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Dynamics of Digitalisation and Energy Efficiency in Developing Countries: An Empirical Analysis

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Dynamics of Digitalisation and Energy Efficiency in Developing Countries: An Empirical Analysis

Iqra Mushtaq and Abre-Rehmat Qurat-ul-Ann[*]

ABSTRACT

This study examines the impact of digitalisation on energy and environmental efficiency in developing countries using panel data from 2010 to 2020. Energy efficiency is measured by Energy Intensity per unit of output, while Environmental Efficiency is assessed through CO_2 *emissions per economic output. The two-step system Generalised Method of Moments (GMM) estimates reveal that all proxies of digitalisation, except telephone subscriptions, have a negative effect on energy intensity, leading to improved energy efficiency. The findings indicate a distinct difference in the impact of digitalisation on energy intensity and carbon emission intensity. While developing countries benefit from digitalisation in achieving environmental efficiency, they still require targeted efforts to enhance energy efficiency and achieve the United Nations Sustainable Development Goals. This study provides valuable insights into promoting digital transformation, particularly in the energy sector, where developing countries face challenges in accelerating the impact of digitalisation.*

Keywords: Digitalisation, Energy Efficiency, Environmental Efficiency, Carbon Emissions Efficiency, Renewable Energy Consumption, Generalised Method of Moments, Developing Countries.

JEL Classification Code: O13; O31; O33; P18; P28; P33; Q21

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1. INTRODUCTION

Digitalisation integrates digital technologies and data-driven approaches into various aspects of business operations and processes (Baidya et al., 2021). It incorporates the use of digital technologies, including Internet of Things (IoT), big data analytics, Artificial Intelligence (AI), cloud computing, and automation, to optimise energy systems, enhance efficacy, and improve decision-making (IEA 2020). As far as the energy sector is concerned, digitalisation facilitates using digital technologies, data analytics, and advanced communication to transform how energy is generated, transmitted, distributed, and consumed (Avom et al., 2020).

Digital technologies allow optimisation of energy infrastructure using real-time monitoring and control capabilities (Barbour et al., 2018). Sensors and smart metres collect data on energy generation, consumption, and grid performance, assisting operators in diagnosing faults, detecting inefficiencies, and managing energy systems effectively (Omitaomu and Niu 2021). According to IEA (2017), this optimisation improves reliability, reduces energy losses, and enhances grid management. Moreover, digitalisation allows for integrating renewable energy sources into the energy mix because real-time data analytics and advanced forecasting models efficiently manage the intermittent nature of renewable sources, including solar and wind power (Beier et al., 2018; Xiong et al., 2022). Big data analytics and AI algorithms enhance energy systems by managing excess energy storage during low-demand periods and ensuring efficient distribution during peak hours. Consequently, digitalisation strengthens grid stability and improves reliability of energy systems (Barbour et al., 2018).

Additionally, digitalisation aids efficient electrification in various sectors, including building and transportation, leading toward reduced carbon emissions (Monteiro et al., 2018). Smart buildings, electric vehicles and intelligent transportation systems would be possible only by adopting digital technologies (Foley et al., 2010; Teng et al., 2021). Furthermore, digitalisation allows for efficiency improvements as smart energy management systems and demand response programmes empower consumers to monitor and manage their energy consumption more effectively (Tan et al., 2021). Digitalisation promotes behavioural changes and allows for more efficient energy consumption by providing insights into energy usage patterns, resulting in energy savings and reduced carbon emissions (Wen et al., 2021). According to the United Nations (UN), digitalisation is crucial for achieving the Sustainable Development Goals (SDGs) (UN DESA 2019). Literature further strengthens the potential of digitalisation in promoting data-driven decision-making (Czernich et al., 2011).

1.1 Background and Rationale

Energy security has become a serious concern for the world, particularly for developing countries striving to achieve SDGs, specifically SDG7 (Ha 2022). Digitalisation brings an opportunity to optimise energy systems, improve efficacy, and ensure the reliability and resilience of energy infrastructure (Gasser 2020). According to the IEA, digitalisation has been transforming the global energy landscape, playing a fundamental role in achieving energy security using various methods (IEA 2017). The operational understanding of these methods is essential for policymakers and energy operators to develop effective strategies that ensure the resilience and reliability of energy systems. Therefore, understanding the relationship between digitalisation and energy security is crucial for developing countries as it could help them to plan effective strategies to address challenges towards energy transition. Digitalisation affects energy security in the following ways:

First, digitalisation facilitates real-time energy infrastructure monitoring and optimisation (Lang et al., 2021). Data analytics, internet-connected devices and advanced sensors allow system operators to identify vulnerabilities and enable them to respond swiftly to disruptions and enhance the resilience of an energy system. Real-time monitoring capability of the energy system strengthens energy security by reducing downtime, preventing surging failures, and ensuring stable energy generation, transmission and distribution (Diamantoulakis et al., 2015).

Second, digitalisation advocates the integration of renewable energy sources into the grid. A 2017 ITU report emphasised that digital technologies, including advanced control systems and smart grids, promote efficient coordination between renewable energy generation and energy demand. By leveraging digitalisation, energy systems can improve integration of renewables, enhance grid flexibility, and reduce dependence on traditional fossil fuel-based power generation (Lee et al., 2023). The aforementioned integration contributes toward system security by expanding energy sources and reducing exposure to price volatility and supply disruptions (Nazari and Musilek 2023).

Third, digitalisation plays an effective role in demand-side management and energy efficiency (Simion et al., 2023). By deploying smart meters, energy monitoring tools and home automation systems, consumers can participate in energy management and make informed choices regarding energy consumption patterns (Shahbaz et al., 2022). In this way, digitalisation empowers consumers to manage energy usage, reduce waste, and contribute to energy security by promoting a sustainable and balanced energy demand profile (Galperova and Mazurova 2019). With advancement in digitalisation, developing countries have experienced increased energy consumption, such as increased use of Information and Communication Technologies (ICTs), data centres, and other digital technologies (Xu et al., 2022). However, digitalisation brings opportunities for these countries to optimise energy by employing smart technologies, demand-side management strategies and energy-efficient solutions (Xiao, 2023).

Fourth, reducing carbon emissions and meeting net-zero emissions targets are a global priority in the fight against climate change (Lu et al., 2018). Digitalisation significantly reduces carbon emissions through various means, including efficient technologies, smart grids, and the integration of renewable energy sources (Chourabi et al., 2012). It enables integration of different sectors, such as industry, transportation, and buildings, into a low-carbon ecosystem (Thanh et al., 2023). Using smart grid technologies, energy management systems can connect these sectors, leading to comprehensive coordination and energy optimisation (Tan et al., 2021). In this regard, integration facilitates electrification, promotes energy-efficient practices, and supports transition to renewable energy sources, thus driving progress towards a net-zero carbon future (Simion et al., 2023). Thus, examining the relationship between digitalisation and carbon emissions in developing countries contributes to identifying effective pathways for sustainable development.

1.2 Significances and Contribution of the Study

Developing countries face serious energy security, efficiency, and carbon emissions challenges. According to International Energy Agency (IEA, 2020), about 759 million people have limited access to electricity in developing countries which signifies the challenges associated with energy security in these regions. The Global Energy Outlook 2021 report indicated that developing countries are the largest contributors to global carbon emissions due to rising energy demands and heavy reliance on fossil fuels (Newell et al., 2021). CO_2 emissions in developing economies accounted for two-thirds of global emissions in 2021 (Newell et al., 2021). Mitigating carbon emissions and reducing energy consumption requires a comprehensive approach, such as integration of renewable energy, improving energy efficiency and developing policy frameworks to promote sustainable development. Digitalisation is an emerging solution to overcome these challenges. However, limited attention has been given to the subject in developing countries.

In this regard, this study aims to examine the role of digitalisation in achieving energy efficiency and mitigating carbon emissions in developing countries. Although literature is available on digitalisation, energy efficiency, and environmental sustainability (Avom et al., 2020; Lange et al., 2020; Ren et al., 2021; Thanh et al., 2023; Lyu et al., 2023), a review highlights several gaps.

Existing literature examines the impact of digitalisation on various aspects of the energy sector separately. This study contributes to the discourse by arguing that digitalisation enhances energy security through improved efficiency and reduced carbon emissions, achieved by integrating renewable energy sources and utilising smart grids. Therefore, assessing the influence of digitalisation on the energy sector is crucial.

1.3 Research Objectives

This study peruses the following research objectives:

- Examine the impact of digitalisation on energy efficiency in developing countries.
- Estimate the effect of digitalisation on carbon emissions efficiency in developing countries.

2. DATA AND METHODOLOGY

2.1 Data

The empirical analysis employed in this study uses panel datasets of 91 developing countries spanning from 2010 to 2020. The selection criterion of countries is rooted in the availability and reliability of data. A list of developing countries is shown in Appendix A.

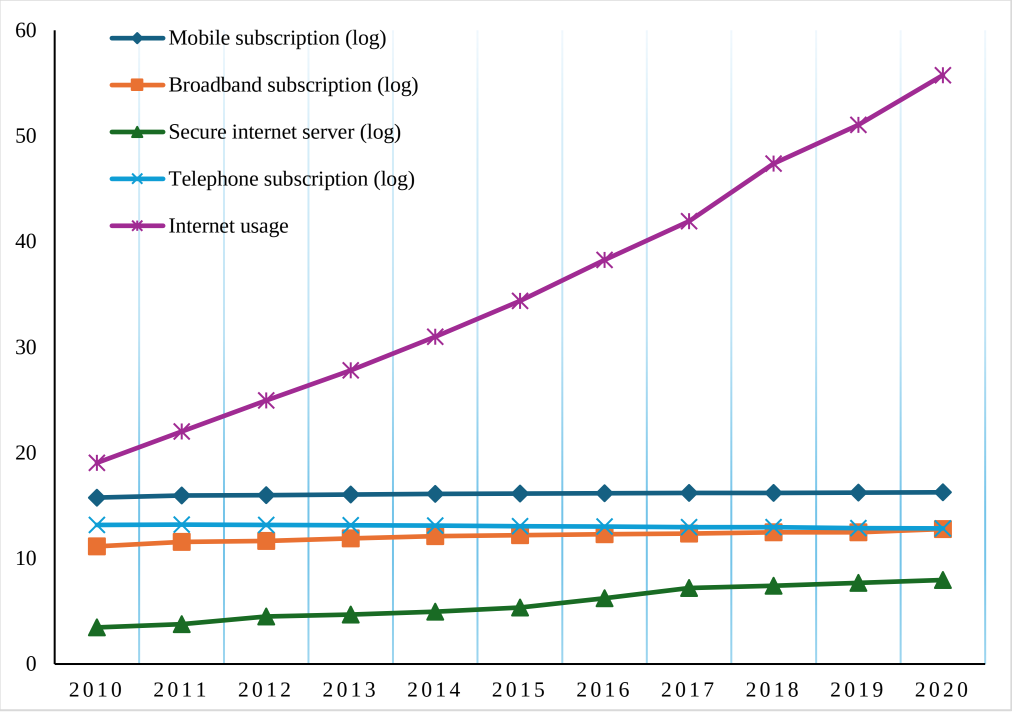
To meet the research objectives, two primary dependent variables, energy intensity and carbon emissions intensity, were employed. Carbon emissions intensity was measured using CO_2 emissions per unit of GDP, while energy intensity was measured in terms of the energy intensity level of primary energy per unit of output. These variables serve as proxies for energy and environmental efficiency, respectively, under the assumption that countries with lower values exhibit higher efficiency. Digitalisation is the core independent variable.

Literature uses different indicators to capture digital transformation. For instance, Wen et al., (2021), Beier et al., (2018), Kunkel and Matthess (2020), Higón et al., (2017) and Avom et al., (2020) use ICT as a proxy for digitalisation. Ren et al., (2021), Barrutiabengoa et al., (2022), Roller and Waverman (2001), Koutroumpis (2009) and Czernich et al., (2011) use internet development, internet penetration, mobile penetration, telephone connections and broadband connections as proxy for digitalisation. More recently, Lyu et al., (2023), Niu et al., (2022), Sultanova, Djuraeva and Turaeva (2022) used digitalisation index to measure digital transformation.

In contrast, this study opts to measure the separate effects of various indicators of digitalisation. The purpose of using separate dimensions of digital transformation is to rigorously understand which indicator will be more effective in achieving the SDGs in developing countries. Such analysis helps in directing policymakers toward making more focused and targeted policies. Thus, this study employs five indicators to capture digitalisation including mobile subscriptions, broadband subscriptions, secure internet servers, telephone subscriptions, and internet usage. These indicators are chosen because of their increasing trend as well as their capacity to capture the multifaceted nature of digitalisation penetration.

Over the past decade, developing countries have witnessed a rapid integration of digital technologies, as illustrated in Figure 1. The data reveals a steady increase in mobile subscriptions, with an average annual growth rate of 0.050. Broadband subscriptions experienced a more pronounced upward trend, averaging 0.164 annually, reflecting expanded broadband access. Notably, secure internet servers have grown at an average annual rate of 0.449, highlighting substantial advancements in digital security infrastructure. Similarly, internet usage has surged at an average annual rate of 3.67%, surpassing other digital variables, indicating a significant rise in internet penetration and connectivity across developing countries.

Figure 1: Trends of Digital Transformation in Developing Countries



Source: World Bank 2020.

In contrast, telephone subscriptions exhibit a slight decline, suggesting a shift toward digital communication methods. Including this indicator allows for a comparative analysis of the potential impact of conventional versus digital communication. Figure 1 highlights the dynamic evolution of the digital landscape in developing countries, underscoring the need to understand its implications for energy efficiency and carbon emissions. To account for other factors influencing energy efficiency, this study incorporates a set of control variables, including renewable energy consumption, terms of trade, urban population, Foreign Direct Investment (FDI), industrial structure, and Gross Domestic Product (GDP). These variables are selected based on empirical evidence suggesting their relevance and potential impact on the efficiency measures being studied including Wen et al., (2021), Barrutiabengoa et al., (2022), Thanh et al., (2023), Opoku and Boachie (2020), Shen et al., (2023), Ren et al., (2021), Niu et al., (2022) and Lyu et al., (2023). The list of variables and their description is shown in Table 1:

Table 1: List of Variables

	Variables	**Type**	**Mean**
Energy and Environment Efficiency	Energy Intensity	**Dependent Variables**	4.932
	CO_2 Emissions Per GDP		0.545
Digitalisation Proxy	Mobile Subscriptions	**Core Independent Variables**	16.095
	Broadband Subscriptions		12.081
	Secure Internet Servers		5.759
	Telephone Subscriptions		13.041
	Internet Usage		35.751
Control Variables	Renewable Energy Consumption	**Regional, Demographic & Economic Variables**	38.161
	Trade		74.167
	Urban Population		50.407
	FDI		3.3736
	Industrial Structure		0.26219
	GDP		24.115

Source: Authors' own.

2.2 Econometric Model

This study uses eight different models to examine the impact of digitalisation on energy efficiency and carbon emission efficiency in developing countries. The following econometric models were employed to estimate the above-said relationship:

$$EF_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \qquad (1)$$

$$CO2_{it} = \alpha_0 + \alpha_1 Dig_{it} + \alpha_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \qquad (2)$$

Here EF reflects energy efficiency measured through energy intensity, CO_2 emission reflects carbon emission per GDP used to measure environment efficiency, Dig refers to digitalisation. The research used five different dimensions to measure digitalisation which include mobile cellular subscription, broadband subscription, secure internet servers, internet use and telephone subscription. μ_i is an individual fixed effect, δ_t is a time-fixed effect, and ε_{it} reflects random error. X is the vector representing control variables, including GDP, FDI, trade, population growth and industrial structure.

3. RESULTS AND DISCUSSION

Equation 1 and 2 were estimated, considering eight different scenarios. Model 1 and model 5 show the direct effect of digitalisation on energy efficiency and environment efficiency, respectively. These models are restricted to digitalisation variables only as this paper tries to explore the effect of digitalisation on the energy sector by controlling the effect of regional, economic, demographic, and industrial characteristics. Models 2 and 6 are estimated by adding demographic and regional characteristics including renewable energy consumption, trade, and urban population. Models 3 and 7 allow for the inclusion of industrial specific variables in understanding the relationship between digitalisation and the energy sector. Lastly, Models 4 and 8 incorporate economic indicators to examine the role of national income in shaping the relationship between digitalisation and energy efficiency. These models are estimated using the fixed effects model. For empirical estimations, various panel data econometric techniques were applied, including Least Squares Dummy Variable (LSDV) Regression, Fixed Effects, and Random Effects models. The final selection of the Fixed Effects model across all specifications was based on the Hausman test, which confirmed its suitability.

3.1 Digitalisation and Energy Efficiency

The first objective of this study was to examine the impact of digitalisation on energy efficiency in developing countries. The dependent variable, energy intensity, served as a measure of the energy efficiency of these economies, defined as the amount of energy required to produce one unit of output. A lower energy intensity signifies greater energy efficiency, indicating that less energy is used to generate equivalent levels of economic activity.

Models 1 to 4 in Table 2 showed a negative and statistically significant effect of mobile subscriptions on energy intensity, indicating that increased mobile connectivity was substantially associated with improved energy efficiency. This relationship underlined the role of mobile technology in improving communication and optimising business processes, which contributed to more efficient energy use (Simion et al., 2023).

Similarly, the estimates showed negative and statistically significant effects of broadband subscriptions on energy intensity, demonstrating the significance of broadband access in improving energy efficiency.

Table 2: Empirical Results of Fixed Effect Model

	Model 1	**Model 2**	**Model 3**	**Model 4**
Mobile Subscriptions	-0.315*** (-3.23)	-0.371*** (-3.51)	-0.364*** (-3.46)	-0.366*** (-3.47)
Broadband Subscriptions	-0.059* (-1.94)	-0.0791*** (-2.66)	-0.081*** (-2.74)	-0.083*** (-2.78)
Secure Internet Servers	-0.113*** (-5.47)	-0.144*** (-7.00)	-0.139*** (-6.75)	-0.139*** (-6.72)
Telephone Subscriptions	-0.093 (-1.49)	-0.110* (-1.79)	-0.112* (-1.82)	-0.109* (-1.78)
Internet Usage	0.002 (0.91)	0.0001 (0.06)	-0.001 (-0.44)	-0.001 (-0.52)
Renewable Energy Consumption		-0.029*** (-4.97)	-0.032*** (-5.36)	-0.033*** (-5.38)
Trade		0.006*** (3.40)	0.006*** (3.40)	0.007*** (3.43)
Urban population		0.062*** (3.52)	0.062*** (3.49)	0.062*** (3.50)
FDI			0.001 (0.31)	0.002 (0.704)
Industrial structure			-1.980** (-2.21)	-1.859** (-2.01)
GDP				-0.003 (-0.53)
Constant	7.13*** (0.000)	11.612*** (5.79)	12.245*** (6.06)	12.220*** (6.04)
σ_u	2.620	3.450	3.485	3.495
σ_e	0.527	0.502	0.502	0.502
ρ	0.961	0.979	0.979	0.979
F Test	186.95 P=0.000	181.05 P=0.000	180.36 P=0.000	180.20 P=0.000

Source: Authors' own.

Note: Dependent variable is energy intensity.

The negative coefficients associated with mobile and broadband subscriptions across all models align with findings by Sadorsky (2013), who found that the diffusion of ICT is instrumental in reducing energy consumption in both developed and developing countries. The negative and significant effect of secure internet servers on energy highlights the role of digital security and data integrity in energy efficiency. Table 2 shows that the increase of secure internet servers reduces energy intensity per unit of output which is in line with Wu et al., (2021) and Ren et al., (2021), indicating that internet adoption in energy systems leads to substantial energy savings. An efficient energy system strengthens the ability to monitor and regulate energy flows in smart grids and other intelligent infrastructure, resulting in low system losses (Ishida 2015).

The coefficient of telephone subscriptions in Models 2 to 4 showed a negative effect on energy intensity. However, this effect was relatively small compared to other indicators, suggesting that traditional telephony had a less direct or influential role in energy efficiency compared to digital connectivity (Shahbaz et al., 2022). Nevertheless, the insignificant coefficient of internet use implied that the internet itself was not as crucial for energy efficiency as the supporting infrastructure and services, such as mobile and broadband subscriptions, and secure servers, that facilitate and secure internet access.

The inclusion of economic and demographic variables in Models 2 to 4 revealed that renewable energy consumption had a negative and statistically significant effect on energy intensity, highlighting the critical role of clean energy in reducing the energy required for production. This finding aligned with global efforts to transition toward more sustainable and less carbon-intensive energy sources (Thanh et al., 2023).

The coefficient of urban population showed a positive and significant relationship with energy intensity, suggesting that higher levels of urbanisation were associated with increased energy use per unit of output. This could have reflected the complex dynamics of urban areas, where intensified economic activities and potential inefficiencies in infrastructure might have led to higher energy consumption (Ren et al., 2021). The inclusion of industrial structure in Model 3 showed a negative and significant effect on energy efficiency. These results were consistent with Thanh et al., (2023).

3.2 Digitalisation and Environmental Efficiency

The second objective of this study was to examine the impact of digitalisation on carbon emission efficiency. Models 5 to 8 showed the relationship between digital transformation and carbon intensity. Contrary to the findings of Models 1 to 4, Models 5 to 8 depicted an insignificant effect of digitalisation on carbon emission intensity, except when digital transformation was measured using secure servers (see Table 3).

The coefficient of mobile subscriptions showed a statistically insignificant effect on carbon intensity in Models 4 to 7. However, with the inclusion of GDP in Model 8, the positive and statistically significant coefficient of mobile subscriptions revealed that an increase in mobile use raised the demand for carbon-intensive energy technologies, further increasing carbon emissions.

Table 3: Empirical Results of Fixed Effect Model

	Model 5	Model 6	Model 7	Model 8
Mobile Subscriptions	0.082 (4.88)	0.019 (1.30)	0.020 (1.36)	0.044*** (2.74)
Broadband Subscriptions	0.007 (0.136)	-0.004 (-1.06)	-0.005 (-1.16)	-0.002 (-0.40)
Secure Internet Servers	-0.023*** (-6.61)	-0.029*** (-9.99)	-0.028*** (-9.59)	-0.025*** (-8.10)
Telephone Subscriptions	0.002 (0.24)	-0.010 (-1.18)	-0.010 (-1.23)	-0.009 (-1.07)
Internet Usage	0.0004 (1.06)	-0.002 (-0.74)	-0.004 (-1.19)	-0.001 (-0.42)
Renewable Energy Consumption		-0.012*** (-14.37)	-0.012*** (-14.30)	-0.0131*** (-14.83)
Trade		0.007*** (2.58)	0.006** (2.22)	0.0006** (2.48)
Urban Population		0.015*** (6.05)	0.015*** (6.07)	0.017*** (6.88)
FDI			0.002** (2.54)	0.001** (2.29)
Industrial Structural			-0.219* (-1.69)	0.015 (0.11)
GDP				-0.164*** (-4.05)
Constant	-0.790*** (-2.59)	0.227 (0.78)	0.294 (1.01)	3.608*** (4.16)
σ_u	0.383	0.503	0.503	0.572
σ_e	0.091	0.072	0.072	0.072
ρ	0.946	0.979	0.979	0.984
F Test	147.26 P = 0.000	175.35 P= 0.000	176.01 P=0.000	153.52 P= 0.000

Source: Authors' own.

Note: Dependent variable is carbon emission intensity.

Table 3 shows that the negative and significant coefficient of secure internet servers across all models (Models 5-8) indicated that secure internet servers contributed to reducing carbon intensity, implying an improvement in carbon emission efficiency. These results were consistent with Wen et al. (2021). The findings reflected the role of secure digital services in enabling energy-efficient practices and innovations (Wen et al., 2021; Shahbaz et al., 2022). Secure internet servers facilitate the development of smart grids and other intelligent energy management systems, which optimise energy consumption by ensuring that power is used more efficiently and by minimising waste. For example, secure servers are integral to demand-response systems, which adjust energy use in real time based on current supply and demand conditions. This results in lower overall energy use and, consequently, reduced carbon emissions (Li et al., 2020).

The negative and significant effect of renewable energy consumption on carbon emission intensity in Models 6 to 8 signifies the role renewable energy in enhancing carbon emission efficiency in developing countries. In contrast, a positive and significant coefficient of trade in Models 7 and 8 suggests that increase in trade volume increases carbon intensity by urging nations to use energy intensive technologies which potentially reduce environmental efficiency. Urban population showed a positive and statistically significant effect on carbon intensity, showing that higher levels of urbanisation lead to reduced carbon emissions efficiency. With the increase in urban population, demand for energy consumption increases that contributes to emissions in urban areas, driven by factors such as transportation, heating, and cooling demands. Consistent with Barrutiabengoa et al. (2022), the research showed a negative and statistically significant coefficient of GDP in Model 8, indicating that higher economic output reduced carbon emissions per unit of output. This finding suggests that wealthier nations within developing countries might have achieved environmental efficiency through advanced technologies and structural changes in the economy as they grew (Opoku and Boachie 2020).

3.3 Robustness Checks

The robustness of the empirical results was ensured through diagnostic tests, including autocorrelation, heteroskedasticity, and endogeneity. These tests were applied to the final models of energy efficiency and carbon emission efficiency, as these models included all necessary factors that could have affected the relationship between digitalisation and energy efficiency. The results in Table 4 confirm the presence of autocorrelation and heteroskedasticity in Models 4 and 8. Moreover, the Durbin-Wu-Hausman test was used to assess the presence of endogenous variables in these models. The probability value of the Durbin-Wu-Hausman test rejected the null hypothesis that the variables were exogenous, indicating that the OLS estimates obtained in Models 4 and 8 were biased and inconsistent. Therefore, empirical estimations were further extended by employing the Generalised Method of Moments (GMM) to address potential endogeneity problems.

This study employed the dynamic panel estimator proposed by Arellano–Bover/Blundell–Bond (Arellano and Bover 1995; Blundell and Bond 1998). These estimators are used when the dependent variable is dynamic, independent variables are not strictly exogenous due to correlation with past or current error terms, and when autocorrelation and heteroskedasticity are present among individual and fixed effects (Roodman 2009).

The Arellano–Bover/Blundell–Bond, or system GMM, estimator is considered superior to the Arellano-Bond estimator as it extends the difference GMM estimator and introduces an additional assumption that the first difference of instrumental variables is uncorrelated with individual fixed effects (Hansen 1982). This extension enables the inclusion of more instruments and yields a system of original and transformed equations with enhanced efficiency (Baum et al., 2003).

Accordingly, this study employed the two-step system GMM because it provides greater efficiency in parameter estimation. Unlike one-step GMM estimators, which use weight matrices independent of estimated parameters, the two-step GMM estimator enhances precision by weighing moment conditions with a consistent estimate of their covariance matrix. This weight matrix was constructed using an initial consistent estimate of the parameters in the model. By incorporating this information, the two-step approach effectively utilised both moment conditions and instrumental variables, resulting in more precise parameter estimates (Blundell et al., 2001).

Table 4: Diagnostic Test

	Energy Efficiency Model	**Environmental Efficiency Model**
Wooldridge Test for Autocorrelation	92.382 (0.000)	154.798 (0.000)
Modified Wald Test for Heteroskedasticity	38450.29 (0.000)	1.0e+05 (0.000)
Durbin	3.642 (0.056)	4.922 (0.0265)
Wu-Hausman	3.606 (0.057)	4.880 (0.0274)

Source: Authors' own.

3.4 Estimates of Two-Step System GMM

The robustness test of the two-step system GMM estimator was conducted. Given that the number of instruments exceeded the potentially endogenous variables, this research employed the Sargan statistic and the robust Hansen J statistic to test the joint exogeneity of moment conditions. The validity of the over-identifying restrictions was confirmed across all estimations (Table 5).

Table 5: Empirical Results of Two step System GMM

	Model 9	**Model 10**
Variables	Coefficients	Coefficients
Mobile Subscriptions	-0.291	-0.023**
	(0.280)	(0.009)
Broadband Subscriptions	-0.285***	-0.009***
	(0.069)	(0.002)
Secure Internet Servers	-0.073***	-0.017***
	(0.014)	(0.001)
Telephone Subscriptions	0.466***	-0.038***
	(0.098)	(0.007)
Internet Usage	-0.019***	-0.0007***
	(0.003)	(0.001)
Renewable Energy Consumption	-0.016**	-0.015***
	(0.006)	(0.0007)
Trade	0.016***	0.0008***
	(0.002)	(0.0001)
Urban Population	0.414***	0.019***
	(0.049)	(0.002)
FDI	-0.006**	0.001
	(0.002)	(0.0001)
Industrial Structure	-5.160*	-0.003***
	(2.715)	(0.089)
GDP	-0.0004 ***	-0.00003***
	(0.0000)	(0.0000)
Constant	-1.054***	1.483***
	(3.596)	(0.151)
Tests		
AR (1)	0.008	0.074
AR (2)	0.803	0.515
Sargan Test for Overidentification $(prob > \chi^2)$	0.986	0.999
Hansen Test of overid. Restrictions $(prob > \chi^2)$	0.395	0.253
Difference in Hansen Test of Exogeneity$(prob > \chi^2)$	0.422	0.188
Number of Observations	958	958
Number of Groups	91	91
Number of Time Periods	11	11
Number of Instruments	48	77

Source: Authors' own.

To establish valid moment conditions, the study assumed no serial correlation in the error terms of the system GMM estimator. The Arellano-Bond test was used to assess autocorrelation, applied to the residuals in the first-difference equation (Arellano and Bond

1991). Models 9 and 10 confirmed the presence of first-order serial correlation in differences (see AR(1) in Table 5). Furthermore, the Arellano-Bond tests indicated the rejection of higher-order autocorrelation, signifying the strong performance of the estimation (see AR(2) in Table 5).

The coefficients in Model 9 revealed several significant findings. First, both Mobile Subscriptions and Broadband Subscriptions showed negative and statistically significant effects on energy intensity, indicating that increased mobile and broadband connectivity are associated with improved energy efficiency. Li et al., (2020) argued that broadband infrastructure leads toward efficient energy consumption behaviour by ensuring mechanisms such as optimisation of logistics, facilitation of remote work, and provision of real-time energy usage data. The presumed mechanism is that digitalisation facilitates more efficient energy use and optimisation of production processes, as supported by Lee et al., (2023), who argue that ICT advancements enable better monitoring and management of energy resources.

Similarly, the negative and statistically significant effect of secure internet servers on energy intensity highlights the importance of digital security and data integrity in energy efficiency. Lange et al., (2020) argued that secure digital infrastructure enables more reliable and efficient data processing and transmission, which is essential for energy management systems and smart grid technologies. Additionally, the negative coefficient associated with Renewable Energy Consumption suggests that the use of clean energy sources is critical in reducing the energy required for production, aligning with global efforts towards sustainable energy (Thanh et al., 2023).

In contrast with fixed effect estimates, telephone subscriptions show a positive effect on energy intensity, albeit relatively higher compared to other indicators, suggesting that traditional telephony reduces energy efficiency in developing countries (Shahbaz et al., 2022). Furthermore, while the coefficient of internet usage was negative and statistically significant, its magnitude is smaller compared to other infrastructure and service indicators, implying that the infrastructure and services supporting internet access, such as mobile and broadband subscriptions, are more crucial for energy efficiency.

The inclusion of economic and demographic variables revealed that urban population has a positive and significant relationship with energy intensity, indicating that higher levels of urbanisation are associated with increased energy use per unit of output. This may reflect the complexities of urban areas, where economic activities and potential infrastructure inefficiencies contribute to higher energy consumption (Ren et al., 2021). Conversely, the negative and significant effect of industrial structure on energy intensity suggests that certain industrial structures are associated with higher energy efficiency (Thanh et al., 2023).

Model 10 presents the estimates of the two-step GMM to assess the impact of digitalisation on carbon emission intensity. In contrast to previous estimates (Models 5 to 8), all digitalisation variables exhibit a negative and statistically significant effect on carbon emissions, indicating improved environmental efficiency in developing countries.

Among the various proxies for digitalisation, mobile and telephone subscriptions demonstrate a stronger effect, whereas broadband subscriptions and internet usage show a minimal impact on environmental efficiency. The deployment of mobile and telephone infrastructure often leads to advancements in energy efficiency, particularly when renewable energy sources are used to power cell towers and base stations. This reduces reliance on fossil fuels and lowers carbon emissions associated with energy production (Thanh et al., 2023).

Similarly, the expansion of mobile and telephone subscriptions enhances access to information, including weather forecasts, market prices, and traffic updates. This helps individuals and businesses plan their activities more efficiently, reducing unnecessary trips and optimising resource use, which in turn lowers carbon emissions.

Similar to the estimates from Models 5 to 8, renewable energy consumption exhibited a negative and statistically significant effect on carbon emission intensity, confirming that renewable energy consumption plays a crucial role in reducing carbon emissions in developing countries (Barrutiabengoa et al., 2022). Meanwhile, trade and urban population showed a positive and significant coefficient on carbon emissions, indicating that an increase in trade volume and urban population raises carbon intensity. This suggests that as nations expand trade and experience urban growth, they may adopt energy-intensive technologies, often compromising environmental sustainability in pursuit of economic gains.

4. CONCLUSION AND POLICY RECOMMENDATIONS

This study examined the impact of digitalisation on energy and environmental efficiency in developing countries over the period 2010 to 2020. By employing the two-step system GMM, the study shed light on the complex relationship between digitalisation and SDGs, particularly in relation to energy and environmental efficiency.

The analysis provides compelling evidence that digitalisation, characterised by increased mobile and broadband subscriptions and a secure internet infrastructure, contributes significantly to energy and environmental efficiency in developing countries. These findings suggest that digital technologies not only facilitate economic growth but also foster a pathway toward more sustainable energy use.

However, the positive and significantly larger impact of telephone subscriptions on energy intensity indicates that increased telephone connectivity led to higher energy use, potentially due to the reliance on energy-intensive sources for telecommunications infrastructure. Based on these findings, this study proposes the following recommendations to strengthen the role of digital transformation in achieving energy and environmental efficiency in developing countries:

First, enhancing the use of internet technologies within the energy sector is imperative, particularly in fostering their integration with both energy production and consumption processes. As part of the broader strategy to cultivate the digital economy, it is crucial for governments to steer the modernisation and advancement of industries with high energy demands. This involves incorporating digital economy technologies, notably secure server connections, into the evolution and modernisation of conventional manufacturing sectors. There should be a concerted effort to facilitate smart enhancement of various energy-related domains, including production, transportation, and usage, thereby facilitating refinement and betterment of the industrial framework.

Second, the relationship of secure internet servers with lower energy intensity highlights the importance of secure and reliable digital infrastructure in energy efficiency. Thus, investing in secure digital infrastructure can not only enhance data security but also contribute to the sustainable use of energy resources. Policymakers in developing countries are further suggested to expand access to broadband and mobile networks, especially with a focus on energy-efficient technologies as it enhances the efficient use of energy devices.

Third, it is imperative for governments to refine the benchmarking criteria and evaluation mechanisms for the digital transformation within businesses, while progressively enhancing and extending the legal and regulatory framework governing digital transition. Such initiatives would help developing nations invest in digital connections and clean energy to yield positive environmental dividends.

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APPENDIX A

List of Developing Countries

Burkina Faso	Cabo Verde	Nepal	Brazil	North Macedonia
Burundi	Cambodia	Nicaragua	Bulgaria	Paraguay
Central African Republic	Cameroon	Pakistan	China	Peru
Chad	Comoros	Philippines	Colombia	Russian Federation
Ethiopia	Cote d'Ivoire	Samoa	Dominica	Serbia
Gambia	Egypt, Arab Rep.	Senegal	Dominican Republic	South Africa
Madagascar	El Salvador	Solomon Islands	Ecuador	Thailand
Mali	Eswatini	Sri Lanka	Equatorial Guinea	Tonga
Niger	Ghana	Tanzania	Fiji	Türkiye
Rwanda	Honduras	Timor-Leste	Gabon	Vietnam
Togo	India	Tunisia	Georgia	Albania
Uganda	Indonesia	Ukraine	Jamaica	Moldova
Zambia	Iran, Islamic Rep.	Uzbekistan	Jordan	Montenegro
Angola	Kenya	Zimbabwe	Kazakhstan	Namibia
Algeria	Kyrgyz Republic	Argentina	Belarus	Malaysia
Bangladesh	Lao PDR	Armenia	Bosnia and Herzegovina	Mauritius
Belize	Lesotho	Azerbaijan	Botswana	Mexico
Benin	Mauritania	Bhutan	Morocco	Mongolia
Bolivia				

Note: Country classification is based on the classification system of the United Nations Development Programs (UNDP), the International Monetary Fund (IMF) and the Work Bank (WB). Countries are classified as developing countries by UNDP, which are like low-income and middle-income countries as per WB and emerging and developing economies as per IMF (A4ID 2024). The above list classifies the countries into low- and middle-income groups.