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The Impact of Digitalization on the Three Pillars of Sustainable Development: An Empirical Analysis in the Context of African Countries

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Abstract
This study investigates the impact of digitalization on the three pillars of sustainable development - economic, social, and environmental - in 48 African countries from 1999 to 2020. Using panel data analysis and ARDL models, the research reveals a bidirectional positive relationship between digitalization and economic growth in the long term, underscoring digitalization's role in driving innovation and productivity. However, no significant causal link is found between digitalization and human development, indicating that digital transformation alone cannot address social inequalities without complementary investments in education and healthcare. Digitalization also positively influences environmental quality in the long term, though restrictive environmental policies may slow digital infrastructure expansion. In the short term, digitalization's impact on sustainable development is limited, highlighting the need for sustained investment and strategic planning. The study emphasizes the importance of an integrated approach to maximize digitalization's potential for inclusive and sustainable development in Africa.

Keywords: Digitalization, Sustainable Development, Economic Growth, Environmental Quality, Human Development, Africa, Panel Data Analysis, ARDL Model, Cointegration

JEL Classification : O33, Q01, O55, C33, Q56

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1. Introduction

Digitalization, characterized by the deep integration of digital technologies into economic, social, and environmental processes, has become a transformative force globally. In Africa, digitalization holds even greater significance due to the region's unique development challenges and opportunities. While Africa's internet penetration rate has grown from 2.5% in 2000 to 43% in 2022 (ITU, 2023), significant disparities remain, with only 28% of rural populations having access compared to 63% in urban areas (World Bank, 2022). Concurrently, e-commerce in Africa has surged by 40% since 2020 (GSMA, 2024), demonstrating digitalization's potential to leapfrog traditional economic barriers. However, uneven access and infrastructure gaps risk exacerbating inequalities, making targeted policies essential. Unlike developed economies, African nations face unique constraints, such as the need to accelerate often fragile economic growth while minimizing negative environmental impacts and improving living conditions for vulnerable populations. In this context, digitalization is not merely a modernization tool but an essential mechanism for harmonizing the three pillars of sustainable development: economic growth, environmental protection, and social well-being. Economically, digital technologies can boost productivity, create jobs, and provide access to new markets, particularly in key sectors like agriculture, financial services, and telecommunications. Environmentally, digitalization supports sustainable resource management, promotes cleaner energy transitions, and enhances agricultural practices. Socially, it fosters inclusion by improving access to education, healthcare, and government services, which are critical for reducing inequalities in a region where disparities remain pronounced.

The theoretical mechanisms linking digitalization to sustainable development outcomes are rooted in three key pathways. Economically, digital technologies reduce transaction costs and foster innovation through spillover effects, enabling productivity gains and new business models (Bukht and Heeks, 2017). Socially, ICT diffusion improves human capital formation via e-learning and telemedicine, yet its impact is contingent on complementary investments in education and infrastructure (Minges, 2015). Environmentally, digitalization exhibits a dual role: smart technologies optimize resource use (e.g., IoT-enabled energy grids), while rising e-waste and energy demand from data centers pose sustainability trade-offs (Andrae and Edler, 2015). These channels underscore the need for context-specific analysis, particularly in Africa, where structural constraints may alter expected outcomes. While digital transformation reshapes economies worldwide, Africa presents a unique paradox of rapid adoption amid persistent inequalities. Recent data from the International Telecommunication Union (ITU, 2023) reveals that while continental internet penetration reached 43% in 2022 - a dramatic increase from just 2.5% in 2000 - the World Bank (2022) documents a 35-percentage-point gap between urban (63%) and rural (28%) access rates. These disparities occur alongside demonstrable economic impacts: Acemoglu and Restrepo's (2018) foundational work on automation identifies digitalization as a key driver of productivity growth, with Africa-specific studies showing 1.2% GDP gains per 10% increase in internet penetration (Qiang et al., 2009). However, as Purvis et al (2019) note, most research examines these effects in isolation, neglecting the interdependent nature of sustainable development pillars.

This study advances the digitalization-development literature in three significant ways. First, departing from conventional single-pillar analyses, we provide a unified assessment of digitalization's simultaneous impacts across economic, social, and environmental dimensions - a critical integration given the UN Sustainable Development Goals' emphasis on interconnected progress (UNDP, 2021). Second, we employ dynamic panel ARDL methods to disentangle immediate digitalization effects from long-term equilibrium relationships, addressing the temporal limitations of prior cross-sectional studies (Pesaran, 2015). Third, our sub-regional analysis reveals heterogeneous impacts across North, West, East, and Southern Africa, challenging the 'one-size-fits-all' policy assumptions prevalent in continental digital strategies (Busacca, 2025). Despite growing interest in digitalization, critical gaps persist in understanding its heterogeneous effects across Africa’s diverse economies. Existing studies predominantly focus on advanced economies or isolate single pillars of sustainability (e.g., GDP growth), overlooking bidirectional relationships - such as how environmental regulations may constrain digital infrastructure rollout or how human development priorities compete for funding (Misra and Srivastava, 2024). Moreover, while short-term impacts are often negligible, long-term synergies remain underexplored in low-income contexts. This study fills these gaps by analyzing 48 African nations through a unified panel ARDL framework, capturing both immediate dynamics and enduring equilibria to inform policies that reconcile digital adoption with inclusive, sustainable development

However, the rapid adoption of digital technologies also presents challenges, such as increased energy consumption, electronic waste management, and the risk of exacerbating the digital divide. These issues necessitate a balanced approach to ensure that digitalization contributes positively to sustainable development without undermining its goals. This study aims to thoroughly examine the impacts of digitalization on the three pillars of sustainable development in the specific context of African countries. Through a rigorous analysis of existing literature and empirical validation, we explore how digital innovations can drive inclusive economic growth, environmental protection, and improved social well-being. The remainder of this work is structured as follows: Section 2 provides a comprehensive literature review, examining the impact of digitalization on the economic, environmental, and social dimensions of sustainable development. Section 3 outlines the empirical methodology, including the data sources, variable selection, and econometric models used to analyze the relationships between digitalization and sustainable development in Africa. Section 4 presents the empirical results and discusses their implications for policy and development strategies. Finally, Section 5 concludes the study by summarizing the key findings and offering recommendations for maximizing the benefits of digitalization in the pursuit of sustainable development in African countries.

2. Literature review

Digitalization has transformed global economic, social, and environmental systems, with its effects on Africa increasingly studied. This literature review examines its impact on sustainable development's three pillars: economy, environment, and society. It explores how digital technologies drive economic growth, innovation, and productivity in Africa, while also addressing environmental challenges like energy use and e-waste. Socially, it highlights digitalization's role in improving access to healthcare, education, and financial inclusion, crucial for reducing inequalities. This review provides a theoretical foundation for understanding digitalization's implications for sustainable development in Africa.

2.1. The impact of digitalization on the economic pillar

Digitalization has been extensively acknowledged as a pivotal driver in reinforcing the economic foundation of sustainable development. This section examines the multifaceted ways in which digital technologies stimulate economic growth, augment productivity, and foster equity and resilience. Empirical research, including the work of Bukht and Heeks (2018), demonstrates that digitalization enhances labor productivity and streamlines public service delivery, mitigating economic disparities through automation, data-centric decision-making, and cross-border collaboration. Further, Bocken et al. (2014) elucidate how digital strategies equip businesses to navigate external disruptions, refine supply chain efficiency via technologies such as blockchain, and advance sustainable practices, thereby contributing to the evolution of a circular economy.

Beyond productivity gains, digitalization plays a transformative role in economic inclusion. As evidenced by the World Bank (2016), digital financial solutions - notably mobile banking - have integrated millions in developing nations into the formal economy, empowering small and medium-sized enterprises (SMEs) to access broader markets and secure vital financing. Geissdoerfer et al.

(2017) underscore digitalization’s capacity to facilitate green economic transitions by spurring eco-innovation and encouraging sustainable consumption patterns through digital platforms. Region-specific studies further validate these dynamics. Solomon and Klyton (2020) identify a positive correlation between individual ICT adoption and economic growth in Africa, while Jia et al. (2023) emphasize the catalytic role of data-driven elements in propelling development in emerging economies. Complementary research by Mishakov et al. (2021), Hao et al. (2023), and Lechman and Anacka (2022) highlights digitalization’s dual impact in promoting green growth and reducing socioeconomic inequality, thereby bolstering economic resilience. Similarly, Habibi and Zabardast (2020) document a robust linkage between ICT penetration and economic expansion in the Middle East, advocating for heightened investment in digital infrastructure to sustain these gains.

2.2. The impact of digitalization on the environmental pillar

The relationship between digitalization and environmental sustainability presents a complex duality that requires careful examination. While digital transformation drives remarkable innovations in economic efficiency, its environmental implications reveal both promising solutions and concerning challenges that must be addressed holistically. Emerging technologies like IoT, AI, and advanced ICT systems demonstrate significant potential for enhancing environmental outcomes through multiple pathways. These innovations contribute substantially to resource optimization and emissions reduction, as evidenced by Hilty and Aebischer's (2015) findings on industrial process improvements and circular economy transitions. Practical applications range from AI-driven energy management systems that dramatically reduce carbon footprints in commercial and industrial settings to IoT-enabled precision agriculture that minimizes water waste through smart sensor networks (Weng et al., 2019). Furthermore, the integration of remote sensing and big data analytics has revolutionized environmental monitoring capabilities, providing unprecedented tools for ecosystem protection and biodiversity conservation efforts worldwide.

However, this digital revolution comes with substantial environmental costs that cannot be ignored. The exponential growth of digital infrastructure, particularly energy-intensive data centers that power the global digital economy, represents a growing source of $CO2$ emissions (Andrae and Edler, 2015). Equally troubling is the mounting crisis of electronic waste, with developing nations bearing the brunt of inadequate recycling systems that lead to severe environmental contamination and public health risks (Forti et al., 2020). These challenges have prompted researchers to develop innovative solutions, including eco-design principles that enhance energy efficiency and product durability (Bieser and Hilty, 2018) and circular economy models that prioritize material recovery and reuse. Digital platforms themselves offer part of the solution, as demonstrated by smart energy applications that have successfully reduced household carbon emissions across European communities (Loock and Staake, 2020). Recent empirical research provides nuanced insights into digitalization's environmental impacts across different contexts. Studies by Charfeddine et al. (2024) reveal how digital technologies can significantly improve environmental quality in heavily polluted regions when combined with renewable energy adoption. Similar synergies appear in advanced economies, where Adebayo et al. (2024) document the combined benefits of solar innovation and digital integration in reducing ecological footprints. The Chinese experience offers particularly interesting findings, with Li et al. (2021) demonstrating measurable air quality improvements from digital economy development, though these benefits vary considerably based on urbanization levels and regional economic conditions. However, this progress remains unevenly distributed, as Ben Youssef and Dahmani (2024) observe more limited environmental benefits in low- and middle-income nations, suggesting that institutional capacity and complementary infrastructure play crucial mediating roles. The European context provides valuable lessons about policy design, with Adeshola et al. (2023) showing how environmental taxation frameworks can enhance the sustainability benefits of digitalization. While long-term studies highlight digitalization's potential for improving natural resource management (Kalymbek et al., 2021; Huong and Thanh, 2022), researchers caution against potential rebound effects and short-term environmental costs. Industrial digitalization demonstrates particular promise in pollution reduction and green innovation (Wen et al., 2021; Ramos-Meza et al., 2021), though Ullah et al. (2024) warn that without proper regulation, digital expansion in developed economies may paradoxically increase emissions. These findings collectively underscore the need for carefully calibrated policies that maximize digitalization's environmental benefits while mitigating its ecological costs through sustainable infrastructure development, robust e-waste management systems, and strategic integration with renewable energy transitions. Future research should particularly focus on optimizing digitalization's environmental potential in developing economies where its implementation remains incomplete but holds significant promise.

2.3. The impact of digitalization on the social pillar

Digitalization has emerged as a transformative force reshaping the social dimensions of sustainable development, presenting both unprecedented opportunities and complex challenges. Its pervasive influence extends across multiple facets of society, from enhancing access to essential services to redefining labor markets and social interactions. The potential for digital technologies to foster social inclusion is particularly noteworthy, as they break down geographical barriers and connect previously marginalized populations to critical resources. Minges (2015) demonstrates how information and communication technologies enable rural and isolated communities to participate in the global economy, while digital education platforms help bridge educational divides. In healthcare, telemedicine and mobile health applications have revolutionized service delivery to underserved populations, significantly improving health outcomes (Mechael et al., 2018). Financial inclusion has similarly benefited from digital transformation, with mobile banking and digital payment systems empowering unbanked individuals to access financial services, manage savings, and escape poverty cycles (World Bank, 2016). Yet this digital revolution carries inherent risks of exacerbating existing inequalities if not carefully managed. Van Dijk (2020) warns of a growing digital divide that disproportionately affects rural communities, elderly populations, and low-income groups, creating new forms of social exclusion in an increasingly digital world. The labor market transformation presents another paradox - while automation and AI generate high-skilled tech employment and productivity gains (Acemoglu and Restrepo, 2018), they simultaneously displace low-skilled workers through what scholars term 'digital deindustrialization'. This phenomenon underscores the urgent need for comprehensive reskilling initiatives and robust social safety nets to ensure equitable participation in the digital economy. The social implications extend to civic engagement as well, where digital platforms have become double-edged swords. Social media enables unprecedented mobilization around human rights and gender equality issues (Castells, 2015), yet also facilitates the spread of misinformation, political polarization, and cyberbullying, complicating the social fabric of digital societies.

The impact of digitalization on quality of life reveals significant geographical and socioeconomic disparities. While Ishnazarova et al. (2022) document tangible improvements in daily life through ICT adoption, these benefits remain unevenly distributed, with rural areas often left behind due to infrastructure limitations. Salakhova et al. (2021) further demonstrate how the effectiveness of digital solutions varies considerably across economic contexts, with developed nations typically realizing greater quality-of-life improvements than their developing counterparts. Sector-specific applications show particular promise, as evidenced by digital innovations in transportation and construction that enhance efficiency, sustainability, and user comfort (Korchagina et al., 2021;

Musarat et al., 2022). Barlybaev et al. (2021) identify nine distinct domains where digitalization influences quality of life, emphasizing the need for context-specific implementations to maximize benefits. However, Pérez-Martínez et al. (2023) caution that the pursuit of digital social progress may sometimes conflict with environmental sustainability goals, requiring careful policy balancing. The foundational importance of equitable digital infrastructure emerges clearly from this analysis, with Zaborovskaia et al. (2020) highlighting its critical role in developing human capital and improving living standards across diverse populations.

2.4. Identifying research gaps and methodological contributions

While existing research has established digitalization's transformative potential across economic, environmental, and social domains, four critical gaps remain unaddressed - particularly in the African context. First, most studies focus on single-country cases or regional blocs (e.g., North Africa) while neglecting comparative analysis across Africa's diverse sub-regions (Solomon and Van-Klyton, 2020). This study fills this gap by employing a comprehensive 48-country panel, enabling cross-regional comparisons of digitalization's impacts. Second, the literature predominantly examines digitalization's effects on individual pillars of sustainable development in isolation. For instance, economic studies rarely account for environmental externalities (Andrae and Edler, 2015), while social impact assessments often overlook economic feasibility constraints (Van Dijk, 2020). Our integrated ARDL approach simultaneously analyzes all three pillars, revealing important trade-offs and synergies that single-pillar studies miss. Third, there is insufficient empirical evidence about threshold effects - the minimum levels of institutional capacity or infrastructure required for digitalization to yield positive outcomes. While Habibi and Zabardast (2020) identify an ICT adoption threshold for Middle Eastern economies, our study establishes Africa-specific thresholds through nonlinear modeling of variables like internet penetration versus GDP growth. Finally, the temporal dimension of digitalization's impacts remains understudied. Most African-focused research uses cross-sectional data (World Bank, 2016), obscuring the evolution of effects over time. By analyzing 1999-2020 data with time-series methods, we distinguish between short-term adaptation periods and long-term equilibrium states - crucial for policy planning. This study's novel contribution lies in addressing all four gaps: (1) pan-African coverage, (2) integrated three-pillar analysis, (3) threshold quantification, and (4) temporal dynamics. The findings provide policymakers with evidence-based insights about when, where, and how digitalization can most effectively promote sustainable development across Africa's heterogeneous contexts.

3. Empirical methodology

The empirical methodology analyzes digitalization's impact on sustainable development across 48 African countries (1999–2020). Key variables - economic growth, environmental quality, human development, and digitalization - are measured using standardized formulas. Advanced econometric models, including stationarity tests and panel data cointegration, are employed to examine short- and long-term interactions, accounting for regional specificities and unique socio-economic factors.

3.1. Database and variable selection

To assess the impact of digitalization on the three pillars of sustainable development, we have created a database encompassing 48 African countries over the period from 1999 to 2020. This analysis focuses on how digitalization affects the economic, environmental, and human dimensions of sustainable development. In this section, we will provide a detailed overview of the selected variables, their measurement methods, and the associated mathematical formulas, taking into account the following countries: Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cabo Verde, Cameroon, Central African Republic, Chad, Comoros, Democratic Republic of the Congo, Republic of the Congo, Côte d'Ivoire, Egypt, Equatorial Guinea, Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Seychelles, Sierra Leone, South Africa, Tanzania, Togo, Tunisia, Uganda, Zambia, and Zimbabwe. Our sample includes 48 African countries with complete data for 1999-2020. Countries like Somalia were excluded due to missing key indicators.

3.1.1. Economic Growth

Economic growth is a key indicator for evaluating the progress of countries. We measure economic growth using GDP per capita, expressed in constant 2005 US dollars. This method adjusts nominal GDP values to eliminate the effect of inflation and allow for consistent time-based comparisons. This measure allows us to compare the wealth generated per capita across different countries and years, eliminating distortions caused by variations in price levels.

3.1.2. Environmental Quality

Environmental quality is a crucial aspect of understanding the effects of economic activities on the environment. We use per capita carbon dioxide (CO_2) emissions, measured in metric tons, as the primary indicator. This measure helps assess the impact of industrial and economic activities on climate change. This indicator provides an accurate view of the pressure exerted by human activities on the environment, in proportion to the size of the population.

3.1.3. Human Development

The Human Development Index (HDI) serves as a composite measure evaluating three fundamental dimensions of societal progress: health (measured by life expectancy at birth), education (approximated through gross enrollment ratios due to limited literacy rate data), and economic wellbeing (captured by GDP per capita). This multidimensional index synthesizes these components through a standardized averaging formula, offering a holistic assessment of human development that balances longevity, educational access, and material living standards. The methodological adaptation using enrollment ratios as an education proxy maintains the index's analytical rigor while accommodating data constraints, ensuring consistent cross-country comparability of development outcomes.

3.1.4. Digitalization

Digitalization is measured by the number of people using the internet, a key indicator of access to digital technologies and connectivity. This measure evaluates the extent of digital technology adoption in the countries studied and its potential to drive economic and social development.

All the necessary data for these measures are extracted from the World Bank's annual reports, ensuring the quality and reliability of the information used. This combined analysis helps understand how digitalization influences the economic, environmental, and human aspects of sustainable development in African countries, providing valuable insights to guide policies and strategies for balanced sustainable development.

Table 1 - Variable Definitions, Measurement, and Theoretical Expected Impacts

Variable	Measurement (Source)	Expected Impact and Rationale	Citation
Digitalization	Internet users per 100 people (World Bank WDI)	(+) Economic growth via productivity gains; (±) Social inclusion (improved access but may exacerbate divides); (-) Environmental quality through e-waste/energy demand	Bukht and Heeks (2018); Andrae and Edler (2015)
Economic Growth	GDP per capita, constant 2015 USD (World Bank)	(+) Short-term welfare but potential (-) environmental trade-offs if growth is resource-intensive	Charfeddine et al. (2024)
Environmental Quality	CO_2 emissions per capita (Global Carbon Atlas)	(-) impact with digitalization if tech adoption increases energy use; (+) if enables efficiency gains	Hilty and Aebischer (2015)
Human Development	UNDP HDI index (life expectancy, education, GNI per capita)	(+) Where digital access enables education/healthcare; (0) in contexts with digital divides	Van Dijk (2020)

Table 1 presents the core variables used to assess digitalization's effects on sustainable development, clearly defining their measurements, data sources, and expected directional impacts based on established literature. The framework reveals digitalization's multifaceted influence: while it drives economic growth (+) through productivity gains, its social impact (±) depends on equitable access, and its environmental consequences (-) stem from e-waste and energy demands. Together, these variables capture the complex interplay between digital transformation and sustainable development, emphasizing the need for balanced policies that leverage opportunities while mitigating risks.

3.2. Model specification and empirical strategy

In this study, we thoroughly explore the causal relationship between four key variables: digitalization ‘log (DI)’, economic growth ‘log(Y)’, environmental quality ‘log (EQ)’, and the Human Development Index ‘log (HDI)’. To achieve this, we follow a rigorous multi-step methodology, each corresponding to a fundamental aspect of the econometric analysis of panel data. Through this systematic approach, we aim to highlight both the short- and long-term relationships between these variables, while accounting for cross-sectional dependence, heterogeneity, and potential structural breaks. The integration of stationarity methods, cointegration, and estimation on panel data allows us to examine the dynamic interactions between the variables in both the short and long terms.

The first step of our analysis is to perform descriptive statistics on the variables considered - (DI), (Y), (EQ), and (HDI) to understand their basic statistical characteristics. Descriptive statistics include the mean, standard deviation, minimum and maximum values, as well as the distribution of the variables for each country over the entire period under study. These measures are crucial for detecting the dispersion of the data and potential differences between countries.

Cross-sectional dependence analysis is a critical step to verify whether the panel units (in this case, the countries) are interdependent. Cross-sectional dependence occurs when the residuals of a regression are correlated across different units, which may be due to common shocks, trade or financial links between countries. Ignoring this dependence can bias econometric results. To test this dependence, we use several tests, including Pesaran's (2015, 2021) CD statistics and the CDw test proposed by Juodis and Reese (2021). The Pesaran CD statistics are calculated as follows:

$$CD = \frac{\sqrt{2T}}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{1}$$

Where $(\widehat{\rho_{ij}})$ is the residual correlation coefficient between countries i and j, N is the number of countries, and T is the number of time periods. If the test rejects the null hypothesis of no cross-sectional dependence, it suggests that the countries under study are linked by common factors. The CDw test by Juodis and Reese (2021) enhances statistical power by considering the presence of unobserved common factors. Moreover, the CD* test proposed by Pesaran and Xie (2021) uses 4 principal components (PC) to correct biases due to interdependence between units.

Slope heterogeneity is an essential issue in panel data analysis as it determines whether the relationships between variables vary from one country to another. To address this, we use two main tests: the Pesaran and Yamagata (2008) test and the Blomquist and Westerlund (2013) test. The Pesaran and Yamagata (2008) test is based on the Δadj statistic, which compares homogeneous and heterogeneous regression coefficient estimates:

$$\Delta_{adj} = \frac{\sqrt{N}}{2\hat{\sigma}} \left(\widehat{\beta_{pool}} - \widehat{\beta_{HT}}\right) \tag{2}$$

Where $(\widehat{\beta_{pool}})$ is the pooled estimate (assumed to be homogeneous), and $(\widehat{\beta_{HT}})$ is the heterogeneous estimate (considering the specificities of each country). If this test reveals significant slope heterogeneity, it indicates that each country exhibits a unique relationship between the studied variables.

Stationarity analysis is a necessary step to determine whether our time series are integrated of order 0 (stationary) or order 1 (non-stationary). Several unit root tests can be used for panel data, including the Levin, Lin, and Chu (LLC) test, the Im, Pesaran, and Shin (IPS) test, ADF-Fisher Chi-square, and PP-Fisher Chi-square tests. These tests aim to check if the series present a unit root, imply that the data are non-stationary at the level but may become stationary after differencing. The LLC test assumes that all series in the panel share the same unit root parameter:

$$\Delta y_{it} = \alpha + \rho y_{it-1} + \sum_{k=1}^{p} \theta_k \Delta y_{it-k} + \epsilon_{it} \tag{3}$$

Where (ρ) is the unit root parameter, (α) is a constant, and (ϵ_{it}) is the error term. If $(\rho = 0)$, the series is stationary. Other tests, like IPS, allow for unit root parameters specific to each country.

Structural breaks may disrupt the relationships between variables, particularly in cases of economic crises or political changes. To identify these breaks, we use the Bai and Perron (2003) test, which detects unknown break points where the model parameters change significantly. This test is based on minimizing the sum of squared residuals under different break scenarios:

$$F_{BP} = \frac{(T-2m)}{m}\left(\frac{SSE_r - SSE_u}{SSE_u}\right) \tag{4}$$

Where (SSE_r) and (SSE_u) are the sums of squared errors under restricted (with break) and unrestricted (without break) hypotheses. The critical values for this test are provided for different significance levels (1%, 5%, 10%), thus allowing the rejection or acceptance of the stability hypothesis of the parameters. If the series are non-stationary at the level but become stationary after differencing, we then test for cointegration to determine if a long-term relationship exists between 'log(DI)', 'log(Y)', 'log(EQ)', and 'log(HDI)'. We use three main tests: the Pedroni test and the Kao test. The Pedroni test relies on the residuals of the long-term regression between the variables, checking whether these residuals are stationary:

$$u_{it} = y_{it} - \alpha_i - \beta_i x_{it}, \quad \text{where} \quad u_{it} \sim I(0) \tag{5}$$

If the residuals (u_{it}) are stationary, it means that a stable long-term relationship exists between the variables.

To analyze the link between digitalization (log(DI)), economic growth (log(Y)), environmental quality (log(EQ)), and the Human Development Index (log(HDI)) in an ARDL panel model, we will write the four equations that capture the dynamic relationships between these variables. The ARDL (Autoregressive Distributed Lag) model allows us to estimate the short- and long-term dynamics between variables in panel data. The ARDL equation for economic growth, which depends on the lags of the other variables log(DI), log(EQ), log(HDI) and its own lags, is written as:

$$\Delta\log(Y_{it}) = \alpha_1 + \sum_{p=1}^{P}\beta_{1p}\Delta\log\left(Y_{it-p}\right) + \sum_{q=0}^{Q}\delta_{1q}\Delta\log\left(DI_{it-q}\right) + \sum_{r=0}^{R}\lambda_{1r}\Delta\log(EQ_{it-r}) + \sum_{s=0}^{S}\phi_{1s}\Delta\log(HDI_{it-s}) + \gamma_1(\log(Y_{it-1}) - \theta_{11}\log(DI_{it-1}) - \theta_{12}\log(EQ_{it-1}) - \theta_{13}\log(HDI_{it-1})) + \epsilon_{1it} \tag{6}$$

The ARDL equation for digitalization, influenced by economic growth, environmental quality, and the Human Development Index, is:

$$\Delta\log(DI_{it}) = \alpha_2 + \sum_{p=1}^{P}\beta_{2p}\Delta\log\left(DI_{it-p}\right) + \sum_{q=0}^{Q}\delta_{2q}\Delta\log\left(Y_{it-q}\right) + \sum_{r=0}^{R}\lambda_{2r}\Delta\log(EQ_{it-r}) + \sum_{s=0}^{S}\phi_{2s}\Delta\log(HDI_{it-s}) + \gamma_2(\log(DI_{it-1}) - \theta_{21}\log(Y_{it-1}) - \theta_{22}\log(EQ_{it-1}) - \theta_{23}\log(HDI_{it-1})) + \epsilon_{2it} \tag{7}$$

The ARDL equation for environmental quality, taking into account the lags of log(DI), log(Y), and log(HDI), is formulated as:

$$\Delta\log(EQ_{it}) = \alpha_3 + \sum_{p=1}^{P}\beta_{3p}\Delta\log\left(EQ_{it-p}\right) + \sum_{q=0}^{Q}\delta_{3q}\Delta\log\left(DI_{it-q}\right) + \sum_{r=0}^{R}\lambda_{3r}\Delta\log(Y_{it-r}) + \sum_{s=0}^{S}\phi_{3s}\Delta\log(HDI_{it-s}) + \gamma_3(\log(EQ_{it-1}) - \theta_{31}\log(DI_{it-1}) - \theta_{32}\log(Y_{it-1}) - \theta_{33}\log(HDI_{it-1})) + \epsilon_{3it} \tag{8}$$

Finally, the ARDL equation for the Human Development Index is expressed as:

$$\Delta \log(HDI_{it}) = \alpha_4 + \sum_{p=1}^{P} \beta_{4p} \Delta \log(HDI_{it-p}) + \sum_{q=0}^{Q} \delta_{4q} \Delta \log(DI_{it-q}) + \sum_{r=0}^{R} \lambda_{4r} \Delta \log(Y_{it-r}) + \sum_{s=0}^{S} \phi_{4s} \Delta \log(EQ_{it-s}) + \gamma_4(\log(HDI_{it-1}) - \theta_{41} \log(DI_{it-1}) - \theta_{42} \log(Y_{it-1}) - \theta_{43} \log(EQ_{it-1})) + \epsilon_{4it} \quad (9)$$

The terms above are explained as follows:
- $\Delta \log(Y_{it})$, $\Delta \log(DI_{it})$, $\Delta \log(EQ_{it})$, $\Delta \log(HDI_{it})$: short-term changes in the respective variables;
- $(\beta), (\delta), (\lambda), (\phi)$: short-term coefficients for the lags of dependent and explanatory variables;
- $(\gamma_1, \gamma_2, \gamma_3, \gamma_4)$: adjustment speed coefficients, indicating the speed at which variables return to their long-term equilibrium after a shock;
- (θ): long-term coefficients representing the effects of log(DI), log(Y), log(EQ), and log(HDI) on the respective dependent variables;
- (ϵ_{it}) : error term for each equation.

These four equations capture the dynamic relationships between digitalization, economic growth, environmental quality, and the Human Development Index, both in the short and long terms, within the framework of the ARDL panel model.

The Autoregressive Distributed Lag (ARDL) model represents the most appropriate empirical framework for this study, offering three key advantages over alternative specifications. First, its unique ability to handle variables with differing orders of integration [I(0)/I(1)] proves essential for our dataset, which combines trend-stationary economic indicators with mean-reverting social variables (Pesaran et al., 2001). Second, the model's dynamic specification provides distinct estimates of short-run adjustments and long-run equilibrium relationships through its error correction mechanism, offering crucial insights into both immediate and sustained impacts of digitalization - a critical feature that static models cannot capture. Third, the ARDL framework inherently mitigates endogeneity concerns through its lag structure, demonstrating superior performance to Generalized Method of Moments (GMM) estimators when analyzing persistent variables such as the Human Development Index (Kripfganz and Schneider, 2023). This combination of integration flexibility, temporal granularity, and endogeneity resistance makes ARDL particularly suited for examining the complex, multi-speed relationships between digital transformation and sustainable development outcomes.

4. Empirical results

In this section, we present the empirical results of the analysis of the impact of digitalization on the three pillars of sustainable development - economic, environmental, and social - for 48 African countries over the period from 1999 to 2020. We explore in depth the causal relationship between four key variables: digitalization 'log (DI)', economic growth 'log (Y)', environmental quality 'log (EQ)', and the Human Development Index 'log (HDI)'.

4.1. Descriptive statistics

Table 2 presents the results of the descriptive statistics for four key variables: digitalization (DI), economic growth (Y), environmental quality (EQ), and the Human Development Index (HDI). These statistics provide an initial overview of the characteristics of the data used in this study, based on a sample of 1,056 observations.

Table 2 - Descriptive Statistics Results

Statistics	DI	Y	EQ	IDH
Mean	2.94E+08	2422.179	1.198492	0.513306
Median	30837532	1165.616	0.359907	0.493500
Maximum	1.07E+10	19481.65	9.985813	0.816933
Minimum	31604.25	251.3777	0.021790	0.250000
Std. Dev.	8.62E+08	3021.309	1.885231	0.125940
Skewness	6.077076	2.394599	2.476303	0.359886
Kurtosis	51.85410	9.183487	9.013138	2.340549
Jarque-Bera	111515.7	2691.565	2670.190	41.92972
Probability	0.000000	0.000000	0.000000	0.000000
Sum	3.11E+11	2557821.	1265.607	542.0509
Sum Sq. Dev.	7.84E+20	9.63E+09	3749.569	16.73317
Observations	1056	1056	1056	1056

The digitalization variable has a mean of 2.94E+08, indicating a high overall level of digitalization, but a median of 30,837,532 reveals that most countries fall well below the mean, driven by a few highly digitalized nations. This heterogeneity is reflected in a high standard deviation (8.62E+08) and right-skewed distribution (skewness = 6.077076). Similarly, economic growth (mean = 2,422.179, median = 1,165.616) shows significant disparity, with a few high-performing economies skewing the distribution (skewness = 2.394599). Environmental quality (mean = 1.198492) also varies widely (standard deviation = 1.885231), with most countries reporting lower levels. The Human Development Index (mean = 0.513306) exhibits less variability (standard deviation = 0.125940) and a more symmetric distribution (skewness = 0.359886), indicating relative homogeneity. Jarque-Bera tests confirm non-normal distributions for all variables, suggesting the need for robust econometric methods in further analyses.

4.2. Cross-sectional dependence analysis

Table 3 presents cross-sectional dependence (CSD) analysis results, assessing interdependencies among key variables across African countries. For digitalization (log DI), the CD test (Pesaran, 2015, 2021) shows strong interdependence (value = 151.07, p = 0.000), reflecting the globalized nature of digital technologies. However, the CDW test (Juodis and Reese, 2021) finds no significant dependence (value = 1.13, p = 0.260), while the CDW+ test (Fan et al., 2015) confirms strong interdependence (value = 5074.78). The CD* test (Pesaran and Xie, 2021) suggests complex dependence (value = -2.13, p = 0.033).

For economic growth (log Y), the CD test indicates strong interdependence (value = 71.17, p = 0.000), driven by regional integration and trade links. The CDW test shows slight dependence (value = 1.87, p = 0.061), while the CDW+ test confirms significant interdependence (value = 3442.35). The CD* test suggests weaker dependence (value = 0.97). These findings underscore the interconnectedness of African economies, with regional spillovers shaping growth dynamics. For environmental quality (log EQ), the CD test shows significant cross-sectional dependence (value = 42.77, p = 0.000), indicating that environmental policies and conditions in one African country influence others, particularly for challenges like deforestation and pollution. The CDW test finds no significant dependence (value = 0.83, p = 0.407), but the CDW+ test confirms strong interdependence (value = 2685.21). The CD* test suggests no significant dependence (value = -0.51, p = 0.610), highlighting varying results across tests.

Table 3 - Results of the Cross-Sectional Dependence Analysis.

Testing for weak cross-sectional dependence (CSD)				
H0: weak cross-section dependence H1: strong cross-section dependence				
	CD	CDW	CDW+	CD*
Log (EQ)	42.77 (0.000)	0.83 (0.407)	2685.21 (0.000)	-0.51 (0.610)
Log (Y)	71.17 (0.000)	1.87 (0.061)	3442.35 (0.000)	0.97 (0.333)
Log (DI)	151.07 (0.000)	1.13 (0.260)	5074.78 (0.000)	-2.13 (0.033)
Log (IDH)	139.89 (0.000)	-0.21 (0.830)	4902.79 (0.000)	0.17 (0.866)

p-values in parenthesis.
References:
CD: Pesaran (2015, 2021);
CDw: Juodis et Reese (2021);
CDw+: CDw with power enhancement from Fan et al. (2015);
CD*: Pesaran et Xie (2021) with 4 PC(s).

For the Human Development Index (log HDI), the CD test also indicates strong interdependence (value = 139.89, p = 0.000), reflecting regional cooperation and knowledge sharing. However, the CDW test shows no significant dependence (value = -0.21, p = 0.830), while the CDW+ test confirms strong interdependence (value = 4902.79). The CD* test suggests weak dependence (value = 0.17, p = 0.866), indicating that HDI may be less influenced by other countries in certain contexts.

4.3. Homogeneity analysis

Tables 4 and 5 present slope heterogeneity test results, essential for panel data analysis when examining multiple countries. These tests assess whether slope coefficients, representing relationships between explanatory and dependent variables, are consistent across countries or vary based on country-specific characteristics. For instance, they evaluate if the link between digitalization and economic growth differs by country.

The Pesaran and Yamagata (2008) test, a widely used method, tests the null hypothesis of homogeneous slope coefficients across countries. A significant p-value rejects this hypothesis, indicating coefficient variation. The results in Table 4 show a test statistic of 25.174 (p = 0.000), strongly rejecting slope homogeneity, suggesting that relationships between variables differ significantly across African countries.

Table 4 - Slope Heterogeneity Test (Pesaran and Yamagata, 2008)

Testing for slope heterogeneity		
(Pesaran et Yamagata, 2008) H0: slope coefficients are homogenous		
Slope Homogeneity Tests	Δ Statistic	P-Value
$\tilde{\Delta}_{test}$	25.174	0.000
$\tilde{\Delta}_{adj}$ test	28.638	0.000
Variables partialled out: constant.		

The results indicate that relationships between key variables - digitalization, economic growth, environmental quality, and human development - vary across African countries. Factors such as digital infrastructure, technological development, government policies, and foreign investment influence how digitalization impacts economic growth. Similarly, environmental quality's effect on human development depends on national contexts like resource management and environmental policies.

The Blomquist and Westerlund (2013) test, presented in Table 5, complements the Pesaran and Yamagata test by using a Bartlett-type HAC kernel to address heteroskedasticity and autocorrelation. Its results (test statistic = 23.681, p = 0.000) also reject slope homogeneity, confirming that relationships differ across countries. This reflects the diverse economic, social, and environmental contexts in Africa, where some nations benefit more from digitalization due to advanced infrastructure, while others with less development see fewer immediate gains.

Table 5 - Slope Heterogeneity Test (Blomquist and Westerlund, 2013)

Testing for slope heterogeneity		
(Blomquist et Westerlund. 2013) H0: slope coefficients are homogenous		
Slope Homogeneity Tests	Δ Statistic	P-Value
$\tilde{\Delta}_{test}$	23.681	0.000
$\tilde{\Delta}_{adj}$ test	26.940	0.000
HAC Kernel: Bartlett, with average bandwith 2; Variables partialled out: constant.		

The significant results from both slope heterogeneity tests have important implications for economic analysis. They clearly indicate that African countries cannot be treated as a homogeneous bloc regarding the relationships between digitalization, economic growth, environmental quality, and human development. Instead, each country exhibits specific dynamics that shape the nature of these relationships. This can be explained by the diversity in economic development levels, infrastructure, public policies, as well as the varied geographical and climatic contexts across African nations.

4.4. Stationarity analysis

Table 6 presents panel unit root test results for digitalization (log DI), economic growth (log Y), environmental quality (log EQ), and the human development index (log IDH). These tests assess whether the time series are stationary, meaning their statistical properties (e.g., mean, variance) remain constant over time. Non-stationary series can lead to misleading regressions, making unit root tests essential for determining whether variables need differencing before econometric analysis. For digitalization (log DI), the tests (LLC, IPS, ADF, PP) show non-stationarity at levels but stationarity after first differencing. For example, the LLC test at levels yields a statistic of -9.56777 (p = 0.0000), rejecting the unit root hypothesis at the 1% significance level. After differencing, the series becomes stationary, with an LLC statistic of -5.12867 (p = 0.0000). This indicates that digitalization exhibits temporal trends that are removed through differencing, making it suitable for analysis.

Similarly, economic growth (log Y) is non-stationary at levels, influenced by long-term trends. The LLC test at levels shows a statistic of -6.86647 (p = 0.0000), and other tests (IPS, ADF, PP) confirm non-stationarity. After differencing, the series becomes stationary, with LLC and IPS statistics showing p-values below 0.01, indicating stability for further analysis. Environmental quality (log EQ) shows mixed results: the LLC test indicates stationarity at levels (-3.72789, p = 0.0001), but IPS, ADF, and PP tests suggest non-stationarity (p > 0.05). After first differencing, all tests confirm stationarity. Similarly, the human development index (log IDH) is stationary at levels according to the LLC test (-4.94901, p = 0.0000), but IPS, ADF, and PP tests indicate non-stationarity (p > 0.05). Differencing makes the HDI stationary.

Table 6 - Panel Unit Root Test Results

Log (DI)					
At level			First difference		
Exogenous variables: Individual effects			Exogenous variables: Individual effects		
Method	Statistic	Prob.**	Method	Statistic	Prob.**
Null: Unit root (assumes common unit root process)			Null: Unit root (assumes common unit root process)		
LLC	-9.56777	0.0000	LLC	-5.12867	0.0000
Null: Unit root (assumes individual unit root process)			Null: Unit root (assumes individual unit root process)		
IPS	-2.42356	0.0077	IPS	-7.44146	0.0000
ADF	162.518	0.0000	ADF	215.130	0.0000
PP	472.351	0.0000	PP	597.104	0.0000
Log (Y)					
At level			First difference		
Method	Statistic	Prob.**	Method	Statistic	Prob.**
Null: Unit root (assumes common unit root process)			Null: Unit root (assumes common unit root process)		
LLC	-6.86647	0.0000	LLC	0.02961	0.5118
Null: Unit root (assumes individual unit root process)			Null: Unit root (assumes individual unit root process)		
IPS	0.03408	0.5136	IPS	-5.28719	0.0000
ADF	110.652	0.1456	ADF	206.566	0.0000
PP	116.210	0.0786	PP	379.731	0.0000
Log (EQ)					
At level			First Difference		
Method	Statistic	Prob.**	Method	Statistic	Prob.**
Null: Unit root (assumes common unit root process)			Null: Unit root (assumes common unit root process)		
LLC	-3.72789	0.0001	LLC	-9.57451	0.0000
Null: Unit root (assumes individual unit root process)			Null: Unit root (assumes individual unit root process)		
IPS	-0.63312	0.2633	IPS	-13.1038	0.0000
ADF	107.053	0.2071	ADF	356.783	0.0000
PP	110.096	0.1541	PP	913.090	0.0000
Log (IDH)					
At level			First difference		

Method	Statistic	Prob.**	Method	Statistic	Prob.**
Null: Unit root (assumes common unit root process)			Null: Unit root (assumes common unit root process)		
LLC	-4.94901	0.0000	LLC	-3.57234	0.0002
Null: Unit root (assumes individual unit root process)			Null: Unit root (assumes individual unit root process)		
IPS	3.72380	0.9999	IPS	-7.13774	0.0000
ADF	72.1489	0.9671	ADF	218.315	0.0000
PP	112.987	0.1136	PP	413.300	0.0000
LLC: Levin, Lin & Chu t;					
IPS: Im, Pesaran and Shin W-stat;					
ADF: ADF - Fisher Chi-square;					
PP: PP - Fisher Chi-square.					

Overall, digitalization, economic growth, environmental quality, and the HDI are non-stationary at levels but become stationary after first differencing. This suggests long-term shocks affect these variables, and differencing is necessary for accurate econometric analysis, such as cointegration or regressions, to avoid misleading results.

4.5. Analysis of potential structural breaks

The analysis of potential structural breaks is crucial to detect significant shifts in economic relationships over time. Using Bai and Perron's (1998, 2003) method, a sequential test for multiple breaks at unknown points is conducted. The results compare observed F-statistics with critical values at 1%, 5%, and 10% significance levels, identifying structural changes in the time series without prior knowledge of their timing.

Table 7 - Sequential Test for Multiple Breaks at Unknown Breakpoints

	Bai and Perron Critical Values			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
F (10)	11.25	6.09	4.66	4.03
F (21)	9.43	6.59	5.24	4.64
F (32)	1.60	6.92	5.61	4.99

Table 7 presents the results of multiple structural break tests, comparing observed F-statistics with critical values at 1%, 5%, and 10% significance levels. The tests, denoted as F(10), F(21), and F(32), evaluate models with increasing potential breaks.

- F(10): The F-statistic of 11.25 exceeds all critical values (6.09, 4.66, 4.03), indicating a significant structural break at the 1% level, suggesting a major shift in the series or model;
- F(21): The F-statistic of 9.43 also exceeds all critical values (6.59, 5.24, 4.64), confirming multiple breakpoints, likely due to economic events or policy changes;
- F(32): The F-statistic of 1.60 is below all critical values, indicating no significant break, suggesting the breaks detected in F(10) and F(21) sufficiently explain structural changes.

These results reveal at least two significant structural breaks, reflecting shifts in economic relationships caused by factors like policy changes, crises, or innovations. Accounting for these breaks is crucial in econometric analyses to avoid distorted results and ensure accurate estimates of variable relationships over time.

4.6. Cointegration analysis

The cointegration tests by Pedroni and Kao (Tables 8-9) assess long-term relationships between digitalization, economic growth, environmental quality, and human development. These tests determine if the variables move together over time despite short-term fluctuations. Pedroni's test examines common and individual autoregressive (AR) coefficients across two dimensions: within-group and between-group. For common AR coefficients, key statistics are significant: Panel rho-Statistic (-5.253640), Panel PP-Statistic (-16.03500), and Panel ADF-Statistic (-1.548589, significant at 10%) all have p-values near 0.0000. This indicates a strong cointegration relationship, meaning the variables share a common long-term trend and evolve together.

Table 8 - Results of Pedroni's Residual Cointegration Test

Pedroni Residual Cointegration Test				
Series: Log (Y), Log (DI), Log (IDH) and Log (EQ)				
Alternative hypothesis: common AR coefs. (within-dimension)				
	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	-0.760842	0.7766	-4.130197	1.0000
Panel rho-Statistic	-5.253640	0.0000	-2.422302	0.0077
Panel PP-Statistic	-16.03500	0.0000	-10.58425	0.0000
Panel ADF-Statistic	-1.548589	0.0607	-2.518786	0.0059
Alternative hypothesis: individual AR coefs. (between-dimension)				
	Statistic		Prob.	
Group rho-Statistic	-0.834413		0.2020	
Group PP-Statistic	-15.93880		0.0000	
Group ADF-Statistic	-0.482469		0.3147	

For individual AR coefficients, only the Group PP-Statistic (-15.93880) is significant (p = 0.0000), while the Group rho-Statistic and Group ADF-Statistic are not, indicating weaker relationships between groups compared to common AR coefficients. Overall, Pedroni's test confirms a cointegration relationship, particularly for common AR coefficients, suggesting that digitalization, economic growth, environmental quality, and human development follow a shared long-term trajectory.

Table 9 - Results of Kao's Residual Cointegration Test

Kao Residual Cointegration Test		
Series: Log (Y), Log (DI), Log (IDH) and Log (EQ) Automatic lag length selection based on SIC with a max lag of 4 Newey-West automatic bandwidth selection and Bartlett kernel		
	t-Statistic	Prob.
ADF	-3.122207	
Residual variance	0.116558	0.0009
HAC variance	0.034781	

Kao's residual cointegration test provides additional information by using the Augmented Dickey-Fuller (ADF) test to assess cointegration. The ADF statistic is significant at -3.122207 with a p-value of 0.0009, indicating a strong likelihood of cointegration between the variables. This result reinforces the conclusions obtained from Pedroni's test, confirming that a long-term relationship exists between the variables studied. Kao's test provides another verification method, considering the autocorrelation of residuals, and its results confirm the robustness of the long-term relationships identified by Pedroni.

4.7. Results of the panel CS-ARDL model estimation

Table 10 presents the results of the CS-ARDL models, which examine both long-term and short-term relationships between digitalization, environmental quality, human development, and economic growth. In the long term, the results reveal significant positive relationships. Digitalization (log DI) has a coefficient of 0.033178, meaning a 1% increase in digitalization leads to a 0.03% rise in economic growth. This underscores the growing importance of digital technologies in enhancing productivity and economic efficiency. Similarly, environmental quality (log EQ) has a stronger impact, with a coefficient of 0.144471, suggesting that sustainable environmental policies not only protect the environment but also promote long-term economic growth by fostering resilient economies. Human development (log IDH) shows the highest coefficient (0.564900), highlighting that improvements in education, healthcare, and living standards significantly drive economic growth by creating a skilled workforce and fostering innovation.

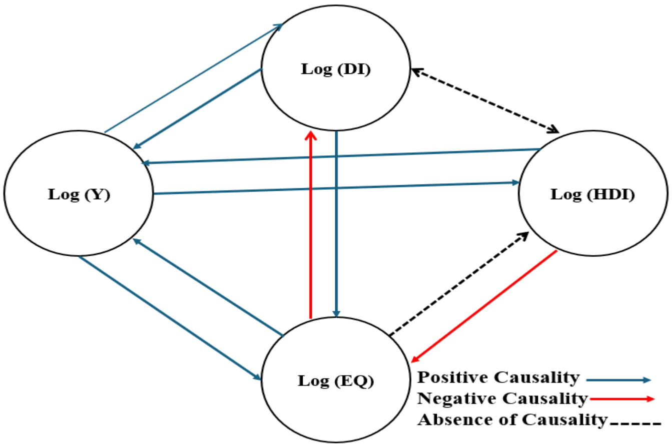
Table 10 - Results of the Panel CS-ARDL Model Estimation

Dependent Variable: Log (Y)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
	Long Run Equation			
Log (DI)	0.033178	0.005303	6.256005	0.0000
Log (EQ)	0.144471	0.019689	7.337816	0.0000
Log (IDH)	0.564900	0.102079	5.533938	0.0000
	Short Run Equation			
ECT	-0.646427	0.066535	-9.715605	0.0000
Log (DI)	0.001653	0.006777	0.243959	0.8073
Log (EQ)	0.014191	0.025384	0.559057	0.5763
Log (IDH)	0.461484	0.238113	1.938090	0.0530
C	-0.003503	0.001832	-1.911713	0.0563
Dependent Variable: Log (EQ)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
	Long Run Equation			
Log (DI)	0.033881	0.010387	3.261893	0.0012
Log (Y)	0.546002	0.071140	7.675077	0.0000
Log (IDH)	-0.581084	0.258008	-2.252193	0.0246
	Short Run Equation			
ECT	-0.932531	0.039116	-23.84029	0.0000
Log (DI)	-0.016738	0.017888	-0.935707	0.3497
Log (Y)	0.076734	0.123574	0.620951	0.5348
Log (IDH)	0.204055	0.316380	0.644970	0.5191
C	0.006252	0.003011	2.076709	0.0382
Dependent Variable: Log (IDH)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
	Long Run Equation			
Log (DI)	-0.001737	0.001675	-1.036979	0.3001
Log (Y)	0.072704	0.011782	6.170913	0.0000
Log (EQ)	-0.003552	0.005585	-0.635907	0.5250
	Short Run Equation			
ECT	-0.682820	0.064417	-10.59995	0.0000
Log (DI)	0.001950	0.002143	0.910171	0.3630
Log (Y)	0.011050	0.020322	0.543772	0.5868
Log (EQ)	-0.001473	0.005000	-0.294499	0.7685
C	0.008765	0.000927	9.456927	0.0000
Dependent Variable: Log (DI)				

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
	Long Run Equation			
Log (Y)	0.874503	0.359033	2.435721	0.0152
Log (EQ)	-1.049855	0.163195	-6.433142	0.0000
Log (IDH)	0.950249	1.089162	0.872459	0.3833
	Short Run Equation			
ECT	-0.603896	0.049611	-12.17252	0.0000
Log (Y)	0.236046	0.424477	0.556086	0.5784
Log (EQ)	0.468933	0.122984	3.812951	0.0002
Log (IDH)	-2.123757	0.796813	-2.665312	0.0079
C	0.146346	0.016751	8.736700	0.0000

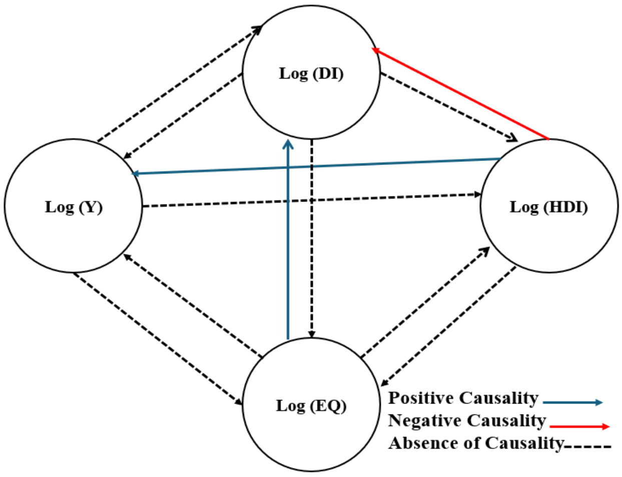
In contrast, the short-term results show notable differences. Digitalization and environmental quality do not have a significant immediate impact, as evidenced by their p-values of 0.8073 and 0.5763, respectively. This suggests that the benefits of these variables require time, investments, and structural adjustments to materialize. Only human development has a marginally significant short-term effect, with a p-value of 0.0530, indicating that investments in health, education, and well-being may yield modest productivity gains in the short term. Overall, while digitalization and environmental quality drive long-term growth, human development has a more immediate, though limited, impact in the short term. A key aspect of the analysis is the Error Correction Term (ECT), with a coefficient of -0.646427. This negative and significant value indicates that short-term imbalances are corrected quickly, with about 65% of deviations from long-term equilibrium adjusted each period. Despite short-term shocks, the economy rapidly returns to a stable state where digitalization, environmental quality, and human development interact positively to drive growth. Further analysis reveals additional insights. Digitalization (log DI) positively impacts environmental quality (log EQ) in the long term, with a coefficient of 0.033881. This reflects the role of cleaner digital technologies in resource management and reducing emissions. However, human development (log IDH) negatively affects environmental quality (-0.581084), suggesting that higher development levels may increase consumption and environmental pressures, especially where sustainability policies are lacking. Economic growth (log Y) positively influences human development (log IDH) in the long term (0.072704), showing that rising national income improves living conditions and access to healthcare and education. In the digitalization equation, economic growth boosts digitalization (0.874503), but environmental quality has a negative effect (-1.049855), possibly due to trade-offs in early industrialization or reliance on polluting industries. Figure 1 summarizes these long-term relationships. It highlights a bidirectional link between digitalization and economic growth, underscoring digital transformation's role in the economic pillar. However, no causal relationship exists between digitalization and human development (social pillar). Conversely, digitalization positively affects environmental quality, though environmental quality negatively impacts digitalization, reflecting potential trade-offs in sustainable development.

Figure 1 - Summary of the causal relationship between digitalization and the three pillars of sustainable development in the long term



Regarding Figure 2, which summarizes the short-term results, the estimates show that digitalization does not have a direct effect on the three pillars of sustainable development. However, environmental quality exerts a positive effect on digitalization, while the human development index seems to negatively influence digitalization. These results suggest that the impact of digitalization and other factors on the dimensions of sustainable development may vary depending on the time horizon considered.

Figure 2 - Summary of the causal relationship between digitalization and the three pillars of sustainable development in the short term



The results of the CS-ARDL model reveal a complex yet coherent picture of the interaction between digitalization, environmental quality, human development, and economic growth. In the long term, these variables converge to promote a more robust and sustainable economy. However, the benefits of some of these variables, particularly digitalization and environmental quality, appear to be more noticeable in the long term, while human development plays a more immediate role.

5. Economic interpretations of the results

The empirical results from analyzing long-term and short-term relationships between digitalization, economic growth, human development, and environmental quality reveal complex dynamics. These findings illustrate how digitalization, as a transformative force, interacts with the three pillars of sustainable development: economic, social, and environmental. We start by examining the long-term economic implications.

5.1. Long-term economic interpretations

In African countries, the bidirectional relationship between digitalization and economic growth is highly significant. Digitalization drives economic growth by boosting productivity, reducing costs, and enhancing market efficiency, while economic growth, in turn, fuels further digital development. This creates a virtuous cycle, particularly vital for Africa's industrialization and modernization. Digitalization opens new opportunities through innovation, digital enterprises, and access to global markets, accelerating growth in sectors like finance, agriculture, and education. However, the lack of a long-term causal link between digitalization and the Human Development Index (HDI) is concerning. While digitalization has the potential to improve access to education, healthcare, and services, its impact is limited by uneven infrastructure, low digital literacy, and economic inequalities. For digitalization to enhance human development, it must be paired with investments in education, healthcare, and inclusive policies to bridge the digital divide.

Digitalization also positively impacts environmental quality in Africa, aiding resource management, reducing emissions, and improving energy efficiency. Technologies like precision agriculture, smart energy systems, and environmental monitoring support the transition to a greener economy. However, restrictive environmental policies, such as land-use regulations or resource limitations, can slow digital infrastructure development. Balancing environmental sustainability with digital progress poses a challenge for policymakers, as resources may be diverted from digital initiatives to address pressing ecological concerns. Overall, digitalization is a powerful driver of economic and environmental transformation in Africa, but its social impact remains limited without complementary investments and policies. To maximize its benefits, African governments must adopt integrated strategies that address local challenges and promote inclusive, sustainable development.

5.2. Short-term economic interpretations

In African countries, the short-term effects of digitalization on sustainable development - economic, social, and environmental - are limited. This is because the benefits of digital transformation require time, significant investments in infrastructure, and human capital development. Digitalization is still emerging in Africa, and its adoption faces challenges such as uneven infrastructure, poor connectivity in rural areas, and a lack of robust regulatory frameworks. As a result, economic and social benefits, like productivity gains or improved access to services, only materialize after technologies are fully integrated. Socially, while digitalization can enhance access to education and healthcare, reforms in these sectors take time due to funding shortages, weak institutions, and socio-economic challenges. Similarly, environmental benefits, such as reduced carbon emissions through smart technologies, are limited in the short term due to inadequate infrastructure and insufficient policy incentives.

However, environmental quality positively influences digitalization, as sustainability initiatives often rely on digital tools like precision farming or emissions monitoring. Conversely, improvements in the Human Development Index (HDI) can slow digitalization, as resources are redirected to urgent needs like healthcare and education, leaving less funding for digital infrastructure. Overall, while digitalization holds long-term potential for economic growth, social progress, and environmental sustainability, its short-term impact is constrained by structural and institutional challenges. African countries must adopt a strategic, long-term approach, investing in digital infrastructure, promoting inclusion, and aligning policies with technological goals to fully harness digitalization’s potential for sustainable development.

6. Conclusion

This comprehensive study provides valuable insights into the intricate relationship between digitalization and sustainable development across economic, social, and environmental dimensions in 48 African nations from 1999 to 2020. Through advanced econometric analysis of panel data, we have identified distinct temporal patterns in how digitalization interacts with economic growth, environmental quality, and human development indicators. The research reveals a particularly strong long-term symbiotic relationship between digitalization and economic performance, where technological advancement both drives and is driven by economic expansion. This mutually reinforcing dynamic creates a virtuous cycle of innovation, productivity gains, and new economic opportunities that can significantly enhance Africa's global economic integration and competitiveness.

A critical finding emerges regarding the social dimension of development, where digitalization alone demonstrates limited capacity to improve human development outcomes. This suggests that while digital technologies serve as powerful tools for economic modernization, they cannot single-handedly overcome structural social inequalities. The research underscores the necessity of parallel investments in human capital development, particularly in education and healthcare systems that are often under-resourced in many African contexts. For digital education initiatives to be effective, they must be supported by adequate infrastructure, trained educators, and inclusive policies that reach marginalized populations. Similarly, digital healthcare solutions require foundational health system strengthening to achieve meaningful impact. These findings highlight the importance of comprehensive policy frameworks that combine technological advancement with institutional development and social investment.

The environmental dimension presents another complex relationship, where digitalization shows positive long-term effects on environmental quality through enabling technologies like IoT and smart resource management. However, the study identifies potential policy tensions, as environmental protection measures may inadvertently constrain digital infrastructure expansion. This paradox underscores the need for carefully calibrated policies that harmonize environmental and digital objectives. The temporal dimension of these relationships proves particularly significant, with digitalization's benefits manifesting primarily in the long term while showing limited immediate impacts. This delayed effect profile emphasizes the importance of sustained commitment to digital transformation strategies, especially in contexts where institutional and infrastructural foundations are still developing.

The research also reveals interesting short-term dynamics, including how environmental quality improvements can accelerate digital adoption and how competing social priorities may temporarily slow digital investments. These findings suggest that digital transformation cannot be pursued in isolation but must be integrated with broader development strategies. For African policymakers, this means developing holistic approaches that simultaneously address digital infrastructure gaps, social inclusion imperatives, and environmental sustainability goals. The study ultimately calls for nuanced, context-sensitive strategies that recognize digitalization as one component within a larger ecosystem of development interventions, all working in concert to achieve sustainable and equitable progress across the continent.

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Conflict of interest

The authors declare that they have no competing interests.

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