Artificial Intelligence and Digital Transformation as Drivers of Sustainable Development: An Empirical Analysis of Emerging Economies

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Abstract
In an era of rapid change and resulting economic disparities, particularly among emerging economies, artificial intelligence (AI) and digital transformation are crucial for navigating these shifts. This study highlights that digital transformation necessitates AI to achieve Sustainable Development Goals (SDGs). This underscores the importance of research exploring the synergistic relationship between AI and digital transformation as key drivers for achieving the SDGs in emerging economies. While previous studies have addressed these two technologies separately, this study employs an empirical framework based on ordinary least squares (OLS) data analysis of 25 emerging markets in the year 2023, using data available from the World Bank. The findings indicate that increased AI readiness is associated with improved governance efficiency, leading to better SDG outcomes. The results emphasize that for AI to become a true driver of sustainable development, policy frameworks must prioritize AI capabilities and good governance to mitigate the risks of the new digital expansion. This analysis provides a roadmap for policymakers to align investments with long-term environmental and social justice.

Introduction

The global economy has recently experienced extreme structural transformations due to rapid advancements in digital technologies (AI and digital transformation). These technologies have become key drivers of economic growth and productivity, as well as playing a vital role in achieving Sustainable Development Goals. Given the escalating global challenges related to climate change, depletion of natural resources and widening development gaps, the need to leverage smart technologies effectively to promote economic, social, environmental and institutional development has become paramount.

According to the World Bank report, potential growth in emerging and developing economies is projected to decline to an average of 4.1 percent annually during the period (2020–2029), compared to an average of 5.3 percent annually during the period (2010–2019) (World Bank, 2025). This implies a decrease in the production capacity of these economies. This slowdown can be attributed to degraded labor supply, weak capital accumulation, slower pace of digital transformation, in addition to the long-term impact of COVID-19 pandemic and climate change. In this context, a significant research gap emerges concerning the lack of clarity regarding the vital role that artificial intelligence (AI) and digital transformation can play in revitalizing growth pathways, boosting productivity and transforming this slowdown into opportunities. Therefore, the research objective aims to focus on the extent to which AI technologies and digital transformation initiatives can overcome the structural constraints facing these economies, enhance resource efficiency and support the achievement of the dimensions of sustainable development within a global environment characterized by augmenting uncertainty.

This study seeks to answer the main research question

Does adopting Artificial Intelligence and Digital Transformation contribute to achieving sustainable development in emerging economies?

While studies examining the relationship between digital transformation and economic growth are increasing, research exploring the relationship between AI and sustainable development within a comprehensive framework remains limited, particularly in the context of emerging economies. This study aims to bridge this research gap by analyzing the dynamic impact of adopting AI and Digital Transformation on Sustainable Development in Emerging economies.

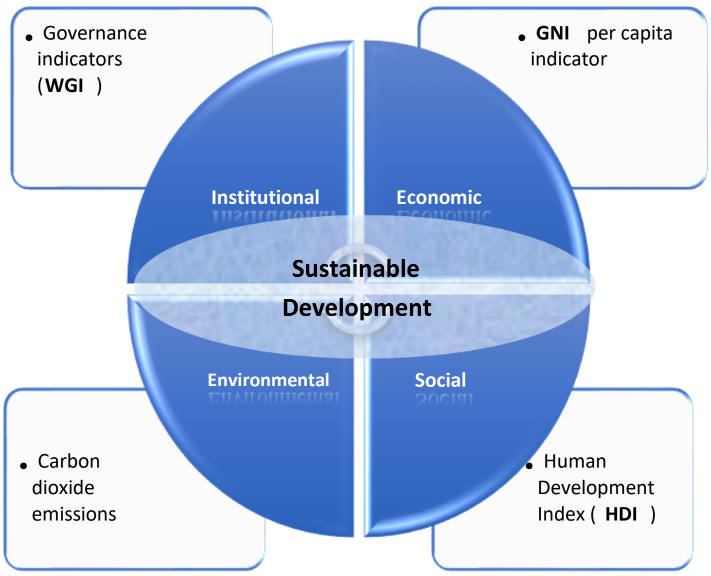
The remainder of the study is organized as follows. The next section presents previous literature about AI, digital transformation and how they relate to sustainable development. The research methods used for this study are presented in the following section. After that, the research's main findings were presented. And finally, the conclusion rounds out the research.

Literature Review

Artificial Intelligence and Sustainable Development

Artificial intelligence (AI) has emerged as a dominant force for accelerating progress toward sustainable development through boosting productivity, improving resource allocation and enabling data-driven decision-making. The role of AI in achieving a carbon-neutral economy in emerging economies emphasizes that its effectiveness depends on technological readiness and policy alignment (Mansour, M., et al., 2026). Recent studies also confirm that AI can contribute to environmental sustainability (Toderas, M., 2025). Therefore, the need to implement Sustainable Development Goals (SDGs), which are of concern to economists, is highlighted by the continuous population growth compared to limited resources. Sustainable development is a multidimensional concept, encompassing economic, social, environmental and institutional dimensions each measured by quantitative indicators that reflect the level of developmental progress. Figure (1) illustrates the main dimensions of sustainable development.

Figure (1) illustrates the sustainable development pillars.



Source: made by the researcher.

The main dimensions of sustainable development, as illustrated in Figure (1), are economic, social, environmental and institutional. These dimensions encompass 17 goals and 169 targets, covering a wide range of sustainable development issues in accordance with the 2030 Agenda for Sustainable Development. At the economic level, the Gross National Income (GNI) is used as a primary measure of economic well-being and per capita income, reflecting productive capacity and living standards. The social dimension is measured by the Human Development Index (HDI), a composite index that combines health (life expectancy), education, and income levels, providing a comprehensive assessment of human well-being that goes beyond purely economic indicators. Regarding the environmental dimension, carbon dioxide (CO_2) emissions are used as a key indicator to measure the environmental impact of economic activity, the pressure on natural resources, and the limits of environmental sustainability, as high emissions are linked to environmental degradation and climate change (Hickel, J., 2020). Finally, the institutional dimension is measured by the World Governance Indicators (WGI), which reflect the quality of institutions in terms of government effectiveness, rule of law, regulatory quality and anti-corruption efforts which are critical elements for ensuring inclusive and stable sustainable development (World Bank, 2025).

Digital Transformation and Sustainable Development

Digital transformation plays a vital role in reshaping economic structures and enabling sustainable development pathways. It facilitates innovation and improves access to services. An exploration of organizational factors indicates that the outcomes of digital transformation depend primarily on the readiness of institutions (Michelotto, F., et al., 2024). This suggests that digital transformation alone may not directly translate into improved sustainable outcomes without complementary conditions.

Previous studies have highlighted how artificial intelligence enhances sustainable outcomes by improving decision-making, predictive environmental management, and optimal resource allocation (Vinuesa et al., 2020; Abdeldjalil et al., 2024). Table (1) below summarizes the relevant literature, including the variables used, methodology, and main findings of each study.

Table 1. Summary of Literature Review

Author(s) & Year	Variables Used	Methodology / Sample	Main Findings
Acheampong, Alex O. (2018)	Energy consumption, GDP, population growth	Panel VAR (sub-Saharan Africa)	Energy use and economic growth increase emissions; population growth contributes to environmental pressure.
Dong, Kangyin et al. (2018)	Trade openness, GDP, energy consumption	Panel data (global sample)	Trade openness affects emissions through scale and technique effects; GDP and energy remain dominant drivers.
Ibrahim, Mustapha & Ajide, Kazeem (2021)	ICT, governance, CO_2 emissions	Panel data (African countries)	ICT development reduces emissions when supported by strong governance; highlights importance of institutional quality.
Zhang, Y. et al. (2022)	GDP growth, industrialization, energy use, urbanization	Panel ARDL (developing countries)	Industrialization and energy consumption strongly increase CO_2 emissions; economic growth and urbanization reinforce environmental degradation.
Wei, Yifang et al. (2026)	GDP per capita, urbanization, digital technology, circular economy, public management, CO_2 emissions	Panel data (E-7 emerging economies, 2000–2023), panel quantile regression	Digital technology and circular economy significantly reduce CO_2 emissions, while GDP and urbanization increase emissions; governance (public management) strengthens the environmental benefits of digitalization.
Gafsi, Nesrine et al. (2026)	AI readiness, FinTech adoption, blockchain activity, macroeconomic controls, sustainable development (SDG index)	Panel data (G20 countries, 2015–2023)	AI, FinTech, and blockchain have positive and significant effects on sustainable development, with strong complementarities; coordinated digital adoption enhances sustainability outcomes.

Source: made by the researcher using various databases

Previous studies review the literature that addressed the relationship between economic activity and sustainable development from multiple perspectives, focusing on the determinants of carbon emissions and the role of technology and institutions in mitigating their effects. In this context, the study by Acheampong (2018) focused on the relationship between energy consumption, economic growth, and population growth in sub-Saharan Africa. It concluded that both energy consumption and economic growth contribute to increased emissions, with population growth playing an additional role in exacerbating environmental pressures. Similarly, the study by Dong et al. (2018) highlighted the importance of trade liberalization, demonstrating that its impact on emissions is mediated by scale and technology, while GDP and energy consumption remain the primary determinants of emissions. The study by Ibrahim & Ajide (2021) showed that information and communication technologies can contribute to reduction of emissions only with strong institutions, thus emphasizing the crucial role of good governance. The study by Zhang et al. (2022) also emphasized this point. Industrialization, energy consumption, and urbanization are among the main factors exacerbating environmental degradation in developing countries, reinforcing the hypothesis that traditional growth paths are associated with high environmental costs.

Although previous literature has often discussed digital innovation and sustainability as distinct phenomena, the study of Atieh et al. (2026) shows the overlap of the phenomenon, in which technological capabilities can be translated into sustainability performance. Recent studies have focused on the role of digital transformation and advanced technologies. Wei et al. (2026) demonstrated that digital technology and the circular economy contribute to reducing carbon dioxide emissions, with this effect being enhanced by improved public governance. Gafsi et al. (2026) also concluded that artificial intelligence, financial technology and blockchain technologies have a significant positive impact on achieving the SDGs, especially when adopted in an integrated manner.

Despite this diversity, the literature reveals a clear research gap: most studies have focused either on the environmental dimension (emissions) or on the role of technology in isolation, without providing an integrated framework that links artificial intelligence and digital transformation, on the one hand, and the four dimensions of sustainable development, on the other, particularly in the context of emerging economies. Therefore, the contribution of the current research is to bridge this gap by providing comprehensive cross-sectional evidence analysis from 25 emerging economies integrating technological, economic, environmental and institutional variables. Also, understanding of the role of digital transformation and artificial intelligence as key drivers for achieving sustainable development.

Research Methodology

Model Specification

To examine the impact of AI and DT on sustainable development, this study employs a cross-sectional Ordinary Least Squares (OLS) regression model using data for 25 emerging economies according to available data for the year 2023. The empirical model is specified as follows:

$$\mathrm{LNSD}_{it} = \beta_0 + \beta_1 \mathrm{AI}_{it} + \beta_2 \mathrm{DT}_{it} + \beta_3 \mathrm{GDP}_{it} + \beta_4 \mathrm{Energy}_{it} + \beta_5 \mathrm{GOV}_{it} + \beta_6 \mathrm{TRADE}_{it} + \varepsilon_{it}$$

Where LNSD_{it} represents the logarithmic transformation of Sustainable Development Indicator,
AI_{it} represents Artificial Intelligence Indicator,
DT_{it} represents Digital Transformation Indicator,
GDP_{it} represents Gross Domestic Product per capita indicator,
Energy_{it} represents Energy use (kg of oil equivalent per capita),
GOV_{it} represents Governance quality, captured by government effectiveness (GOV_EFF),
TRADE_{it} represents Trade Openness,
α, β represent the variable coefficients,
ε represents the error term.

Hypothesis of the study

Considering previous literature and the identified research gap, the research hypothesis can be formulated as follows:

Main Hypothesis (H1)

Artificial intelligence and digital transformation contribute positively and significantly to promoting sustainable development in its four dimensions (economic, social, environmental and institutional) in emerging economies.

Data Description

The following table (2) defines the variables used in the study, including their units of measurement adopted for each indicator. It also lists the data sources used, which were obtained from reliable international databases to ensure the accuracy and comparability of the results.

Table 2. Description of the study variables and data sources.

Variable	Description	Data source
Sustainable Development, proxied by per capita CO_2 emissions (log)	Using the log-transformed value of per capita CO_2 emissions allows to reduce scale differences between variables, prevent heteroscedasticity, and identify elasticities. It is considered a global indicator for sustainable development. Indexed by Carbon dioxide (CO2) emissions excluding LULUCF per capita (t CO2e/capita).	World Bank
AI Preparedness Index (AI)	AI Preparedness Index (AIPI) assesses the level of AI preparedness across 174 countries, based on a rich set of macro-structural indicators.	International Monetary Fund (IMF)
Digital Transformation (DT)	Digital transformation is the integration of digital technology into all areas of a business, fundamentally changing how you operate and deliver value to customers.	World Bank
GDP per Capita	is the total value of a country's finished goods and services (gross domestic product) divided by its total population (per capita). Gross domestic product per capita is often used as a proxy of a country's standard of living.	World Bank
Energy use (kg of oil equivalent per capita)	measures the average annual primary energy consumption per person, standardized to the energy content of 1 kg of crude oil. It indicates development levels, with high-income countries often using five times more energy per capita than low-income countries.	World Bank
Government Effectiveness (GOV_EFF)	An index of the six indicators of good governance. Including: Voice and Accountability, Political Stability, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption. This index was selected to reflect governance performance diversity	World Bank
Trade Openness	measures an economy's involvement in global trade, defined by the sum of exports and imports as a percentage of GDP.	World Bank

Source: Prepared by the researcher, using various databases.

The following table (3) presents the descriptive statistics for the study variables, including arithmetic means, standard deviations, and minimum and maximum values. These statistics aim to provide an initial overview of the data characteristics and distribution, supporting an understanding of the nature of the variables before proceeding with the econometric analysis.

Table 3. Descriptive Statistics.

	LNSD	AI	DT	GDP	ENERGY_USE	GOV_EFF	TRADE
Mean	1.384538	0.536446	0.743750	1.826981	1824.337	0.156022	71.36159
Median	1.354873	0.533881	0.750000	2.043855	1840.801	0.047914	63.20230
Max	2.222489	0.646222	0.900000	8.230531	3509.348	1.114011	158.3857
Min	0.573017	0.394054	0.600000	-2.137035	754.1796	-0.546764	26.67695
Std. Dev.	0.500260	0.064524	0.109354	2.823586	771.3212	0.477217	40.44195
Skewness	0.099831	-0.173592	0.006170	0.593538	0.485522	0.359528	0.871564
Kurtosis	1.997169	2.893447	1.770727	2.768455	2.650288	2.048572	2.515633
Jarque-Bera	0.697023	0.087927	1.007510	0.975176	0.710150	0.948172	2.182072
Probability	0.705738	0.956989	0.604257	0.614106	0.701121	0.622454	0.335868
Sum	22.15261	8.583141	11.90000	29.23169	29189.39	2.496358	1141.785
Sum Sq. Dev.	3.753902	0.062449	0.179375	119.5896	8924047.	3.416043	24533.28
Obs.	16	16	16	16	16	16	16

Source: Prepared by the researcher, using EViews Statistical Package.

Table (3) represents the descriptive statistics of the variables employed in the analysis for a sample of 16 emerging economies in the year 2023. Overall, the data exhibits moderate variability with no significant departures from normality, making it suitable for econometric analyses. The dependent variable (LNSD) has a mean of 1.385 and a median of 1.355, indicating a symmetric distribution, supported by low skewness (0.099) and near-normal kurtosis (1.997). Key explanatory variables, AI and DT, show low variability, while GDP per capita has high dispersion and positive skewness (0.594), indicative of income inequality in emerging economies. Energy use also varies significantly, suggesting differing consumption patterns across countries. Governance effectiveness demonstrates moderate dispersion, reflecting governance performance diversity. Trade openness has notable variability and positive skewness (0.872), showing some countries are much more trade open than others. Jarque–Bera tests affirm normality across variables, solidifying the model's reliability. Overall, the analysis highlights moderate cross-country heterogeneity, stable distributions for AI and DT, and no major normality violations. These characteristics collectively support the robustness of the empirical model and provide a solid foundation for further econometric investigation.

Diagnostic Tests

To ensure the validity and reliability of the estimated model, several post-estimation diagnostic tests are conducted.

Multicollinearity (VIF)

Multicollinearity among explanatory variables is assessed using the Variance Inflation Factor (VIF). VIF (Variance Inflation Factor) detects multicollinearity, which inflates coefficient variances, making estimates unreliable. High multicollinearity can inflate standard errors and weaken the statistical significance of coefficients. A Centered VIF > 10 generally indicates severe multicollinearity, while values 5–10 suggest potential issues. According to (A.1) in the appendix, the outcomes indicate that all VIF values fall within acceptable thresholds: VIF < 5: Excellent, VIF between 5 and 10: Acceptable. This suggests that multicollinearity is not a serious concern in the model, and the estimated coefficients are stable and reliable.

Heteroskedasticity

The study employs Ordinary Least Squares (OLS) regression with heteroskedasticity-consistent (Breusch–Pagan Test) standard errors to account for cross-sectional variance. The presence of heteroskedasticity is examined using the Breusch–Pagan–Godfrey test. The null hypothesis of homoskedasticity (constant variance of residuals) cannot be rejected, as the reported p-values exceed 0.05. Meaning that, if p-value < 0.05 → heteroskedasticity exists. According to (A.2), p-value > 0.05, meaning that there is no heteroskedasticity. This indicates that the error terms are homoskedastic, and the variance of residuals is constant across observations. Nevertheless, robust standard errors are retained to enhance the reliability of inference.

Normality Test (Jarque-Bera)

The normality of residuals is evaluated using the Jarque–Bera test. The results according to (A.3) in the appendix show that the p-value is greater than 0.05, implying that the null hypothesis of normal distribution cannot be rejected. This confirms that the residuals are approximately normally distributed, supporting the validity of hypothesis testing, particularly given the relatively small sample size.

Model specification (Ramsey RESET)

To assess the accuracy of the functional form, the Ramsey RESET test is employed. The test yields a p-value less than 0.05, indicating rejection of the null hypothesis of correct model specification. According to (A.4) in the appendix, the result suggests the potential presence of omitted variables or nonlinear relationships not captured by the current model. While the baseline specification provides useful insights, this finding implies that the model may benefit from further refinement, such as incorporating additional explanatory variables or nonlinear terms.

Results

The diagnostic outcomes provide important context for interpreting the regression findings. The absence of multicollinearity ensures that the estimated effects of AI, DT, and control variables are independently identifiable. The lack of heteroskedasticity confirms that the reported standard errors and significance levels are reliable. The normal distribution of residuals strengthens the validity of statistical inference. However, the RESET test result ($p < 0.05$) indicates potential model misspecification, which helps explain any unexpected signs or statistically insignificant relationships observed in the results section. Overall, the econometric approach provides a reliable basis for inference, with minor scope for model improvement.

Table (4) represents the outcomes of the regression (OLS) using EViews statistical package.

Table 4. Regression (Least Squares)

Variable	Coefficient	Std. Error	t-Statistics	Prob.
AI	0.598155	2.786487	0.214663	0.8348
DT	-0.718163	1.045175	-0.687123	0.5093
GDP_PER_CAPITA	0.015849	0.038763	0.408865	0.6922
ENERGY_USE	0.000692	0.000196	3.527149	0.0064
GOV_EFF	-0.194448	0.218517	-0.889852	0.3967
TRADE	-0.000851	0.002222	-0.383242	0.7104
C	0.396839	0.912669	0.434812	0.6739

R-squared 0.843176	Adjusted R-squared 0.738626	S.E. of regression 0.255757
F-statistic 8.064847	Prob(F-statistic) 0.003256	Mean dependent var 1.384538
S.D. dependent var 0.500260	Hannan-Quinn criter. 0.427763	Durbin-Watson stat 2.590475

Source: Prepared by the researcher, using EViews Statistical Package.

The results as shown in table (4) derived from the cross-sectional estimation of the outcomes of 25 emerging economies in the year 2023, highlighted the relationship between AI, DT, and sustainable development, proxied by per capita CO_2 emissions (log-transformed). The model demonstrates strong overall explanatory power, as indicated by an R-squared of 0.843 and an adjusted R-squared of 0.739, indicating that approximately 74 percent of the variation in emissions across the sampled emerging economies is captured by the explanatory variables. The F-statistic (F = 8.065, p = 0.0033) confirms the joint significance of the repressors and the overall robustness of the model.

The results show a statistical divergence; while AI Index exhibits a positive coefficient (β = 0.598), indicating a potential positive association with sustainable development proxied by per capita CO_2 emissions (log-transformed); however, this effect is statistically insignificant (p = 0.835). The Digital Transformation index (DT) shows a negative coefficient (β = -0.718, p = 0.509). This suggests that the initial stages of digital expansion may require infrastructure-heavy costs that temporarily offset sustainability gains (Kunkel S, Tyfield D, 2021). This finding is consistent with recent evidence suggesting that digital technologies require complementary conditions, such as governance and energy transition; to produce measurable sustainability gains (Gafsi, Nesrine et al., 2026; Ibrahim, Mustapha & Ajide, Kazeem, 2021).

Among the control variables, energy consumption emerges as the only statistically significant determinant of CO_2 emissions. The positive coefficient, significant at the 5-percentage level, confirms that higher energy use is associated with increased emissions, consistent with a large body of literature identifying energy consumption as the primary driver of environmental degradation (Stern, David I., 2010; Shahbaz, Muhammad et al., 2016; Acheampong, Alex O., 2018). This result underscores the vital role of energy structure and consumption patterns in shaping environmental outcomes in emerging economies.

GDP per capita (β = 0.016, p = 0.693) does not exhibit a statistically significant effect on emissions, which may reflect the heterogeneity of development stages across the sampled countries. Related studies' findings regarding emerging economies also reveal mixed or insignificant effects due to structural differences (Khan, S., et al., 2020). Similarly, trade openness displays negative but statistically insignificant coefficient (β = -0.00085, p = 0.710), indicating that while these factors may contribute to environmental improvements, their effects are not robust within the current specification. This is consistent with prior studies showing that trade can exert both scale and technique effects on emissions (Dong, K., et al., 2018).

Governance quality, captured by government effectiveness (GOV_EFF), shows a negative but non-significant association (β = -0.194, p = 0.397), indicating the limited impact of government effectiveness may reflect variations in policy enforcement across emerging economies, where institutional effectiveness plays a critical role in translating rules and regulations into environmental outcomes (Ibrahim, Mustapha & Ajide, Kazeem, 2021).

The Durbin-Watson statistic (DW = 2.590) suggests no evidence of positive autocorrelation among residuals, supporting the reliability of coefficient estimates. The standard error of regression (S.E. = 0.256) indicates reasonably precise estimates given the variation in the dependent variable (SD = 0.500).

Discussion

While the model is statistically robust, the results reveal that energy use is the primary significant driver among the tested variables. Other variables, including AI readiness, digital transformation, governance, GDP per capita, and trade openness, appear to have statistically non-significant impacts in the cross-sectional sample. The effectiveness of digital technologies in promoting sustainability is conditional, requiring an approach that aligns DT with energy transition and governance to achieve SDGs, aligned with recent studies (Balsalobre-Lorente, D., et al., 2020; Bekun, Festus V. et al., 2019).

Conclusion

This study addresses the main question: Does adopting AI and DT contribute to achieving sustainable development in emerging economies? The findings suggest that the integration of AI and DT can lower marginal costs and effectively enhance greater developmental impact across economic, social, environmental and institutional pillars.

While the study offers vital contributions to the growing literature on digitalization and sustainability, exploring the extent of AI and DT to achieve Sustainable Development in the emerging economies, which open paths for future research. First, the empirical analysis is based on aggregate country-level data, which may limit the ability to capture sector-specific variations. Accordingly, future studies are encouraged to extend the analysis to industry-level or firm-level data to enhance the generalizability of the findings. Second, although this research adopts an integrated framework combining AI, DT, and sustainable development, the measurement of AI readiness and sustainability indicators remains subject to data constraints, suggesting the need for more refined and comprehensive indicators in future work.

Recommendations

This study suggests that effective implementation of AI and DT for sustainable development in emerging economies requires all-inclusive approach that harmonizes infrastructure investment, human capital development, good governance, and inclusive and green policy design. This can be achieved through the following key points:

1. Implement a Priority-Based Digital Transformation Strategy through prioritizing high-impact sectors (e.g., agriculture, healthcare, education, energy) and adopt cost-effective technologies (digital platforms e.g., mobile-based platforms, cloud services) as a primary channel for digital inclusion.
2. Upgrade Existing Infrastructure tailored to national requirements through guaranteeing reliable access to electricity, internet connectivity, and data systems.
3. Develop initial data governance frameworks before scaling AI solutions.
4. Prioritize practical digital skills training through enhancing technical and vocational education aligned with digital labor markets.
5. Build Adaptive and Flexible Regulatory Frameworks that can develop enforceable guidelines for data protection and AI ethics and avoid complexity that may hinder innovation.
6. Support SMEs as Drivers of Digital Adoption through financial incentives, microfinance, and Facilitate access to digital platforms and e-commerce ecosystems.
7. Promote Inclusive Access to Digital Technologies by targeting rural communities and addressing gender digital gaps via training initiatives.
8. Align AI and DT Adoption with Environmental Priorities (e.g. AI applications in climate adaptation, water management, and sustainable agriculture). Integrate sustainability criteria into digital investment decisions by encouraging low-energy and green digital solutions.
9. Maximize Cooperation of International Partnerships through participating in regional digital frameworks to exchange knowledge and resources.

Appendix

A.1 Multicollinearity (VIF)

Sample: 1 25
Included observations: 16

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
AI	7.764509	553.9667	7.412891
DT	1.092390	150.8037	2.995615
GDP_PER_CAPITA	0.001503	3.973875	2.747092
ENERGY_USE	3.85E-08	36.62505	5.256806
GOV_EFF	0.047750	2.777994	2.493672
TRADE	4.94E-06	7.998698	1.851041
C	0.832964	203.7476	NA

A.2 Breusch–Pagan–Godfrey test

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

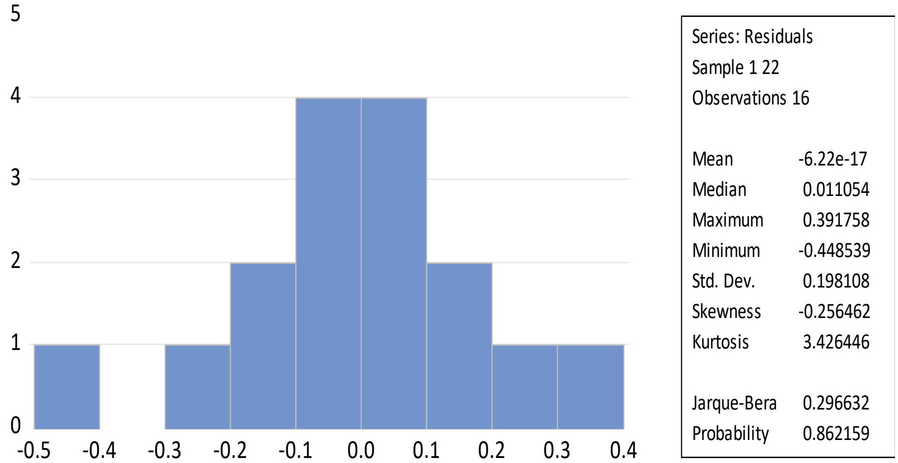
F-statistic	0.384517	Prob. F(6,9)	0.8714
Obs*R-squared	3.264644	Prob. Chi-Square(6)	0.7750
Scaled explained SS	1.253203	Prob. Chi-Square(6)	0.9742

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample: 1 22
Included observations: 16

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000368	0.243294	-0.001511	0.9988
AI	-0.098435	0.742807	-0.132517	0.8975
DT	0.073497	0.278617	0.263792	0.7979
GDP_PER_CAPITA	0.000224	0.010333	0.021660	0.9832
ENERGY_USE	3.09E-05	5.23E-05	0.590407	0.5694
GOV_EFF	-0.051487	0.058251	-0.883886	0.3998
TRADE	-0.000188	0.000592	-0.317880	0.7578

R-squared	0.204040	Mean dependent var	0.036794
Adjusted R-squared	-0.326600	S.D. dependent var	0.059194
S.E. of regression	0.068178	Akaike info criterion	-2.233747
Sum squared resid	0.041834	Schwarz criterion	-1.895739
Log likelihood	24.86997	Hannan-Quinn criter.	-2.216438
F-statistic	0.384517	Durbin-Watson stat	2.427949
Prob(F-statistic)	0.871406		

A.3 Normality (Jarque-Bera)



A.4 Ramsey RESET Test

Ramsey RESET Test
Equation: UNTITLED
Omitted Variables: Squares of fitted values
Specification: LNSD AI DT GDP_PER_CAPITA ENERGY_USE GOV_EFF TRADE C

	Value	df	Probability
t-statistic	1.720615	8	0.1236
F-statistic	2.960515	(1, 8)	0.1236
Likelihood ratio	5.037724	1	0.0248

F-test summary:

	Sum of Sq.	df	Mean Squares
Test SSR	0.159013	1	0.159013
Restricted SSR	0.588703	9	0.065411
Unrestricted SSR	0.429690	8	0.053711

LR test summary:

	Value
Restricted LogL	3.716363
Unrestricted LogL	6.235225

Unrestricted Test Equation:
Dependent Variable: LNSD
Method: Least Squares
Sample: 1 22
Included observations: 16

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AI	2.721958	2.810557	0.968476	0.3612
DT	-3.366903	1.807426	-1.862816	0.0995
GDP_PER_CAPITA	0.032545	0.036441	0.893093	0.3979
ENERGY_USE	0.002173	0.000879	2.472845	0.0385
GOV_EFF	-0.405530	0.232935	-1.740960	0.1199
TRADE	-0.003662	0.002592	-1.412573	0.1955
C	0.306929	0.828675	0.370386	0.7207
FITTED^2	-0.746104	0.433626	-1.720615	0.1236

R-squared	0.885535	Mean dependent var	1.384538
Adjusted R-squared	0.785378	S.D. dependent var	0.500260
S.E. of regression	0.231757	Akaike info criterion	0.220597
Sum squared resid	0.429690	Schwarz criterion	0.606891
Log likelihood	6.235225	Hannan-Quinn criter.	0.240378
F-statistic	8.841491	Durbin-Watson stat	2.290822
Prob(F-statistic)	0.003170		

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