnEI (0.746***), and $lnCO_2$ (0.756***), reflecting the close relationship between digital economic development and economic size, human resource quality, and emission levels. This suggests that countries with larger economies and higher levels of education tend to have more developed digital economies and higher CO_2 emissions, which both drive the digital economy and pose a greater concern as digital transformation must go hand in hand with emission reduction. However, the effectiveness of government (lnGE) does not show a statistically significant correlation with lnDE, indicating that governments are not overly concerned about the digital economy. Furthermore, the impact of FDI highlights a regional issue, as foreign direct investments utilizing digital technology in the region account for a very small percentage.

Table 3. Table of results for cross-sectional dependence test

Variable	LM adj test		CD test	
	Statistic	p-value	Statistic	p-value
lnDE	3.29^{***}	0.001	2.916^{***}	0.003
lnGDP	24.79^{***}	0.000	9.51^{***}	0.000
lnEI	5.313^{***}	0.000	1.241	0.214
lnFDI	-2.727^{***}	0.006	0.397	0.690
lnGE	-1.974^{**}	0.048	-0.481	0.630
$lnCO_2$	2.41^{**}	0.016	-0.938	0.348

*Note: *** and ** indicate statistical significance at the 1% and 5% levels, respectively.*

Table 3 presents the results of testing for cross-dependency between observed units in panel data using two common tests: the LM adjusted test and the Pesaran CD test. Testing for cross-dependency is necessary in the context of the increasing economic, trade, and technological integration of Southeast Asian countries, which means that economic, policy, and environmental shocks in one country can spread to others.

The test results show that most variables in the model exhibit cross-dependency to varying degrees, especially when considered using the LM adjusted test.

Specifically, regarding the level of digital economic development (lnDE), both tests showed statistically significant results at the 1% level (LM adj = 3.29, p = 0.001; CD = 2.916, p = 0.003), indicating strong interdependence between countries. This implies that a country's digital economic development process does not occur independently but is influenced by digitalization trends, technology diffusion, and digital policies in the region.

Regarding economic size (lnGDP), the test results show very clear interdependence, with both the LM adjusted and CD tests showing statistical significance at the 1% level (LM adj = 24.79; CD = 9.51). This result reflects the high degree of interconnectedness between economies in the region through trade, investment, and supply chains, causing economic growth fluctuations to tend to be positively correlated across countries.

Meanwhile, the education index (lnEI) showed cross-dependency according to the LM adjusted test (p = 0.000) but not significant according to the CD test (p = 0.214). This difference indicates that while cross-dependency of lnEI exists, it is not uniform and not strong enough across the entire sample, reflecting the fact that education policy remains more national in nature than macroeconomic factors.

Similarly, for foreign direct investment (lnFDI) and government performance (lnGE), the LM adjusted test showed cross-dependency at the 1% and 5% significance levels, while the CD test did not detect statistically significant cross-dependencies. This result implies that these variables may be influenced by some common shocks or local linkages, but do not exhibit strong covariates across all countries in the sample.

Regarding CO_2 emissions ($lnCO_2$), the LM adjusted test results showed a 5% cross-dependency, while the CD test showed no statistical significance. This suggests that CO_2 emissions between countries may be influenced by regional factors such as economic growth or investment flows, but the extent of this influence is not strong enough to create a clear cross-dependency according to the strict criteria of the CD test.

Table 4. Results of the unit root test

Variable	CIPS test statistics		Order of integration
	Level	*First-order difference*	
lnDE	-0.251	-4.514 ***	I(1)
lnGDP	-1.292	-3.828 ***	I(1)
lnEI	-1.795	-3.109 ***	I(1)
lnFDI	-3.119 ***	-4.866 ***	I(0)
lnGE	-1.375	-5.358 ***	I(1)
$lnCO_2$	-0.503	-4.447 ***	I(1)

*Note: *** and ** indicate statistical significance at the 1% and 5% levels, respectively.*

Table 4 presents the results of the unit root test using the Cross-sectionally Augmented IPS (CIPS) method, an advanced method designed to handle cross-sectional dependence between countries in the study sample. Performing this test is a mandatory step to ensure the stationarity of the data series and avoid "spurious regression" before conducting more in-depth econometric analyses. The empirical results show that, at the baseline level, most of the principal variables in the model, including: digital economic development level (lnDE), economic size (lnGDP), education index (lnEI), government performance (lnGE), and CO_2 emissions ($\ln CO_2$), have CIPS statistical values that are not significant enough to reject the null hypothesis H_0 (the existence of a unit root). This confirms that in the original state, these data series are all non-stationary series, exhibiting the characteristics of random walks and tending to change over time. However, after performing first-order difference analysis, a significant change was observed. All the above variables became stationary at a statistical significance level of 1% (p-value < 0.01), implying that they are first-order integrated series, denoted as I(1). The fact that the variables reach a stationary state at first-order difference allows us to explore long-term equilibrium relationships between these factors. Specifically for the foreign direct investment (FDI) variable, the CIPS statistic reaches statistical significance at the original level at a significance level of 1% (-3.119^{***}). This result shows that the FDI variable is a stationary series from the beginning and is classified as a zero-order integrated series, I(0). The difference in integration order between FDI and the remaining variables is a noteworthy point in the macroeconomic panel data characteristics of Southeast Asia. Overall, the test results show the existence of mixed integration orders - including both I(0) and I(1) - in the research model. This characteristic is entirely consistent with the macroeconomic panel data practices of developing countries, where economic shocks can have different impacts on each specific variable. More importantly, clearly defining the integration order of the variables has provided a solid methodological basis for selecting appropriate estimation models (such as PMG, MG or panel ARDL) for impact analyses and testing long-term synergistic relationships in the subsequent steps of the study.

Table 5. Westerlund Cointegration Test Results

Statistic	Value	Z value	p-value	Robust p-value
Gt	-1.137	4.190	1.000	0.843
Ga	-1.338*	4.377	1.000	0.080
Pt	-3.110	2.931	0.998	0.595
Pa	-2.127**	2.917	0.998	0.018

*Note: ** and * indicate statistical significance levels at the 5% and 10% levels, respectively.*

Table 5 presents the results of the Westerlund method's panel cointegration test, in which four statistics, Gt, Ga, Pt, and Pa, were used to examine the existence of long-term equilibrium relationships between the variables in the model. The results show that for the Gt statistic, the value is -1.137 with a robust p-value of 0.843, while the Pt statistic has a value of -3.110 and a robust p-value of 0.595; neither rejects the hypothesis of non-cointegration at the usual significance levels. This indicates there is no evidence that all countries in the sample adjust to long-term equilibrium according to the same dynamic mechanism.

Conversely, the Ga and Pa statistics yield statistically significant results when considering the robust p-value. Specifically, the Ga statistic has a value of -1.338 with a robust p-value of 0.080, indicating 10% significance, while the Pa statistic reaches a value of -2.127 with a robust p-value of 0.018, indicating 5% significance. These results suggest the existence of long-term cointegration at both the group mean and overall levels, after adjusting for cross-dependencies between countries. The differences between the group (G) and overall (P) statistics reflect heterogeneity in the error correction mechanisms among countries in the study sample.

Economically, this result implies that the long-term relationship between the level of digital economic development, economic size, foreign direct investment flows, government performance, and CO_2 emissions does not exist uniformly across all countries but is only clearly evident in a segment of countries with similar institutional characteristics, levels of development, and economic structures. Therefore, the Westerlund test results support the hypothesis of heterogeneous long-term cointegration in the model, consistent with the context of multinational macroeconomic panel data.

Table 6. Regression Estimation Results

Variable	Coefficient	Std. Err.	t-Statistic	p-value
Constant	10.411***	1.178	8.83	0.000
lnGDP	-0.745***	0.127	-5.86	0.000
lnEI	4.468***	0.796	5.61	0.000
lnFDI	0.296***	0.087	3.40	0.003
lnGE	-0.093***	0.031	-2.98	0.007
lnCO_2	0.940***	0.119	7.89	0.000
F statistics	49.04			
p-value	0.000			
R^2	0.659			
Root MSE	0.802			
Observation	147			
Number of groups	7			

*Note: *** indicates statistical significance at the 1% level.*

In Table 6, the model shows a high fit with $R^2 = 0.659$, meaning that the independent variables in the model explain 65.9% of the variation in the level of digital economic development. The F-statistic value of 49.04 with a p-value of 0.000 indicates that the model is statistically very significant, confirming that the set of independent variables in the model can significantly explain the variation in the dependent variable. The Root MSE of 0.802 reflects a relatively low average prediction error, indicating that the model's accuracy is acceptable in the context of panel data research. With 147 observations from 7 countries over 21 years, the model has sufficient degrees of freedom to reliably estimate the parameters and test the research hypotheses.

The economic size (lnGDP) showed a strong and statistically significant inverse impact on the level of digital economic development with a coefficient of -0.745*** ($t = -5.86$, $p < 0.001$). With an absolute t-statistic value greater than 5, this is one of the most reliable results in the model. This result means that when GDP increases by 1%, the level of digital economic development will decrease by 0.745%, while keeping other factors in the model constant.

In the correlation matrix, lnEI and lnDE have a correlation coefficient of 0.746*** - already the strongest relationship the dependent variable has with any independent variable. However, when switching to multivariate regression analysis, the magnitude of the effect increased significantly (from 0.746 to 4.468), indicating that when controlling for other factors, the true role of education is much stronger than what was observed in the simple correlation. This is evidence of a positive suppression effect, where the true impact of one variable is "masked" by other variables in the simple correlation analysis.

Foreign direct investment (FDI) showed a positive and statistically significant impact on digital economic development, with a coefficient of 0.296 ($t = 3.40$, $p = 0.003$). With a t-value greater than 3 and a p-value less than 0.01, this result is statistically highly reliable. This implies that when FDI increases by 1%, the level of digital economic development increases by an average of 0.296%, assuming other factors remain constant. However, compared to other explanatory variables in the model, the scale of FDI's impact is relatively modest: only about 1/15 the impact of education (4.468) and about 1/3 the impact of CO_2 emissions (0.940). This result shows that FDI plays a positive but not decisive role in digital economic development in the context of a sample of 7 countries and the study period.

Government performance (lnGE) shows a negative and statistically significant impact on digital economic development, with a coefficient of -0.093 ($t = -2.98$, $p = 0.007$). With an absolute t-value of approximately 3 and a p-value less than 0.01, this relationship reaches statistical significance at the 1% threshold, even though it is the least reliable variable among the statistically significant variables in the model. This result implies that when government performance increases by 1%, the level of digital economic development decreases by an average of 0.093%, assuming other factors remain constant.

Empirical results show that CO_2 ($lnCO_2$) emissions have the strongest and most statistically significant positive impact on the level of digital economic development, with an estimated coefficient of 0.940 ($t = 7.89$, $p < 0.001$). With a t-statistic value of nearly 8, the largest in the entire model, this result has the highest statistical reliability, indicating that when CO_2 emissions increase by 1%, the level of digital economic development increases by a corresponding 0.940%, almost at a 1:1 ratio, when other factors are kept constant. The large size of this coefficient not only reflects statistical significance but also shows a very strong economic impact, significantly exceeding that of other explanatory variables in the model.

5. CONCLUSION

This study contributes a practical perspective, closely adhering to the specific characteristics of Southeast Asia in analyzing the factors impacting the development of the digital economy. Through modern econometric methods, empirical results show clear differences between endogenous and exogenous factors, accurately reflecting the uneven development context among countries in the region.

Notably, although Foreign Direct Investment (FDI) has a positive impact on the digital economy, its influence is limited. The authors argue that the core reason stems from a lack of selectivity in attracting FDI in Southeast Asia. Specifically, the majority of investment capital remains focused on processing and assembly industries or leveraging cheap labor, rather than on developing digital technology and innovation. This leads to a long-term risk where countries in the region may fall behind other economies that are strongly shifting towards knowledge- and technology-based growth models.

Furthermore, the research results affirm the crucial role of education and digital human resources, with a significantly higher impact factor (4.468***). This shows that human capabilities are not only a supporting factor but also a central driving force determining the ability to absorb technology, innovate, and develop the digital ecosystem. This finding is consistent with theories of human capital, in which labor quality plays a decisive role in the transformation of the growth model.

Another noteworthy point is the inverse relationship between traditional GDP growth and the level of digital economic development (coefficient -0.745***). This result implies the existence of a kind of "digital middle-income trap," where economies still depend on the old growth model based on resources and low-cost labor, thereby slowing down the transition to the digital economy. This shows that quantitative growth does not equate to qualitative development, especially in the context of global digital transformation.

We also see that the role of government in the development of the digital economy should not be judged solely on the level of "effectiveness" in the traditional sense, but rather in relation to institutional flexibility and adaptability. A government truly suited to the digital economic context is not only a well-functioning government, but also one that knows how to "controllably loosen restrictions," creating space for innovation, while gradually improving the legal framework to support rather than hinder it. Therefore, the important policy direction is not to maximize control, but to balance management and encouragement, thereby playing a role in creating a favorable environment for the sustainable development of the digital economy.

In addition, the strong positive correlation between the digital economy and CO_2 emissions (0.940***) shows that the digitalization process in the region currently still comes with significant environmental costs, mainly due to increased energy consumption in digital infrastructure and technology production. This highlights the urgent need for a “dual transformation” strategy, where digital economic development must go hand in hand with sustainable environmental goals, such as the application of green technologies, energy optimization, and the development of environmentally friendly digital infrastructure.

Based on these findings, the study proposes restructuring the role of the government, from a traditional management entity to a “facilitator and promoter,” through the creation of policy testing environments (regulatory sandboxes), prioritizing investment in STEM education and digital skills development, and improving the quality of FDI attraction in a selective manner, focusing on high technology and innovation. This is considered a crucial foundation for developing countries, especially Vietnam, to enhance competitiveness and avoid falling into the development trap in the digital age.

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