

DIGITAL TRANSFORMATION AND ECONOMIC GROWTH: A PREDICTIVE PANEL DATA ANALYSIS FOR REIMAGINING SUSTAINABLE LOCAL ECONOMIES IN DEVELOPING COUNTRIES

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Abstract

This study aims to analyze the impact of digital transformation on economic growth, to forecast future economic growth in developing countries, and to provide policy recommendations for reimagining local economies in developing countries across the Asian region. The method employed is a quantitative approach using panel data analysis of nine countries over the period 2015–2022. The best model obtained is the Random Effects Model (REM), estimated using a robust approach to ensure the validity of the results. The variables used include internet, mobile, broadband, education, and energy as determinants of Gross Domestic Product (GDP). The results indicate that digital transformation variables broadband, internet, mobile, energy consumption, have a positive and significant effect on economic growth. Meanwhile, education shows a negative effect in the model. Predictive analysis suggests that continuous improvements in digital transformation will drive a positive economic growth trend during the 2023–2030 period. This study contributes by integrating explanatory and predictive analysis within a panel data framework and provides policy recommendations. The importance of strengthening digital infrastructure, energy, and improving human capital quality to support sustainable local economic transformation in developing countries.

Keywords: Digital Transformation, Economic Growth, Panel Data, Random Effects Model, Forecasting

INTRODUCTION

Digital transformation is a comprehensive change based on digital technology that aims to make activities more effective, innovative, and relevant to current developments. It provides opportunities for developing countries to expand market reach by leveraging technologies such as digital platforms and electronic commerce, thereby enhancing their competitiveness at the global level (Ateeq, 2025; Nithya et al., 2025). This means that the development of information and communication technologies, such as the internet, mobile technology, and broadband, can transform the ways production, distribution, and consumption are carried out across various economic sectors. In this regard, digital transformation can influence economic growth through improvements in productivity and efficiency. Digital technologies enable expanded market access, reduced transaction costs, and increased innovation across different sectors.

The impact of digital transformation on economic growth in developing countries depends on differences in each country's level of readiness, both in terms of infrastructure and the quality of human resources. Therefore, it is important to gain a deeper understanding of how digital transformation truly affects economic growth. From an infrastructure perspective, digital transformation can be measured through energy, as well as the availability and quality of information and communication technologies, such as internet penetration rates, mobile network

usage, and broadband access, which reflect a country's digital connectivity capacity. This implies that economic growth is influenced by internet penetration (Bajja et al., 2025), mobile usage (Čihák, 2019) and broadband access (Briglauer et al., 2025; Koh et al., 2024), and energy (Farooqi et al., 2021; Mohammadi et al., 2023). From the perspective of human capital quality, education also has an impact on economic growth (Baker, 2025; Coronel & Díaz-Roldán, 2024). Similarly, the unemployment rate is related to GDP, but the relationship is negative (Mohamud et al., 2024). In relation to this, the measurement of digital transformation in its impact on economic growth (GDP) in this study employs indicators such as internet usage, mobile adoption, broadband access, energy consumption, and education.

The relationship between digital transformation and economic output can also have implications for sustainable economic development, particularly at the local level. In this regard, this study also aims to provide recommendations for the reimagining of local economies. Local economies, which are largely dominated by micro, small, and medium enterprises (MSMEs) and the informal sector, play a crucial role in generating employment and improving community welfare. The integration of digital technologies into MSMEs can help them access new markets, increase income, and accelerate economic growth (Modwel, 2025; Telukdarie et al., 2024). Based on this, the study employs control variables consisting of education, and energy, while the main variables of interest are digital transformation indicators, namely internet, mobile, and broadband. These variables are used to analyze their relationship with economic growth (GDP) in developing countries. The results of this analysis will be utilized to design effective policies for local economic development, making it more adaptive to technological changes while still taking sustainability aspects into account.

The analysis employed is data-driven and comprehensive. In this context, a predictive approach is applied. Predictive analysis enables researchers and policymakers not only to understand the historical relationships between variables but also to project the impact of digital transformation on future economic growth. Thus, the policies formulated can be more targeted and adaptive to evolving dynamics. If the analysis were limited to descriptive methods or static relationships between variables, it would be less capable of capturing long-term dynamics. Therefore, a more comprehensive approach is required, namely the use of panel data analysis combined with predictive models, to provide a more accurate and in-depth understanding. Panel data analysis is utilized because it has a dual dimension (cross-sectional and time-series data). Its estimation methods are based on rigorous mathematical derivations and are widely used in empirical studies in economics and the social sciences (Z. Cheng & Zhao, 2020). Based on the above description, this study is important to conduct with the aim of analyzing the impact of digital transformation on economic growth in developing countries, as well as examining how the results of this analysis can be used to reimagine sustainable local economies.

The primary objective of this study is to analyze the impact of digital transformation on economic growth in developing countries and to project future economic growth trends based on digitalization variables. Specifically, this study aims to: (1) analyze the impact of digital transformation on economic growth; (2) forecast future economic growth in developing countries; and (3) provide policy recommendations for reimagining local economies in developing countries across the Asian region. The scope of this research focuses on developing countries in Asia, covering several countries in Southeast Asia, South Asia, and parts of East Asia.

The contributions of this study encompass both theoretical and practical aspects. Theoretically, this study enriches the literature on the relationship between digital transformation and economic growth by integrating explanatory and predictive approaches within a panel data framework. Practically, this study provides relevant policy recommendations for governments in designing sustainable, digitally driven economic transformation strategies. The practical implications of the findings highlight the importance of strengthening digital infrastructure particularly broadband and internet access, as well as supporting the energy sector to foster economic growth in developing countries.

The novelty of this study lies in the use of a predictive panel data analysis approach, which not only examines causal relationships but also projects future economic trends. In addition, this research integrates the perspective of digital transformation with the concept of sustainable local economic development, empirically examined within the context of developing countries. Therefore, this study not only contributes to the academic literature but also offers a more comprehensive analytical framework for understanding the dynamics of the digital economy.

Thus, this study integrates three main aspects digital transformation, economic growth, and a predictive approach within the framework of reimagining sustainable local economies. This approach is expected to provide a new perspective in understanding the role of digital technology as a key driver of economic development that is not only growth-oriented but also focused on sustainability and equitable welfare distribution. This study is expected not only to contribute to the development of academic literature but also to offer practical implications for policy formulation that supports inclusive, adaptive, and sustainable digital transformation.

LITERATURE REVIEW AND HYPOTHESIS FORMULATION

Economic growth is a primary indicator used to measure the success of a country's development. It reflects an increase in the production and consumption of goods and services, typically measured by Gross Domestic Product (GDP) or GDP per capita, adjusted for inflation and population size (Fosu, 2024; Furaijl et al., 2024). This quantitative measure is very important for assessing economic progress and the utilization of resources (Raj et al., 2025). Neoclassical theory, particularly the Solow–Swan model, explains economic growth as a function of capital accumulation, labor force growth, and exogenous technological progress. This model introduces the concept of diminishing returns to capital, meaning that long-term growth is primarily driven by technological progress rather than capital accumulation alone (Ferrara, 2025). In this context, digital transformation represents a form of technological advancement with significant potential to enhance productivity and economic efficiency.

Digital transformation is the process of utilizing digital technologies to create or modify existing business processes, organizational culture, and customer service experiences. (Alloghani et al., 2022; Hundal et al., 2025). Digital transformation can be measured through indicators such as internet penetration, mobile device usage, broadband access, and the level of digitalization in public services and the industrial sector. Along with technological advancements, digital transformation has become a crucial factor in enhancing economic efficiency and productivity. For instance, companies that adopt digital technologies are able to optimize their working capital structure, improve management efficiency, and enhance the structure of their human resources (Y. Cheng et al., 2023). However, digital transformation does not always produce evenly distributed impacts. In some regions, urban areas benefit more from digital adoption than rural areas. (Issaeva et al., 2024). The success of digitalization is strongly influenced by infrastructure readiness and the quality of human resources. Therefore, analyses of digital transformation need to consider various contextual factors, particularly in developing countries. In endogenous growth theory, technological progress is a key driver of long-term economic growth. Digital transformation is viewed as one of the main determinants of economic growth. Digital technologies such as the internet, mobile communication, and broadband enable greater access to information, improve market efficiency, and expand economic opportunities. Indicators of digitalization such as internet usage, broadband subscriptions, and mobile communication technologies contribute to increases in GDP per capita in developing countries (Mgadmi et al., 2021; Mhaka & Taonezvi, 2024).

High internet penetration enables economic growth through increased productivity. (Bajja et al., 2025). Based on the study (Y. Li, 2019; Novianti et al., 2025; Ochoa-Jimenez et al., 2018), It indicates that an increase in internet usage is positively correlated with an increase in GDP; therefore, in this study, hypothesis H1 can be formulated.

H1: Internet has a positive effect on economic growth (GDP).

Mobile technology enables access to digital financial services, e-commerce, and more efficient communication. Empirical studies show that increased mobile penetration contributes to higher economic activity and GDP growth(Čihák, 2019).

H2: Mobile has a positive effect on economic growth (GDP).

Broadband is a digital infrastructure with high capacity to support technology-based economic activities. Broad access to broadband can increase the speed of information exchange, foster innovation, and enhance economic competitiveness. Study(Briglauer et al., 2025; Koh et al., 2024) indicates that broadband has a stronger effect on economic growth compared to other digital variables.

H3: Broadband has a positive effect on economic growth (GDP).

Education is one of the key factors in Human Capital Theory. The level of education influences economic growth(Baker, 2025; Coronel & Díaz-Roldán, 2024).

H4: Education has an effect on economic growth (GDP).

Energy consumption is an important factor in driving economic growth. Studies show that increases in energy consumption directly raise GDP, both in developed and developing countries(Farooqi et al., 2021; Mohammadi et al., 2023).

H5: Energy consumption has a positive effect on economic growth (GDP).

Based on theoretical foundations and previous studies, it can be concluded that digital transformation, energy, and socio-economic factors play an important role in determining economic growth. Therefore, the hypotheses proposed in this study aim to empirically examine the effect of each of these variables on GDP in developing countries.

RESEARCH METHODS

1. Research Design

This study employs a quantitative research design using a panel data approach. Panel data analysis is used to examine the relationship between digital transformation and economic growth in developing countries. The study integrates both explanatory and predictive analyses, aiming to identify causal relationships and project future economic trends based on digitalization variables.

A panel data approach is capable of combining cross-sectional data (across countries) and time series data (annual), as it can capture dynamic behavior and changes within an entity over time, making it an ideal approach for analyzing temporal effects (Magazzini, 2023). Additionally, by applying panel data, it can be used to evaluate policy impacts by constructing counterfactual scenarios and analyzing causal effects (Shi & Huang, 2023)

The analysis was conducted using EViews. EViews provides tools for model testing and validation, assessing the significance of variables, and detecting autocorrelation, heteroskedasticity, and multicollinearity, which are essential to ensure the accuracy of forecasting models (Kuzheliev et al., 2025). Additionally, the visualization capabilities in EViews can be dynamically customized to enhance the transparency and reproducibility of the research (Mati et al., 2023).

2. Population and Sample (Research Target)

The population in this study consists of developing countries in Asia that have diverse economic characteristics and varying levels of digital transformation.

The research sample was determined using a purposive sampling technique, with criteria including countries classified as developing and representing sub-regions in Asia. The Asian region covers Southeast Asia, South Asia, and East Asia. The selection of these three sub-regions was intended to capture cross-country heterogeneity in a controlled manner. Southeast Asia has emerging economies with a high level of global integration (Ha & Chuah, 2023; Hardi et al., 2024). South Asia is experiencing a slower pace of digitalization compared to other regions(Murshed, 2024). In East Asia, however, digitalization significantly boosts cross-sectoral economic growth (China)(Shahzad, 2025). Based on these criteria, the countries that are the research sample include:

Table 1. Country Tables, ISO Codes, and Asia Sub-Region

Negara	ISO 2 Code	ISO 3 Code	Sub-Kawasan Asia
Indonesia	ID	IDN	Southeast Asia
Malaysia	MY	MYS	Southeast Asia
Thailand	TH	THA	Southeast Asia
Viet Nam	VN	VNM	Southeast Asia
Philippines	PH	PHL	Southeast Asia
India	IN	IND	South Asia
Bangladesh	BD	BGD	South Asia
Pakistan	PK	PAK	South Asia
China	CN	CHN	East Asia

Source: World Bank Data

This study uses balanced panel data with an observation period of 2015–2022. This is because, in balanced panel data, one of them is often used in economic analysis to identify causal relationships and temporal patterns (Z. Cheng & Zhao, 2020). This study uses the period 2015–2022 because it describes the mature stage of digital economy development and is relevant to the Sustainable Development Goals (SDGs) agenda which began to be implemented in 2015. In addition, during this period there has been a significant increase in the adoption of digital technology in developing countries, so that the available data is more consistent and comparable between countries. This period also includes the impact of the COVID-19 pandemic which has brought structural changes to the economy and digitalization.

3. Data Collection Techniques and Instrument Development

This study uses secondary data obtained from the World Bank through World Development Indicators (WDI).

The variables used in this study consist of digital indicators:

- Dependent Variable
 GDP_{it} : Gross Domestic Product (GDP) per capita (USD constant)
- Independent Variable (Digital Transformation)
 $Internet_{it}$: Internet users (% of population)
 $Mobile_{it}$: Mobile subscriptions (per 100 inhabitants)
 $Broadband_{it}$: Fixed broadband subscription (per 100 inhabitants)
- Control Variable
 $Education_{it}$: Education (school participation rate or proxy indicator)
 $Energy_{it}$: Energy use (kg of oil equivalent per capita)

Description: i = Country and t = Time

The data collection technique is carried out through downloading data from the official database, merging and restructuring the data into a panel format, then data cleaning by handling missing values and ensuring data consistency.

4. Tool and Material Specifications

The main tool used for analysis is EViews. EViews is used for Panel data regression analysis. The models used in the Panel Data Analysis in this study are the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM).

In the Common Effect Model, to estimate using the usual least squared method (OLS), because it does not take into account unobserved heterogeneity (Yusra et al., 2019). This means that in the CEM model, there are no individual special effects (cross-section), nor time (time-series), all data are considered homogeneous (pooled). CEM is also called Regression Pooling. Based on (Rizka Zulfikar, 2019), the mathematical model becomes

$$Y_{it} = \beta_0 + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \dots + \beta_k X_{k,it} + \varepsilon_{it} \dots (1)$$

Y_{it} = dependent variables for the- i individuals at the time of the- t

$X_{k,it}$ = independent variable to- k for individuals to- i at the time- t

β_0 = intercept

β_k = the regression coefficient of each independent variable

ε_{it} = error term

The Fixed Effect Model can control for unobserved heterogeneity at the individual or time level and can analyze the relationship between independent and dependent variables by removing bias from unobserved variables (Li et al., 2026; Yang et al., 2025). Based on (Andi et al., 2025) The common forms of FEM are

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

with separate individual effects $\alpha_i = \beta_0 + \mu_i$, Where μ_i as an individual effect (time-invariant).

FEM can also be written with dummy variables (Nurdin et al., 2024):

$$Y_{it} = \beta_0 + \sum_{i=1}^{N-1} \delta_i D_i + \beta_1 X_{1,it} + \dots + \varepsilon_{it} \dots (3)$$

D_i = Dummy for each individual and δ_i = Fixed effect

If individual and time effects are considered, then use Two-Way Fixed Effect FEM with the model

$$Y_{it} = \alpha_i + \lambda_t + \beta X_{it} + \varepsilon_{it} \dots (4)$$

α_i = Individual Effects and λ_t = Time Effect

In the Random Effect Model, it is used if the difference between individuals is considered a random variable, not a fixed parameter as in FEM. General Forms of REM (Hutagalung & Darnius, 2022) is

$$Y_{it} = \beta_0 + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \dots + \beta_k X_{k,it} + u_{it} \dots (5)$$

with $u_{it} = \mu_i + \varepsilon_{it}$, μ_i : Individual specific error (random effect), then

$$Y_{it} = \beta_0 + \beta_1 X_{1,it} + \dots + \beta_k X_{k,it} + \mu_i + \varepsilon_{it} \dots (6)$$

Material specifications include secondary macroeconomic data (GDP, digital indicators). The dataset uses a cross-country timeline-based panel data, with Microsoft Excel (.xlsx) data format converted to a panel structure.

5. Data Analysis Techniques

Panel data analysis is carried out based on (Rizka Zulfikar, 2019) through several stages as shown in Figure 1. as follows:

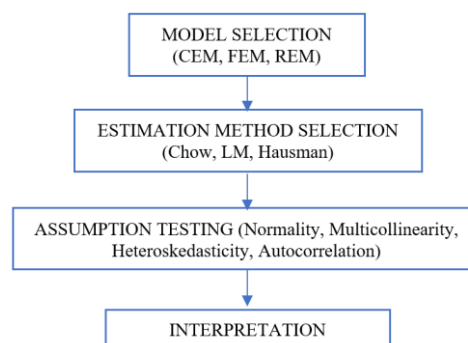


Figure 1. Stages of Panel data analysis

The stages of this research include

- Descriptive Statistics are used to describe the characteristics of each variable, such as mean values, minimums, maximums, and standard deviations.
- Correlation analysis is used to test the relationships between independent variables as well as detect potential multicollinearity. Variance Inflation Factor (VIF) is used to measure the

level of multicollinearity. A high VIF value indicates a significant multicollinearity (Z. Li et al., 2025).

c. Model Regresi Data Panel

The model used in this study is formulated as follows

$$GDP_{it} = \beta_0 + \beta_1 Internet_{it} + \beta_2 Mobile_{it} + \beta_3 Broadband_{it} + \beta_4 Education_{it} + \beta_5 Energy_{it} + \epsilon_{it} \dots\dots\dots (7)$$

ϵ_{it} = error term (contains random effects)

d. Model Selection

The selection of the best model through diagnostic testing is the Chow Test, the Hausman Test and the Lagrange Multiplier Test (Muhith et al., 2022).

Chow test to compare CEM with FEM, provided

H₀ (CEM): There is no difference in characteristics between individuals and Intercept is the same for all units.

H₁ (FEM): There are differences between individuals and each individual has different intercepts

Hausman test to compare FEM with REM, provided that

H₀ (REM): There is no correlation between individual effects (μ_i) and independent variables (X_{it}) and

H₁ (FEM): There is a correlation between individual effects and independent variables.

Uji Lagrange Multiplier (LM) to compare CEM with REM, provided that

H₀ (CEM): Panel data is considered homogeneous and there is no difference between individuals

H₁ (REM): There are differences between individuals and there are differences that are random.

The Chow test aims to detect structural changes in the data. The Hausman test aims to test the correlation between predictor variables and errors. Then the LM test aims to test model suitability, autocorrelation, heteroscedasticity, or causality.

e. Robust Estimation to improve the reliability of results and predictive analytics. Robust estimation is used to improve the reliability of results and overcome potential heteroscedasticity and autocorrelation, estimation is carried out using robust standard errors (White cross-section). This estimate can handle outliers and model deviations (Luu, 2024)

f. Predictive Analysis (Forecasting) is part of a predictive approach using estimation models to project GDP trends in the coming period (2023–2030). Predictions are made until 2030, because the SDGs are for a period of 15 years, starting from 2015 to 2030. assuming growth in digital transformation variables.

The best models can be viewed by value (Akther et al., 2025)

MAE (Mean Absolute Error) : $MAE = |Y - \hat{Y}|$

RMSE (Root Mean Square Error) : $RMSE = \sqrt{(Y - \hat{Y})^2}$

MAPE (Mean Absolute Percentage Error) : $MAPE = \left| \frac{Y - \hat{Y}}{Y} \right| \times 100\%$

g. Policy implications to support sustainable local economic transformation in developing countries.

RESULTS AND DISCUSSION

The dataset in this study was compiled in the form of a balanced data panel with an annual structure covering 9 countries during the period 2015–2022. A graph of time series data is seen in Figure 2., and Figure 3..

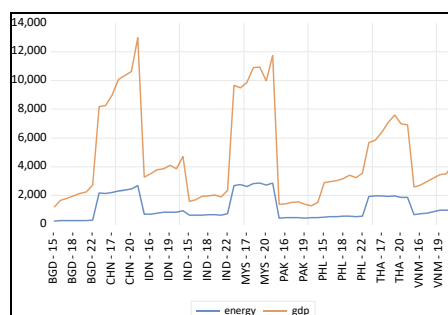


Figure 2. GDP and Energy Data Graph

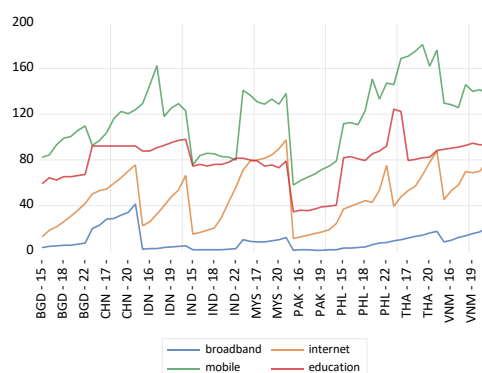


Figure 3. Broadband, Internet, Mobile and Education Data Graph

The graph shows a comparison of several key variables, namely GDP (GDP), internet, mobile, broadband, energy, and education in various countries and time periods in the form of panel data. In general, the GDP line has the highest value and significant fluctuations between countries. This illustrates that there is a considerable difference in the level of economic growth. Countries such as China and Malaysia are seen to have relatively high GDP levels compared to other countries, while some South Asian countries show lower values. Digital transformation variables such as internet, mobile, and broadband use show variations between countries. Internet usage is seen to be quite high in countries with more advanced economies, which indicates a positive relationship between digitalization and income levels. Meanwhile, energy variables also follow a relatively similar pattern to GDP, suggesting that higher economic activity requires greater energy consumption. Overall, this graph shows the differences between countries in terms of economic growth and digital transformation. This shows that countries with higher levels of digitalization and energy consumption tend to have larger GDPs. In addition to using graphs, this can also be seen from the statistical results of the description seen in Table 2.

Table 2. Statistic Descriptive

	GDP	INTERNET	MOBILE	BROADBAND	EDUCATION	ENERGY
Mean	4728.523	47.62754	117.4548	8.997252	79.04589	1181.407
Median	3400.789	47.50500	122.8730	6.045060	81.65585	738.8795
Maximum	12970.61	97.39860	181.2220	41.37360	124.3306	2878.299
Minimum	1224.386	11.00000	57.94060	0.825253	34.67415	237.7132
Std. Dev.	3328.313	23.56960	31.25204	9.052265	18.88889	877.8507
Skewness	0.889700	0.134386	0.010988	1.615809	-0.726125	0.753227
Kurtosis	2.426369	1.936521	2.226142	5.323795	3.917780	1.971307
Jarque-Bera	9.175205	3.158469	1.573266	41.58887	7.747293	8.734987
Probability	0.010177	0.206133	0.455376	0.000000	0.020782	0.012683
Sum	297897.0	3000.535	7399.650	566.8269	4979.891	74428.63
Sum Sq. Dev.	6.87E+08	34442.60	60554.80	5080.497	22120.99	47778557
Observations	63	63	63	63	63	63

Descriptive statistical output of EViews in Table 2. shows that all variables have 63 observations (balanced panel). The GDP variable has an average of around 4728.5 with a fairly high variation (standard deviation of 3328.3), indicating a difference in the level of economic development between countries. Digital transformation variables such as internet and mobile showed relatively high average values (47.6% and 117.5), indicating a fairly wide level of technology adoption, while broadband is still lower and varied. Energy variables also show large variations in line with economic activity.

In terms of distribution, most variables have a positive skewness value (skewed to the right), except for education, and the results of the Jarque-Bera test show that most of the variables are not normally distributed (probability < 0.05), except for mobile, and internet, so the estimation is carried out with a robust estimation approach. Robust regression technique or robust normality test, can reduce the impact of abnormalities and outliers (Yuan & Gomer, 2021). The next step is Covariance Analysis, with the results seen in Table 3.

Table 3. Covariance Analysis

Covariance t-Statistic						
Probability	GDP	INTERNET	MOBILE	BROADBAND	EDUCATION	ENERGY
GDP	10901833 ----- -----					
INTERNET	59699.00 9.525221 0.0000	546.7080 ----- -----				
MOBILE	49924.88 4.363266 0.0001	490.9727 7.190035 0.0000	961.1873 ----- -----			
BROADBAND	21588.58 8.295980 0.0000	126.6674 5.907638 0.0000	101.2021 3.047478 0.0034	80.64282 ----- -----		
EDUCATION	25185.87 3.480821 0.0009	232.6142 4.893175 0.0000	395.2308 7.249820 0.0000	76.01649 3.954771 0.0002	351.1268 ----- -----	
ENERGY	2784169. 30.26450 0.0000	15192.39 8.752002 0.0000	12881.61 4.240076 0.0001	5122.190 6.769738 0.0000	6389.086 3.323217 0.0015	758389.8 ----- -----

The output of Covariance Analysis from EViews shows the relationship between variables through covariance and correlation values. In general, it can be seen that digital transformation variables such as internet, mobile, and broadband have a positive correlation to GDP, which suggests that increased digitalization tends to be followed by increased economic growth. The relationship between energy and GDP is also strong and positive, explaining that energy consumption is closely related to economic activity. The education variable showed a positive correlation between GDP and other digital variables, reflecting the role of education in supporting technology adoption. In addition, the probability values on some pairs of variables show statistical significance ($p\text{-value} < 0.05$), so the relationship can be considered to be empirically quite strong. In a more concise for the correlation analysis is also seen in the Table 4.

Table 4. Correlation Matrix

	GDP	INTERNET	MOBILE	BROADBAND	EDUCATION	ENERGY
GDP	1	0.773	0.488	0.728	0.407	0.968
INTERNET	0.773	1	0.677	0.603	0.531	0.746
MOBILE	0.488	0.677	1	0.363	0.680	0.477
BROADBAND	0.728	0.603	0.363	1	0.452	0.655
EDUCATION	0.407	0.531	0.680	0.452	1	0.392
ENERGY	0.968	0.746	0.477	0.655	0.392	1

The correlation matrix from Table 4 shows that most of the variables have significant and unidirectional relationships. Digital transformation variables such as broadband, internet, and mobile have a positive correlation with GDP, at 0.728, 0.773, and 0.488, respectively, indicating that increased adoption of digital technology is related to increased economic growth. In addition, the education variable also has a positive correlation with digital variables, especially with mobile (0.680) and internet (0.531), which shows that improving the quality of education contributes to technology adoption. There is a fairly high correlation between independent variables, especially between energy and GDP (0.968), which indicates the potential for multicollinearity in the regression model. Therefore, at the next stage of analysis, it is necessary to use a robust estimation approach so that the research results remain valid and unbiased.

Before robust estimation is carried out, a test is carried out first to determine the panel regression model. The results of the chow test can be seen in Table 5.

Table 5. Chow Test

Effects Test	Statistic	d.f.	Prob.
Cross-section F	34.993155	(8,49)	0.0000
Cross-section Chi-square	119.956472	8	0.0000

Results of Redundant Fixed Effects Test in Table 5. from EViews shows that models with fixed effects (FEM) are more appropriate to use than models without fixed effects (CEM). This is shown by the Cross-section value of F of 34.99 with a probability of 0.0000, and the Chi-square value of 119.96 with a probability of 0.0000, both of which are smaller than the significance level of 5%. Thus, the null hypothesis that individual effects (cross-section) are not required is rejected, so it can be concluded that there are significant differences in characteristics between countries that should be included in the model. This means that each country has a specific effect that affects GDP and cannot be ignored in the estimates. Therefore, the use of the FEM model is more relevant because it is able to capture heterogeneity between countries, resulting in more accurate and unbiased estimates than the CEM model. Then to see the comparison between FEM and REM using the Hausman test, which is seen in Table 6.

Table 6. Hausman Test

Test Summary	Chi-Sq.	Chi-Sq. d.f.	Prob.
	Statistic		
Cross-section random	2.442955	5	0.7851

Table 6. explains the results of the Correlated Random Effects Hausman Test from EViews used to determine the best model between FEM and REM. Based on the output, a Chi-Square value of 2.443 with a probability of 0.7851 was obtained, which is much greater than the significance level of 5%. This shows that the null hypothesis cannot be rejected, so REM is more appropriately used than FEM. Conceptually, these results indicate that there is no significant correlation between individual effects (characteristics of each country) and independent variables in the model. Then to see the comparison between REM and CEM using the Lagrange Multiplier Test, which is seen in Table 7.

Lagrange Multiplier (LM) Test for Random Effects results from EViews in Table 7. is used to determine whether REM is more appropriate than CEM. Based on the output, the Breusch-Pagan value for cross-section is 111.097 with a probability of 0.0000, and the value for both effects is also significant (0.0000), indicating that the null hypothesis (absence of effect) is rejected. This means

that there is a significant cross-section effect between countries, so the panel model REM is more appropriate than the pooled model (CEM). Meanwhile, the time effect was not significant (probability 0.1817), which explains that the variation between times is less influential than the variation between countries. These results are also the same as other tests such as Honda and King-Wu which show significance on cross-section dimensions. The REM model is more suitable than CEM because it is able to capture heterogeneity between countries in the analysis of economic growth.

Table 7. Lagrange Multiplier

	Test Hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	111.0974 (0.0000)	1.783384 (0.1817)	112.8808 (0.0000)
Honda	10.54027 (0.0000)	-1.335434 (0.9091)	6.508805 (0.0000)
King-Wu	10.54027 (0.0000)	-1.335434 (0.9091)	5.890736 (0.0000)
Standardized Honda	16.13935 (0.0000)	-1.127462 (0.8702)	5.464906 (0.0000)
Standardized King-Wu	16.13935 (0.0000)	-1.127462 (0.8702)	4.591778 (0.0000)
Gourieroux, et al.	--	--	111.0974 (0.0000)

The next step is to conduct a robust estimate and obtain the results in Table 8.

Table 8. Estimation Robust

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	533.3023	575.1114	0.927303	0.3895
INTERNET	6.939194	1.567025	4.428260	0.0044
MOBILE	4.755768	1.755871	2.708495	0.0352
BROADBAND	92.10833	16.18748	5.690098	0.0013
EDUCATION	-17.57789	5.112596	-3.438155	0.0138
ENERGY	3.273111	0.724457	4.518017	0.0040
Effects Specification				
		S.D.	Rho	
Cross-section random		1036.554	0.9212	
Idiosyncratic random		303.0730	0.0788	
Weighted Statistics				
R-squared	0.864524	Mean dependent var	519.3928	
Adjusted R-squared	0.852640	S.D. dependent var	771.5986	
S.E. of regression	296.1970	Sum squared resid	5000762.	
F-statistic	72.74788	Durbin-Watson stat	1.331221	
Prob(F-statistic)	0.000000			
Unweighted Statistics				
R-squared	0.944493	Mean dependent var	4728.523	
Sum squared resid	38122918	Durbin-Watson stat	0.174622	

The results of estimation using the Random Effect Model (REM) with the EGLS Panel (Cross-section random effects) method on EViews and the robust standard errors (White cross-section) approach show that the model has been adjusted to overcome the potential heteroscedasticity and autocorrelation, so that the estimation results are more reliable. Simultaneously, the model is

significant with a Prob(F-statistic) value of 0.0000, which means that all independent variables together have an effect on GDP.

Partially, the variables of the internet, mobile, broadband, and energy have a positive and significant effect on GDP, showing that increased digital transformation and energy consumption contribute to economic growth. The broadband variable had the strongest influence with a coefficient of 92.10833, followed by internet and mobile which shows the importance of digital infrastructure and energy in driving economic activity. On the other hand, the education variable has a negative and significant effect, which means that the improvement of education has not directly increased economic growth. This can be due to the mismatch between the level of education and the needs of the job market (skill mismatch). An R-squared value of 0.864524 indicates that about 86% of GDP variation can be explained by the model, while a Rho value of 0.9212 indicates that variation stems more from differences between countries than from variation in time. Overall, these results confirm that digital and energy transformation are key factors in driving economic growth in developing countries, with estimates through a robust approach. Based on equation (7), the panel data regression (REM) model of the estimated results is

$$gdp_{it} = 533.3023 + 6.939194 internet_{it} + 4.755768 mobile_{it} + 92.10833 broadband_{it} - 17.57789 education_{it} + 3.273111 energy_{it} - \epsilon_{it} \dots\dots\dots (8)$$

If we use world bank data in 2023, with the amount of Internet of 69,2084, Mobile of 125,238, Broadband of 4.81664, Education of 96.00021203, Energy of 976.9499855 and actual GDP in 2023 of 3308. Based on model (8), the GDP prediction is obtained as 3561.23 with MAE 253.23, RMSE 253.23 and MAPE 7.66%. If simulation data is taken for prediction, and uses equation (8) by entering for all variables, then the prediction results are seen in Table 9.

Table 9. Simulation of GDP Forecasting (2024–2030) based on Random Effect Model

Tahun	Internet	Mobile	Broadband	Education	Energy	GDP Forecasting
2024	62.0	123.0	5.5	75.5	900	3319.92
2025	64.5	126.0	6.0	76.0	910	3432.73
2026	67.0	129.0	8.0	76.5	980	3798.42
2027	70.0	132.0	10.0	77.0	1001	4136.37
2028	73.0	135.0	11.5	77.5	1100	4566.55
2029	76.0	138.0	12.0	78.0	1115	4753.26
2030	79.0	142.0	13.0	78.5	1200	5187.64

The table above shows the results of GDP projections for the period 2024–2030 obtained using the Random Effect model. The projection is made on the assumption that digital transformation variables, such as internet, mobile, and broadband, are gradually increasing, while energy variables are also increasing along with economic activity. The forecast results show a consistent trend of GDP increase from year to year, indicating that accelerating digital transformation and supporting energy infrastructure are instrumental in driving long-term economic growth in developing countries.

Based on the results of estimation and prediction analysis that show that digital transformation variables, especially broadband, internet, and mobile as well as energy consumption, have a significant influence on economic growth, the policy implications that can be formulated are the need to strengthen digital-based development strategies to support sustainable local economic transformation in developing countries. The government needs to prioritize investment in digital infrastructure, especially the expansion of broadband access which has proven to have the greatest impact on increasing GDP, while ensuring equitable distribution of internet access to rural areas to reduce the digital divide. In addition, strengthening the energy sector is important to support the increasing digital economic activities, so policies that encourage energy efficiency and sustainable

energy development are needed. On the other hand, results that show the negative influence of education variables indicate the need to reform the education system to be more in line with the needs of the digital job market, through improving digital skills and technology-based training. Local economic transformation also needs to be supported through digital-based MSME empowerment, increasing financial inclusion through financial technology, and strengthening the innovation ecosystem at the local level. Thus, policies that are integrated between the development of digital infrastructure, education reform, and strengthening the energy sector will be key in reimagining the local economy that is inclusive, adaptive, and sustainable in developing countries.

CONCLUSION

This study aims to analyze the influence of digital transformation on economic growth in developing countries by using a panel data approach and predictive analysis. Based on the results of estimation using the Random Effect model that has been robustly tested, it was found that digital transformation variables, especially broadband, internet, and mobile, have a positive and significant influence on Gross Domestic Product (GDP). In addition, the energy variable also proved to be an important factor in driving economic growth, while the education variable showed a negative influence in the model. The results of the predictive analysis show that the continuous increase in digital transformation will drive a positive economic growth trend in the coming period. This means that digital transformation is a key determinant in shaping economic growth as well as a foundation in redesigning sustainable local economies in developing countries.

The implications of this study emphasize the importance of policies oriented towards strengthening digital infrastructure, especially the development of broadband networks and the expansion of equitable internet access. In addition, the government needs to increase the capacity of the energy sector to support digital economic activities, as well as reform the education system to be more in line with the needs of the technology-based economy. Strengthening MSMEs through digitalization and increasing financial inclusion is an important strategy in encouraging inclusive and sustainable local economic growth.

However, this study has several limitations. First, the use of secondary data with a relatively limited time period (2015–2022) may limit the model's ability to capture long-term dynamics. Second, the variables used are still limited to certain macroeconomic indicators, so they do not fully represent the complexity of digital transformation, such as aspects of institutional quality, innovation, or digital regulation. Third, the analysis is carried out at the aggregate level of the country, so it is not able to describe the specifics of local economic dynamics at the regional or subnational level.

Based on these limitations, further research is recommended to extend the observation period and add other more comprehensive variables, such as innovation index, institutional quality, or more specific digital economy indicators. In addition, the use of more advanced methodological approaches, such as dynamic panel models or spatial approaches, can provide more in-depth results. Future research can also be focused on regional or local level analysis to gain a more detailed understanding of digital-based economic transformation in developing countries.

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