ICT Development, Innovation Diffusion and Sustainable Growth in Sub-Saharan Africa

Mugabe Roger1, Liu Shulin1, and Brima Sesay2

Abstract
This study aims to explore the impacts of ICT and innovation on sustainable economic growth and the direction of causal relationships among them in a trivariate framework. The study employed the DOLS and Panel VECM for causality to study the relationships for 33 Sub-Saharan Africa countries categorized based on income between 2000 and 2020. The study uses annual time-series data that were obtained from the World Development Indicators (WDI) database for the empirical analysis. Results from the DOLS show that both ICT development and innovation contribute positively to sustainable growth in all the categories of countries. However, the marginal effects of innovation on sustainable growth are very small compared to ICT development, especially for low-income countries. The VECM result confirms significant causal relationships among the studied variables in the short and long run. Policies should be geared toward channeling resources to enhance ICT skills, access, and usage in the continent. This can be achieved if organizations engaged in the SSA agenda for prosperity, provide the support needed to complement different governments’ efforts in advancing ICT penetration and innovation diffusion in the continent. Also, it is important for income groups to be considered when establishing and implementing such policies.

Keywords
ICT development, innovation diffusion, sustainable economic growth, DOLS, VECM

Introduction
Information and Communication Technology (ICT) and innovation can be connected to different themes and concepts across different disciplines. For instance, they are highly associated with the term sustainability (Akkemik, 2015; Kumar & Kumar, 2017). Sustainability is the quality and ability to be maintained at a specific rate or level over time (Kumar & Kumar, 2017). A systematic approach toward sustainability constitutes economic, social, and environmental aspects (Ejemeyovwi, Osabuohien et al., 2019; Teh et al., 2021; Zhao et al., 2021). Several extant pieces of literature can be found on the relationship between ICT or innovation and any of the aspects of sustainability. The facts that economies have benefited greatly from the adoption of efficient ICT and innovation cannot be overstated (Akerkar et al., 2016). The maximum interconnection of most of the African countries can be attributed to the

Africa is a developing and frontline economy for utilizing the fourth industrial revolution (industry 4.0) and achieving rapid economic growth and progress (Myovella et al., 2020). Realizing rapid and sustainable growth through industry 4.0 depends on the degree of the “smartness” of these economies (Asongu & Odhiambo, 2019). The maximum interconnection of most of the African countries can be attributed to the

Creative Commons CC BY: This article is distributed under the terms of the Creative Commons Attribution 4.0 License (https://creativecommons.org/licenses/by/4.0/) which permits any use, reproduction and distribution of the work without further permission provided the original work is attributed as specified on the SAGE and Open Access pages (https://us.sagepub.com/en-us/nam/open-access-at-sage).
adoption of modern ICT and innovation (Maneejuk & Yamaka, 2020; Solomon & van Klyton, 2020). Studies have established reciprocal relationships between ICT and growth (Asongu & Le Roux, 2017; Ejemeyovwi, Osabuohien & Bowale, 2021; Iscan, 2012; Pradhan et al., 2018; Yousefi, 2011), innovation and growth (Ejemeyovwi, Osabuohien & Bowale, 2021; Maradana et al., 2017) ICT and Innovation (Ejemeyovwi, Osabuohien & Bowale, 2021; Shehzad et al., 2021). Other studies characterize the ICT-led growth nexus (Alimi & Adediran, 2020; Vu et al., 2020), innovation-led growth nexus (Boot & Marinc, 2010; Nazir et al., 2021). The reasons of ICT development and innovation diffusion for sustainable economic growth and progress in SSA are described as the device for realizing: (1) “smart society” where establishing digitalization minimizes the inequality gap in the SSA region (Asongu & Tchamyou, 2020); and (2) “value-added” to add value to labor productivity for enhanced sustainable growth (Karakara & Osabuohien, 2019; Oluwatobi, 2015; Tchamyou, 2017).

Most SSA economies have relaxed limitations and liberalized the ICT sector since the late 1990s, resulting in an upward trend in ICT infrastructure development in the continent (Asongu & Le Roux, 2017). ICTs’ investment in Africa has been boosted by market forces. Investors from across the globe view Africa as a financial hotspot and investment destination because of the continent’s large population and the better rate of return on investment it offers than other developing economies (Ejemeyovwi & Osabuohien, 2020).

Due to the advancement of wireless mobile communication technologies and the trend of liberalization, the ICT sector in Sub-Saharan Africa (SSA) has experienced a significant resurgence in the past 20 years. Capital investment from both the public and private sectors has poured in as a result of the aforementioned progress. In addition, drastic cost reductions and improved capacity have enabled swift diffusion of innovation (Ejemeyovwi, Osabuohien et al., 2019). Consequently, the mobile penetration rate in the SSA region has more than doubled since the year 2000. Countries like South Africa, Nigeria, the Democratic Republic of Congo, Uganda, and Cote d’Ivoire have more mobile phone lines than fixed lines, and this trend is expected to continue (Ejemeyovwi, Osabuohien & Ebenezer, 2021).

However, in the extant literature, most of the empirical studies on the subject have focused on industrialized and emerging economies on both single country and panel or cross-country perspectives. The single country perspective studies include, but are not limited to those conducted for Brazil (Jung & Lopez-Bazo, 2019), Greece (Tsakanikas et al., 2021), Italy (Daniele, 2006), USA (Whitacre et al., 2014), Japan (Ishida, 2015), Turkey (Iscan, 2012), Australia (Gretton et al., 2002), Singapore (Vu et al., 2020), India (Reddy, 2018; Reddy & Mejiaheen, 2019), and Pakistan (Rahman et al., 2021). Similarly, most empirical studies have looked at it from a panel or cross-country perspective. Here, the first strand of literature focuses on the relationship between innovation and economic growth (Cetin, 2013; Furman et al., 2002; Pradhan et al., 2016; Yang, 2006). Even though most of the studies looked at the effect of innovation on economic growth, characterizing the supply-driven approach, but in fact, it is the rise in economic activity that has the potential to boost the level of innovation in the process of growth and development. This indicates that innovation and economic growth can reinforce each other, which means they can have a bidirectional relationship (Pradhan et al., 2016). In the same line of investigation, Maradana et al. (2017) studied the impact of innovation on economic growth in 19 European countries for the 1989 and 2014 periods. Their findings show a positive contribution of innovation to per capita income growth. They further confirm the bidirectional causal connection between innovation and income per capita growth.

The second strand of the literature considers ICT and growth as the main variables in their studies. For instance, in a study conducted for the NEXT-11 countries, Pradhan, Arvin, Bahmani, et al. (2017) verified the causal connection between ICT and growth. They also argued that the direction of causality was dependent on the level of penetration of the IT indicators used. Similarly, the connection between financial development, ICT, and growth was examined by Cheng et al. (2021) for 72 countries for the 2000 and 2015 periods. From among their findings, they were able to establish that ICT diffusion can boost growth in high-income economies, but its influence is unclear in medium- and low-income countries. Between 1991 and 2012, a panel VAR model was also used by Pradhan et al. (2014) to examine the relationship between ICT development and four other economic indicators for G-20 countries. Their findings show a positive correlation between the expansion of ICT infrastructure and economic growth. In addition, there were long-term causal relationships established between these variables.

The third strand of the literature has pointed out a few studies that studied the relationships among the three variables (ICT, innovation, and growth). In a 15-year study with a sample of 13 G-20 countries, Nguyen et al. (2020) examined the impact of ICT and innovation on carbon dioxide emissions and economic growth. From among their findings, ICT and financial development are the key drivers of economic growth. Also, Pradhan, Arvin, Nair, et al. (2017) studied the contribution of innovation, venture capital, and ICT to sustainable growth in 25 European countries for the 1989 and 2016 periods. By employing the VECM approach, they found a long-run impact of the three variables on sustainable economic growth. The results from their short-run analysis of ICT and innovation dissemination show that the direction of causality varies based on the precise indicators employed to measure ICT and innovation. Similarly, Ejemeyovwi, Osabuohien & Ebenezer (2021) investigated the link between ICT, innovation, and financial development in Africa. They employed the Bayesian Vector Auto-Regressive approach. They found the interaction of ICT and innovation to
contribute positively to financial development. However, they did not account for how ICT and Innovation can both contribute to growth.

It is also clear from the foregoing that studies that take into account all three factors at the same time in a trivariate framework are scarce, particularly for the countries included in this study. To fill this knowledge vacuum, the study used panel Dynamic Ordinary Least Squares (DOLS) estimation to look at the long- and short-run links between innovation diffusion, ICT development, and sustainable economic growth in SSA. Panel vector error correction model (VECM) was also utilized to capture the direction of causality in a trivariate framework.

Moreover, most studies viewed ICT measurements and innovation diffusion measurements as disaggregated indicators in which the variables in ICT and innovation proxies are not aggregated together, however, their components may have a significant causal effect. For instance, aggregating the ICT indicators (ICT access, ICT use, and ICT skills) into a single dimension in this study will yield appealing results. In the case of innovation diffusion, we have used scientific and technical journal articles as a proxy which we later justify in this study. Real per capita output in SSA is a measure of sustainable economic growth in this study. The same measure has been used for sustainable economic growth by Pradhan et al. (2020) for the European Union and by Belloumi and Alshehry (2020) for Saudi Arabia. Given the above, the study poses the following questions: Does ICT development stimulate sustainable growth in SSA? Does innovation diffusion stimulate sustainable growth in SSA? Are there any causal relationships between ICT development, innovation diffusion, and sustainable growth in SSA? These are the questions that this study seeks to answer through DOLS and panel causality approaches. This gap in the literature has gone unnoticed in previous investigations. The fundamental goal of this study is therefore to comprehensively assess the current state of affairs of these three variables in a trivariate framework in SSA. The other sections of this paper are the theoretical framework and summary of hypotheses, materials and methods, results, conclusion, and implications for policy.

Theoretical Framework and Summary of Hypothesis

Innovation Diffusion and Economic Growth

Over the previous half-century, the rapid digitalization of the global economy has had a substantial impact on countries’ inventive potential and economic growth. The interrelationships between these variables are quite complex. Numerous researches have examined the theoretical basis of the dynamic interaction between the variables. This present study examines the relationship between ICT development, innovation, and sustainable economic growth in a three-way approach. According to Schumpeter (1942), technology and innovation diffusion is vital for long-term economic progress. He further stated that the creation of new knowledge through research and development (R&D) and the use of contemporary technology is essential. According to Romer’s (1994) endogenous growth model, technology and innovation are major factors to increase productivity and thus economic growth. Consequently, the study found that countries with a higher level of economic development tend to invest more in innovation and technology. Below, we explain the theoretical basis of the association among the three variables in consideration.

The connections between Innovation, ICT development, and economic growth can be categorized into three distinct categories. First, is the innovation-growth connection, which has attracted a lot of attention in academic circles. Known for its ability to produce new inventions and discoveries, research and development (R&D) is a key contributor to a country’s economic growth. There is also evidence that the wealthiest countries are spending in R&D to maintain their position at the top of the innovation value chain. Recently, some studies have looked at the relationship between these two variables for the OECD countries. Sokolov-Mladenović et al. (2016) and Kacprzyk and Świeszewska (2019) studied the relationship for EU28 countries, and Chawla (2020) studied the relationship for all the OECD countries together. Sokolov-Mladenović et al. (2016), for example, used a dynamic panel data approach to evaluate the relationship between innovation and economic growth by incorporating other macroeconomic variables and found innovation to contribute positively to growth. The GMM approach was used by Kacprzyk and Świeszewska (2019) to examine the linkage between R&D and economic growth and control for other indicators. The findings confirm a positive association between R&D and growth. Similarly, using panel data modeling, Chawla (2020) found a substantial dynamic link between population, R&D, and economic growth. Thus, it is proposed that the following hypotheses be evaluated in this research:

**Hypothesis 1**

\[ H_1: \text{Innovation diffusion positively influences sustainable growth} \]

**Hypothesis 2a**

\[ H_{ID \to EG}: \text{innovation diffusion “Granger Causes” sustainable growth} \]

**Hypothesis 2b**

\[ H_{EG \to ID}: \text{‘sustainable growth’ Granger Causes’ innovation diffusion} \]

ICT Development and Economic Growth

The second viewpoint focuses on the relationship between ICT and economic growth. There are two possible ways in which ICT can contribute to economic growth in this
situation. First, as a means of enhancing economic agents’ efficiency and productivity. Using ICT, agents can have access to new resources, information, market opportunities, and other advantages. Second, because of the increasing worldwide demand for ICT, the sector has grown to be an important source of income for many countries (Arvin & Pradhan, 2014). ICT services get increasingly complex as economies grow, which means that modern services are required by both customers and enterprises. ICT spending by governments across the globe has increased to suit the needs of a wide range of stakeholders in the economy. There have been several recent pieces of research that looked at the relationship between economic growth and ICT in Sub-Saharan Africa and the OECD countries. Using dynamic panel data modeling, Pradhan, Arvin, Nair, et al. (2017), for example, looked at the relationship between innovation, investment, trade openness, ICT infrastructure, and economic growth. In a similar study, Koutroumpis (2019) used a production function technique to show that capital, labor, broadband, and economic growth have a strong link. Using dynamic panel data modeling, Myovallet et al. (2020) discovered a favorable correlation between digitalization and economic growth. Thus, it is proposed that the following hypotheses be evaluated in this research:

**Hypothesis 3**

$H_I$: ICT development positively influences sustainable growth

**Hypothesis 4a**

$H_{ICT \rightarrow Economic~Growth}$: ICT Development “Granger Causes” Sustainable Growth

**Hypothesis 4b**

$H_{Economic~Growth \rightarrow ICT}$: Sustainable Growth “Granger Causes” ICT Development

**ICT Development and Innovation Diffusion**

The third viewpoint studies the Innovation-ICT nexus, which has got less consideration in the academic literature. Over time, governments and corporations have been encouraged to spend in R&D in the ICT sector due to ICT’s ability to boost economic growth and productivity. ICT innovation has increased, which has allowed the various economic actors to raise their production and efficiency. ICT infrastructure investment has also resulted in decreased prices for ICT services, allowing for greater use of ICT in various sectors and fields. Increased funding for new ICT activities like software and application tools has resulted from this. Koutroumpis et al. (2020) found a greater impact on Europe’s economy from R&D investments in ICT companies than from R&D investments in non-ICT industries. This has pushed ICT companies to invest more in R&D. Edquist and Henrekson (2017) studied the link between these two variables for 50 selected industries. Similarly, Saidi and Mongi (2018) examined the dynamic link between these two variables in selected high-income countries, whereas Choi and Yi (2018) examined the relationship in selected 105 countries. Thus, it is proposed that the following hypotheses be evaluated in this research:

**Hypothesis 5a**

$H_{ID \rightarrow ICT}$: Innovation Diffusion “Granger Causes” ICT Development

**Hypothesis 5b**

$H_{ICT \rightarrow ID}$: ICT Development “Granger Causes” Innovation Diffusion

The above hypotheses are summarized in Figure 1.

**Materials and Methods**

**Model Specification**

As previously mentioned, endogenous growth models have demonstrated the importance of ICT and innovation in boosting economic growth (Ejemeyovwi, Osabuohien & Bowale, 2021; Tsakanikas et al., 2021). In the preceding section of this work, we discussed the interplay among these variables. However, there is a paucity of research on the impact of ICT and innovation on economic growth that at the same time accounted for the direction of causality among them in a tri-variate framework (see, Pradhan, Arvin, Nair, et al., 2017). The present study extends the model of Ofori and Asongu (2021) and Rudra et al. (2018) by aggregating the different measures of ICT and innovation. Consequently, the following is a description of the research model that was used via the Cobb-Douglas production function:

$$RGDP_{it} = A_i\beta^{ID}_{it}ICT^{2i}_{it}\epsilon_{it}$$ (1)

After the log transformation, equation (1) can be shown as follows:

$$ln(RGDP_{it}) = \beta_0 + \beta_1ln(ID_{it}) + \beta_2ln(ICT_{it}) + \epsilon_{it}$$ (2)

Where $\beta_0 = \ln(A_i)$; $i (1, 2, \ldots , N)$ denotes a country in the sample; $t (1, 2, \ldots , T)$ signifies the time for each country; and $\beta_i$ (for $i = 1, 2$) signifies the parameters of the model. The onus is to evaluate the parameters in equation (2) and compute for some panel estimations tests on the causal relationships among real GDP per capita (RGDP), innovation diffusion (ID), and ICT development (ICT). The a priori expectation of theory state that ICT and innovation should have a significant positive impact on sustainable growth in SSA.

**Data and Sample**

An empirical approach was presented to investigate the impacts of ICT and innovation on sustainable growth and the
direction of causal relationships among them. The study uses annual time-series data that were obtained from data published by the World Bank, 2021, for a sample of 33 SSA countries selected based on data availability for all the indicators used in the study. The data set used spans from 2000 to 2020. The dataset were further categorized into income groups based on the World Bank classification (Upper Middle Income, Lower Middle income, and low-income countries). Based on their classification, the first panel of countries consists of Botswana, Equatorial Guinea, Gabon, Mauritius, Namibia, Seychelles, and South Africa. The second panel consists of Angola, Cameroon, Comoros, Congo Rep, Cote D’Ivoire, Ghana, Kenya, Nigeria, Senegal, and Sudan. The third panel contains Benin, Burkina Faso, Burundi, CAR, Chad, Congo Dem Rep, Ethiopia, Guinea, Malawi, Mozambique, Niger, Rwanda, Sierra Leone, Tanzania, Togo, and Uganda.

Variables Description

The variables used in this study are innovation diffusion (ID), ICT development (ICT), and real per capita GDP growth (RGDP) as a proxy for sustainable growth (Belloumi & Alshehry, 2020; Rudra et al., 2018). Given that sustainable development index (SDGI) is a critical measure of countries sustainable growth and development, we also incorporated it in the robustness check (Table 4). The innovation diffusion measure was captured by scientific journal articles due to data availability for R&D activities in SSA countries. The same measure has been used by Oluwatobi et al. (2015) and Ejemeyovwi, Adiat et al. (2019). They argued that, apart from data availability, output from innovation can be captured by scientific journal articles as opposed to other measures because of the following reasons: (1) innovative individuals from diverse fields spontaneously convey their ideas through scientific journal papers. Beneficial innovative ideas that emerge from other disciplines other than the engineering areas can readily be kept for reference. Such unique ideas may not need patenting; consequently, scientific and technical journal articles will be an accurate venue for the presentation of such innovative ideas. (2) The procedure of getting a patent and trademark, such as requirements and certifications, is very tedious notably in most Sub-Saharan African countries. For instance, in countries like Nigeria, the process contains bureaucratic requirements, which cause delays in obtaining the security and protection of innovative ideas. Several innovative outputs and ideas may consequently end up becoming insecure and stolen. Others may end up becoming outdated and unnecessary before they are registered. (3) Profits are typically the driving force behind patenting. As a result, new ideas are protected by patents so that they can be licensed and sold for a profit. This

Figure 1. Summary of the hypothesized model.
profit-driven approach excludes new concepts that may not initially appear to have profit potential. ICT is captured via three different ICT development indicators as an aggregated index. The three ICT development indicators are (i) fixed telephone subscription per 100 people (ICT access), (ii) fixed broadband subscriptions per 100 people (ICT use), and (iii) gross secondary school enrollment gender parity ratio (ICT skills). The aggregated index of ICT is represented by ICT in the model.

Principal component analysis (PCA) was applied to compute the index for ICT development. PCA helps to convert the fundamental set of indicators into a reduced set of linear factors. The technique of obtaining this index includes numerous phases. It involves data matrix building, standardized variable creation, correlation matrix computation, identification of eigenvectors, and the principal components (PCs) selection (see, for instance, Pradhan et al., 2018, for more details). The results of the PC are shown in Appendix Table A1. In this paper, ICT is the weighted index of the three ICT development indicators, namely, ICT access, ICT use, and ICT skills. A detailed definition of these variables is available in the WDI database and we summarized them in Table 1.

### Table 1. Variables Description.

| Variable                | Description                                      | Source |
|------------------------|--------------------------------------------------|--------|
| Sustainable growth     | Real per capita GDP growth                       | WDI    |
| Innovation diffusion   | Scientific and Technical Journal                 | WDI    |
| ICT development        | ICT Development Index computed via PCA           | Author |
| ICT access             | Fixed telephone subscription per 100 people      | WDI    |
| ICT use                | Fixed broadband subscriptions per 100 people     | WDI    |
| ICT skills             | Gross secondary school enrollment gender parity ratio | WDI    |

Source. Authors.

Econometric Methodology

Panel unit root test. LLC, IPS, and Hadri’s standard stationarity tests become ineffective if cross-sections between countries in the panels are not independent. To accommodate for cross-country dependencies and give robust results that are consistently consistent, Dickey fuller and Im, Pesaran, and Shin introduced new approaches in their respective fields. Cross-sectional Augmented Dickey-Fuller (CADF) and Cross-sectional Im, Pesaran, and Shin (CIPS) are the names of two new approaches that have just been developed. The test entails estimating the following equation:

$$\Delta Y_{it} = \mu_i + \gamma_i Y_{it-1} + \rho R \sum_{j=1}^{n} \theta_j Y_{it-j} + \epsilon_{it}$$

Where, $Y_{it}$ denotes the variables analyzed in the equation, $\epsilon_{it}$ signifies the error term, $\Delta$ denotes the difference operator and $\mu_i$ and $R$ denotes the constants and trends respectively. The null hypothesis is that all of the panel member variables have a unit root. The alternative hypothesis state that at least one panel has no unit root. A suitable lag length is chosen using Schwarz Bayesian criterion (SBC).

Panel cointegration tests. To assess if the variables have a long-run equilibrium link, a cointegration test is utilized. In other words, if two or more series are cointegrated, the variables in these series are in a long-run equilibrium relationship. In contrast, a lack of cointegration suggests that the variables have no long-run relationship, meaning that they can theoretically move arbitrarily far apart.

Assume that the integration of the variables is of order one. If this is the case, the next step is to perform a cointegration study to examine if the set of possibly “integrated” variables has a long-term relationship. To check for this, an estimated cointegration equation of the following form is used:

$$Y_{it} = \beta_0 + \beta_1 X_{j1t} + \beta_2 X_{j2t} + \& + \beta_3 X_{jkt} + \epsilon_{it}$$

This equation may be re-written as:

$$\epsilon_{it} = Y_{it} - \left( \beta_0 + \beta_1 X_{j1t} + \beta_2 X_{j2t} + \& + \beta_3 X_{jkt} \right)$$

With the cointegration vector defined as:

$$\left[ 1 - \beta_0 - \beta_1 - \beta_2 \& - \beta_3 \right]$$

Johansen (1988) demonstrated that the aforementioned test is incapable of dealing with a panel setting. As a result, we use the Pedroni (1999, 2000, 2004) panel cointegration test to assess whether the variables are cointegrated. On the time-series panel regression setup below, the Pedroni panel cointegration test is used:

$$\Delta Y_{i,t} = \alpha_i + \sum_{j=1}^{p} \beta_j X_{j1t} + \epsilon_{it}$$

$$\epsilon_{it} = \rho \epsilon_{i(t-1)} + w_{it}$$

$Y_{it}$ and $X_{j1t}$ are the observable variables; $\epsilon_{it}$ signifies the panel regression’s disturbance term, and $\alpha_i$ permits country-specific fixed effects. The coefficients ($\beta_j$) above account for
individual country differences. The null hypothesis is that within-dimension estimate is not cointegrated when pooled. Given by:

\[ H_0: \rho_i = 1 \text{ for all } i \text{ against } H_1: \rho_i = \rho < 1 \]  

(9)

In the first hypothesis, the within-dimensional estimation assumes a common value for \( \rho_i \). To sum up, this technique removes any additional sources of heterogeneity among the panel members’ countries. In the pooled, between-dimensions estimation, the null hypothesis for no cointegration is:

\[ H_0: \rho_i = 1 \text{ for all } i \text{ against } H_1: \rho_i = \rho < 1 \]  

(10)

In the alternative hypothesis, the between-dimensions estimation does not assume a common value for \( \rho_i \). As a result, it adds another potential source of variation across the panel’s country members.

To determine whether the cointegration vector is heterogeneous, Pedroni recommends two types of testing. “The first is a test that uses an approach that works inside a single dimension (i.e., a panel test). The four statistics utilized in this test are the panel v-statistic, panel -statistic, panel PP-statistic, and panel ADF-statistic. These statistics, which pool the autoregressive coefficients over numerous panel members, are used to perform unit root tests on the generated residuals. The second test is a group test with three statistics: a group -statistic, a group PP-statistic, and a group ADF-statistic. These figures are based on estimators that average each panel members individually estimated autoregressive coefficients” (Pedroni, 2000).

**Long-run structural parameter estimation.** It is well-known that long-run structural coefficients of the exogenous variables can be estimated once the long-run equilibrium between the variables has been established. Cointegration analysis has an extra advantage in that once it is established; the estimates on the exogenous variables for the endogenous variable are realistic in both statistical and economic terms. However, as there are numerous types of long-run estimators, the problem is which one should be used. There are several regularly used and popular estimators; among them is the Ordinary Least Squares (OLS). The OLS has been replaced by the Dynamic Ordinary Least Squares (DOLS) and the Fully Modified Ordinary Least Squares (FMOLS) because of their superiority in addressing the potential endogeneity issue of explanatory variables and autocorrelation of residuals, allowing the variables to be made asymptotically asymptotic (Pedroni, 2004). When it comes to dealing with the issues of endogeneity and serial correlation, the FMOLS estimate uses a non-parametric approach, whereas the DOLS estimator employs a parametric approach. In this situation, the DOLS estimator outperforms both the OLS and FMOLS estimators in terms of performance and efficiency, particularly in small samples (Fei et al., 2011; Kao & Chiang, 2000; Narayan & Smyth, 2007). It is worth noting that the coefficients derived by the DOLS are unbiased and consistent, according to Pedroni (2001). Also, according to Herreras et al. (2013), the implementation of the DOLS estimator is the most appropriate way to handle the lack of cross-sectional independence among panel series. According to Rudra et al. (2018), the DOLS is the best estimator for studying the ICT-growth relationships. Thus, given the above-mentioned advantages, the DOLS estimator is used in this study to account for the intrinsic variability in long-run variances.

**VECM estimation.** A VECM can be used to do a cause-effect evaluation if the variables are co-integrated (Pesaran et al., 1999). Co-integrating regression can be used in a two-step method to acquire the error terms (Granger, 1988). F-statistic signifies the short-run causality for the short-run explanatory variables while \( \lambda_{\text{ik}} \) which is the coefficient of \( \text{ECT}_{\text{ik}-1} \) that captures the long-run causality. If \( \lambda_{\text{ik}} \) which is the coefficient of \( \text{ECT}_{\text{ik}-1} \) is statistically significant, it, therefore, suggests a long-run causal link between the variables. After establishing that, the following stage is to explore the direction of causality by utilizing the ECT obtained by the long-run VECM.

Here, we will use the panel-based VECM for determining the direction of causality between the variables, namely economic growth, Innovation diffusion, and ICT development as follows:

\[
\begin{bmatrix}
\Delta \ln GDP_{it} \\
\Delta \ln ID_{it} \\
\Delta \ln ICTD_{it}
\end{bmatrix} =
\begin{bmatrix}
\eta_{1i} \\
\eta_{2j} \\
\eta_{3k}
\end{bmatrix} + \sum_{p=1}^{P} \begin{bmatrix}
\alpha_{1k} \\
\alpha_{2k} \\
\alpha_{3k}
\end{bmatrix} \begin{bmatrix}
\beta_{1k} \\
\beta_{2k} \\
\beta_{3k}
\end{bmatrix} \begin{bmatrix}
\text{ECT}_{ik-1} \\
\text{ECT}_{ij-1} \\
\text{ECT}_{ik-1}
\end{bmatrix} + \begin{bmatrix}
\varepsilon_{1it} \\
\varepsilon_{2it} \\
\varepsilon_{3it}
\end{bmatrix} \tag{11}
\]

Lag lengths are an important consideration when attempting to estimate VECM, as causality tests can be heavily influenced by the lag structure used. Bias occurs when there are too few or too many lags. However, short latencies may mean that key variables are being left out of the model, and this can lead to biased regression results, which can lead to incorrect conclusions. While this can save time and reduce the standard error of the estimates, it also reduces the reliability of the data because it wastes observations. The optimal lag length cannot be determined with certainty, yet valid formal model definition criteria exist. This would significantly increase the computing load on a large panel like ours. Although the maximum lag lengths for all three variables can vary between countries, this will not be allowed in our VECM. We will utilize the well-known Akaike Information Criterion (AIC) to find the best lag structure for our model in this study.
Discussion of Results

After grouping the countries by income groups based on the World Bank classification, we presented the empirical findings in four steps. First, we examine the nature of the time series variables’ stationarity as shown in Appendix Table B1. Second, we reveal the mechanism of their cointegration as shown in Appendix Table B2. Third, we estimated the long-run structural parameters via the DOLS regression as shown in Table 2. Lastly, we show confirmation of the direction of Granger causality among the variables that are cointegrated via the VECM as shown in Table 3.

In the context of long-run analysis, it is possible to use co-integration to tackle the problem of series differentiation. By doing the cointegration test, the long-run information about unit root series may gleam more clearly. After determining that the variables have a panel unit root and are of the first difference, the step that follows next is to assess if there is a long-run interaction between the three variables. Panel long-run tests of Pedroni (1999, 2004) are used to determine whether or not the variables used in the model are cointegrated. There are two classifications of cointegration analyses suggested by Pedroni. The first classification is a group of panels characterized by four tests which comprise V-statistic, ρ-statistic, Philips Perron-statistic, and Augmented Dickey-Fuller statistic. These test statistics are clustered on the “within-dimension” and account for cross-sectional autoregressive estimates for the panel countries. The second classification is clustered on the “between-dimension,” and characterized by three tests which comprise Group ρ-statistic, Group Philips-Perron-statistic, and Group Augmented Dickey Fuller-statistic. These 3 tests are based on the common autoregressive estimates for each panel country. In all the tests, the hypothesis of no difference is that there is no cointegration among the variables, whereas the hypothesis of difference is that there is cointegration among the variables. In contrast to other homogeneous co-integration techniques like Johansen (1988) and Kao and Chiang (2000), Pedroni co-integration analysis considers the heterogeneity of the series across cross-sections. The results of the Pedroni cointegration analysis are shown in Appendix Table B2. The results show that the hypothesis of no difference or non-existence of cointegration is rejected at the 1% significance level. Therefore, the Pedroni panel cointegration test suggests a long-run relationship between innovation diffusion, ICT development, and sustainable growth for the overall sample of SSA and the sub-income groups.

DOLS Results

After validating the existence of long-run relationships, we estimated the long-run coefficients via the DOLS and the results are reported in Table 2. We used the overall sample which includes the 33 Sub-Saharan African countries selected for the study. To capture differences in income levels, we divide Sub-Saharan African countries into three groups based on the World Bank classification: UMIC, LMIC, and LIC.

In the estimation, we look at the effect of innovation diffusion and ICT development on sustainable growth. The long-run estimates of the DOLS model analysis are reported in Table 2. The empirical results show that ICT development significantly increases sustainable growth in all the groups (SSA, UMIC, LMIC, and LIC). This implies that a 1% increase in ICT development in SSA, UMIC, LMIC, and LIC increases sustainable growth by approximately 0.23%, 0.24%, 0.12%, and 0.06% respectively. These estimates support the findings of Cheng et al. (2021), Pradhan et al. (2014), and Pradhan, Arvin, Nair, et al. (2017). A possible explanation of this effect of ICT development on sustainable growth could be that since fixed telephone subscription and fixed broadband subscriptions are some of the main components of ICT development, this could be a pointer to the fact that more of the telecommunication indicators have been used in the development of ICT as a whole in SSA, which is an indication that many of the Sub-Saharan African countries can rely on ICT development to boost their economies.

With regards to the relationship between innovation diffusion and sustainable growth, the results follow a similar pattern just as in the relationship between ICT development and sustainable growth. From the DOLS model estimates, innovation diffusion has a positive and significant impact on sustainable growth in all the groups (SSA countries, UMIC, LMIC, and LIC). This implies that a 1% increase in innovation diffusion in SSA, UMIC, LMIC, and LIC increases sustainable growth by approximately 0.08%, 0.15%, 0.05%, and 0.04% respectively. These estimates support the findings of Pradhan et al. (2016) and Maradana et al. (2017).

On the whole, these results indicate that ICT development and innovation diffusion in terms of the DOLS are capable of spurring sustainable growth. However, the magnitude of the long-run elasticity of sustainable growth with respect to ICT development and innovation diffusion in the DOLS is much greater in the model for UMIC than the models for LMIC and LIC respectively. It appears that, although the merits of ICT development and innovation diffusion are evident, however, the diffusion of innovation has been at a slow rate as opposed to ICT development. This implies that ICT development contributes more to sustainable growth followed by innovation diffusion in UMIC, LMIC, and LIC respectively. This confirms the different roles of ICT development and innovation in the sustainable growth process. The finding is in line with the works of Pradhan et al. (2014) and Nguyen et al. (2020) who obtained the same results for G-20 countries. Nguyen et al. (2020) observe that ICT development is more sensitive to variations in economic growth. This greater sensitivity occurs because ICT development activities through the acceleration of fixed telephone subscriptions and fixed broadband subscriptions speed up economic growth. Pradhan, Arvin, Nair, et al. (2017) have a similar result on
### Table 2. Results of Panel DOLS Estimates.

| Variable                        | Coefficient | Standard error | t-statistic | Probability |
|---------------------------------|-------------|----------------|-------------|-------------|
| **Overall Sample of SSA**       |             |                |             |             |
| lnID                            | 0.075***    | 0.009          | 7.737       | .000        |
| lnICT                           | 0.226***    | 0.051          | 4.363       | .000        |
| Diagnostic checking             |             |                |             |             |
| R-squared                       | .849        |                |             |             |
| Adj. R-squared                  | .837        |                |             |             |
| LM = 3.638 (0.573); RESET = 2.738 (0.439); WHET = 4.726 (0.482) | | | | |
| **Upper Middle-Income Countries (UMIC)** | | | | |
| lnID                            | 0.146***    | 0.036          | 3.983       | .000        |
| lnICT                           | 0.243***    | 0.018          | 14.233      | .000        |
| Diagnostic checking             |             |                |             |             |
| R-squared                       | .893        |                |             |             |
| Adj. R-squared                  | .780        |                |             |             |
| LM = 5.960 (0.142); RESET = 4.120 (0.354); WHET = 5.621 (0.881) | | | | |
| **Lower Middle-Income Countries (LMIC)** | | | | |
| lnID                            | 0.052**     | 0.021          | 2.383       | .017        |
| lnICT                           | 0.119***    | 0.037          | 3.175       | .001        |
| Diagnostic checking             |             |                |             |             |
| R-squared                       | .815        |                |             |             |
| Adj. R-squared                  | .750        |                |             |             |
| LM = 3.438 (0.251); RESET = 3.426 (0.637); WHET = 4.522 (0.473) | | | | |
| **Low-Income Countries (LIC)**  |             |                |             |             |
| lnID                            | 0.041**     | 0.018          | 2.246       | .025        |
| lnICT                           | 0.060***    | 0.021          | 2.806       | .005        |
| Diagnostic checking             |             |                |             |             |
| R-squared                       | .821        |                |             |             |
| Adj. R-squared                  | .706        |                |             |             |
| LM = 3.299 (0.382); RESET = 4.632 (0.392); WHET = 3.536 (0.283) | | | | |

Source. Authors computation.

Note. LM = Lagrange multiplier test for serial correlation; RESET = misspecification test; WHET = heteroscedasticity test (White); RGDP = real per capita GDP; ID = innovation diffusion; ICT = information and communication technology.

***Denotes significant at the 1%; ** denotes significant at the 5%; * denotes significant at the 10%.

### Table 3. Results of VECM Granger-Causality Test.

|                     | LnRGDP_{t,i} | lnID_{t,i} | lnICT_{t,i} | ECT_{t,-1} |
|---------------------|--------------|------------|-------------|------------|
| **Overall Sample of SSA** |              |            |             |            |
| lnRGDP              | . . .         | 5.187***   | 2.087**     | -0.153***  |
| lnID                | 4.057*** [0.003] | . . .     | 4.226*** [0.000] | -0.092*** [−7.939] |
| lnICT               | 7.161*** [0.000] | 1.022 [0.266] | . . . | -0.073*** [−5.083] |
| **Upper Middle Income Countries (UMIC)** | | | | |
| lnRGDP              | . . .         | 4.536*** [0.001] | 4.538*** [0.000] | -0.102*** [−7.837] |
| lnID                | 5.326*** [0.000] | . . . | 8.326*** [0.000] | -0.082*** [−6.652] |
| lnICT               | 5.325*** [0.000] | 7.328*** [0.000] | . . . | -0.1309*** [−7.0367] |
| **Lower Middle Income Countries (LMIC)** | | | | |
| lnRGDP              | . . .         | 5.682*** [0.000] | 6.639*** [0.000] | -0.023*** [−4.264] |
| lnID                | 6.268*** [0.000] | . . . | 9.572*** [0.000] | -0.068*** [−5.652] |
| lnICT               | 4.521*** [0.000] | 7.638*** [0.000] | . . . | -0.108*** [−7.536] |
| **Low Income Countries (LIC)** | | | | |
| lnRGDP              | . . .         | 4.908*** [0.000] | 5.063*** [0.000] | -0.077*** [−6.736] |
| lnID                | 2.082** [0.045] | . . . | 5.183*** [0.000] | -0.047*** [−5.748] |
| lnICT               | 5.425*** [0.000] | 5.438*** [0.000] | . . . | -0.091*** [−6.647] |

Source. Authors computation.

***Denotes significant at the 1%; ** denotes significant at the 5%; * denotes significant at the 10%.

Note. RGDP = real per capita GDP; ID = innovation diffusion; ICT = information and communication technology.
the role of ICT development, Innovation diffusion, and venture capital in speeding up economic growth in European countries and consequently agree with the theoretical underpinning.

**Panel VECM Granger Causality Results**

In Table 3, we present the output from the VECM Granger causality for both the short and long run. The short-run results presented in Table 3 reveal two-way causality between innovation diffusion and sustainable growth and between ICT development and sustainable growth for the overall SSA sample. Moreover, the output reveals the existence of one-way causation from ICT development to innovation diffusion in the short run for the overall SSA sample. In other words, ICT development had a substantial impact on innovation diffusion in the short run and not the other way around. This is not surprising because so many new and innovative activities are heavily dependent on ICT services. The demand for greater ICT development appears to rise in tandem with the rate of innovation dissemination, and this relationship was proven to have an effect on ICT development.

The long-run causality output is denoted by ECT_{t-1} and the results are shown in the last column in Table 3. Starting with the overall SSA sample, the model where sustainable growth is the endogenous variable, the ECT_{t-1} is −0.15328. This value exhibits that ICT development and innovation diffusion Granger-cause sustainable growth in the long run with the ability to adjust at a rapid pace of about 15.32%. Additionally, the outputs show that sustainable growth and ICT development Granger-cause innovation diffusion in the long run with the ability to adjust at a rapid pace of around 9.26%. The outcomes further show that sustainable growth and innovation diffusion Granger-cause ICT development in the long run with the ability to adjust at a rapid pace of about 7.38%.

Now moving to the income groups, the outcomes from the long-run results show that ICT development and innovation diffusion Granger-cause sustainable economic growth with the ability to adjust at a rapid pace of around 10.22%, 2.33%, and 7.73%, for UMIC, LMIC, and LIC countries respectively. Likewise, the findings show that the variables converge to a long-run steady-state by approximately 13.09%, 10.88%, and 9.14% for the ICT development model after the occurrence of a shock for UMIC, LMIC, and LIC countries respectively. Also, the outcomes from the long-run results show that sustainable economic growth and ICT development Granger-cause innovation diffusion with the ability to adjust at a rapid pace of approximately 8.26%, 6.82%, and 4.73%, for UMIC, LMIC, and LIC countries respectively.

The overall results reveal that the outcomes of the long-run analysis via the DOLS are consistent with empirical findings in the extant literature regarding the roles of ICT development (Asongu & Le Roux, 2017; Ejemeyovwi, Osabuohien & Bowale, 2021; Iscan, 2012; Pradhan et al., 2018; Yousefi, 2011), and innovation diffusion (Ejemeyovwi, Osabuohien & Bowale, 2021; Maradana et al., 2017) in spurring economic growth. The long-run results also confirm that innovation diffusion, ICT development, and sustainable growth reinforce each other in a trivariate framework via the panel VECM.

**Robustness Check Result**

It has recently become a standard practice in empirical studies to do robustness check. The test is done to verify and validate the base regression model by some modification to visualize its behavior (Leamer, 1983). It is normally done by adding, removing or replacing variables in the base regression model (Ejemeyovwi, Osabuohien & Bowale, 2021). The fact that the coefficients do not alter substantially is considered proof that they are “robust.” If the evaluated regression coefficients’ signs and magnitudes are also reasonable, it is generally assumed that the estimated regression coefficients can be relied upon, with all the implications for policy analysis and economic insight that this implies.

In this study, to check for robustness of the baseline model, the dependent variable was replaced with the sustainable development index (SDGI) of Hickel (2020), which denotes the efficiency of nations in achieving human development. The index is calculated as a measure of two indicators that is: the human development index and the ecological impact index. Consequently, the sustainable development index (SDGI) is computed using the formula:

\[
SDGI_u = \frac{\text{Development Index}_u}{\text{Ecological Impact Index}_u}
\]

Din et al. (2021) applied the SDGI to empirical studies in the literature. The data used for this computation can be found in (https://www.sustainabledevelopmentindex.org/timeseries). Also see Hickel (2020) for detail computation of the index.

The robustness check in Table 4 presents the empirical results for each of the three income groups and the overall SSA countries. The main difference between Tables 2 and 4 is that different measures are used for sustainable growth and development. While Table 2 utilizes real per capita GDP growth, which covers the 33 countries, Table 4 utilizes SDGI, which also covers the 33 countries. Also, the latter indicator is of greater importance in this study. Given that sustainable development index is a critical measure of countries sustainable growth and development, we tend to incorporate it in the robustness check. As shown in Table 4 all models’ coefficients portray no significant differences than the baseline results presented in Table 2 models reported in this paper. Consequently, the study claim that legitimacy informs the DOLS estimator’s consistency of the sustainable growth variables applied in the entire regression model.
Conclusion and Implications for Policy

This study contributes to the debate on how SSA countries can foster sustainable growth. Consequently, we diverge from the existing debate on how this can be achieved through empirical research. Inspired by the significant rise in ICT development and the anticipated rise in innovation diffusion in SSA following the drastic transformation due to the revolution of technology associated with the development of wireless, mobile communication systems and the liberalization process, we examine the long-run and short-run relationships among innovation diffusion, ICT development, and sustainable economic growth in SSA. Annual time series data that spans from 2000 to 2020 for a sample of 33 SSA countries selected based on data availability for all the indicators was used in the study. We provide evidence robust to several specifications from the panel DOLS estimation and the panel VECM that captured the direction of causality among the variables in a trivariate framework to show that: (1) both ICT development and innovation diffusion foster sustainable economic growth in SSA, (2) ICT development, innovation diffusion and sustainable growth, reinforce each other, (3) compared to innovation diffusion, ICT development is more effective in driving sustainable economic growth in SSA.

Considering progress made by most Western and East Asian countries in recent times through ICT development and innovation diffusion, our findings offer sparks of confidence in promoting collective prosperity in SSA. First, our results show that ICT can offer policymakers concerned with the growth agenda of SSA countries, convincing means of addressing problems associated with ICT infrastructural development to induce sustainable growth through enhanced ICT access, ICT use, and ICT skills. Our pathway results on innovation diffusion and ICT development show that making shared prospects in SSA may not just be about improving infrastructural investment, but an innovative ICT infrastructure that gear toward sustainable growth and transformation in the continent.

Table 4. Robustness Test Results Using SDGI as the Dependent Variable.

| Variable                      | Coefficient | Standard error | t-statistic | Probability |
|-------------------------------|-------------|----------------|-------------|-------------|
| Overall Sample of SSA         |             |                |             |             |
| lnID                          | 0.074***    | 0.007          | 10.099      | .000        |
| lnICT                         | 0.223***    | 0.040          | 5.485       | .000        |
| Diagnostic checking           |             |                |             |             |
| R-squared                     | 0.872       |                |             |             |
| Adj. R-squared                | 0.854       |                |             |             |
| LM = 4.152 (0.325); RES = 4.336 (0.372); WHET = 3.918 (0.529) | | |
| Upper Middle-Income Countries (UMIC) | | |
| lnID                          | 0.151***    | 0.029          | 5.110       | .000        |
| lnICT                         | 0.247***    | 0.016          | 14.649      | .000        |
| Diagnostic checking           |             |                |             |             |
| R-squared                     | 0.876       |                |             |             |
| Adj. R-squared                | 0.741       |                |             |             |
| LM = 3.628 (0.271); RES = 5.204 (0.428); WHET = 4.413 (0.692) | | |
| Lower Middle-Income Countries (LMIC) | | |
| lnID                          | 0.048**     | 0.019          | 2.481       | .030        |
| lnICT                         | 0.120**     | 0.040          | 2.964       | .013        |
| Diagnostic checking           |             |                |             |             |
| R-squared                     | 0.839       |                |             |             |
| Adj. R-squared                | 0.770       |                |             |             |
| LM = 4.319 (0.272); RES = 4.493 (0.528); WHET = 4.382 (0.373) | | |
| Low-Income Countries (LIC)    |             |                |             |             |
| lnID                          | 0.039**     | 0.010          | 3.761       | .018        |
| lnICT                         | 0.071**     | 0.024          | 2.948       | .037        |
| Diagnostic checking           |             |                |             |             |
| R-squared                     | 0.842       |                |             |             |
| Adj. R-squared                | 0.718       |                |             |             |
| LM = 4.518 (0.426); RES = 4.522 (0.628); WHET = 3.662 (0.419) | | |

Source. Authors computation.

Note. LM = Lagrange multiplier test for serial correlation; RESET = misspecification test; WHET = heteroscedasticity test (White); SDGI = sustainable development goal index; ID = innovation diffusion; ICT = information and communication technology. *** denotes significant at the 1%; ** denotes significant at the 5%.
Based on the findings above, it is proposed that policymakers should focus their efforts on improving the continent’s ICT capabilities, accessibility, and adoption. This can be achieved if entities engaged in the SSA agenda for prosperity, such as the ADB and the World Bank provide the support needed to complement different governments’ efforts in advancing ICT penetration in the continent. Additionally, legislative actions are needed to help grow the continent’s tech hubs to aid in the marketing of high-tech products, as well as to help establish patents so that the continent’s young and innovative population may help build the continent.

In summary, ICT sector advances are changing the global economy at an unprecedented rate. ICT advancement and innovations are having a greater impact on countries’ sustainable economic growth. Development plans should incorporate initiatives to boost ICT penetration rates and to establish national innovation systems that can have a stronger multiplier effect on the national economic gain. ICT penetration and innovation diffusion can be bolstered by the introduction of effective governmental measures to assure long-term economic growth.

Limitations and Suggestions for Further Studies

The study has limitations as in any other research. Given the sample countries covered in the study, the study used scientific journal articles as a proxy for innovation diffusion which might not be too accurate as a measure of innovation, we therefore suggest that the United Nations database on Science, Technology and Innovation be a primary source of information for innovation diffusion of future research. These data can be used to test if the study’s empirical model holds up when combined with additional measures of innovation, however sparse they may be. To further explore the relationship between sustainable growth and innovation, some of this data can be used as an explanatory variable and incorporated into the model.

Appendix A

Table A1. Results of Principal Component Analysis of ICT Development.

| Overall Sample of SSA |         |         |
|-----------------------|---------|---------|
|                       | ICT access | ICT use | ICT skills |
| ICT access            | 1.000    |         |            |
| ICT use               | 0.127    | 1.000   |            |
| ICT skills            | 0.219    | 0.131   | 1.000      |

| Eigen analysis of correlation matrix |
|-------------------------------------|
| PCs | Eigen value | Proportion variance | Cumulative percentage |
|-----|-------------|---------------------|-----------------------|
| 1   | 3.019       | 0.942               | 0.942                 |
| 2   | 0.642       | 0.039               | 0.981                 |
| 3   | 0.083       | 0.019               | 1.000                 |

| Eigen vectors (component loadings) |
|-----------------------------------|
|                                  |
| PC1 | PC2 | PC3 |
| ICT access | 0.428 | -0.372 | 0.283 |
| ICT use | 0.510 | 0.049 | 0.527 |
| ICT skills | 0.271 | 0.115 | 0.162 |

| Upper Middle-Income Countries (UMIC) |
|-------------------------------------|
| Correlation matrix |
|---------------------|
| ICT access | ICT use | ICT skills |
| ICT access | 1.000 |         |            |
| ICT use | 0.136 | 1.000   |            |
| ICT skills | 0.195 | 0.178 | 1.000 |

(continued)
### Lower middle-income countries (LMIC)

#### Correlation matrix

|          | ICT access | ICT use | ICT skills |
|----------|------------|---------|------------|
| ICT skills | 0.251      | 0.173   | 0.182      |
| ICT access | 1.000      |         |            |
| ICT use    | 0.206      | 1.000   |            |
| ICT skills | 0.174      | 0.238   | 1.000      |

#### Eigen analysis of correlation matrix

| PCs | Eigen value | Proportion variance | Cumulative percentage |
|-----|-------------|---------------------|-----------------------|
| 1   | 3.510       | 0.752               | 0.752                 |
| 2   | 0.677       | 0.108               | 0.860                 |
| 3   | 0.036       | 0.140               | 1.000                 |

#### Eigen vectors (component loadings)

|          | PC1 | PC2 | PC3 |
|----------|-----|-----|-----|
| ICT access | 0.436 | 0.417 |       |
| ICT use    | 0.448 | 0.183 | −0.196 |
| ICT skills | 0.319 | 0.172 | 0.157  |

### Low-Income Countries (LIC)

#### Correlation matrix

|          | ICT access | ICT use | ICT skills |
|----------|------------|---------|------------|
| ICT access | 1.000      |         |            |
| ICT use    | 0.142      | 1.000   |            |
| ICT skills | 0.286      | 0.227   | 1.000      |

#### Eigen analysis of correlation matrix

| PCs | Eigen value | Proportion variance | Cumulative percentage |
|-----|-------------|---------------------|-----------------------|
| 1   | 3.042       | 0.889               | 0.889                 |
| 2   | 0.495       | 0.068               | 0.957                 |
| 3   | 0.062       | 0.043               | 1.000                 |

#### Eigen vectors (component loadings)

|          | PC1 | PC2 | PC3 |
|----------|-----|-----|-----|
| ICT access | 0.363 | −0.366 |       |
| ICT use    | 0.315 | 0.173 | −0.183 |
| ICT skills | 0.287 | 0.191 | 0.149  |
Appendix B

Table B1. Cross-sectional Augmented Dickey-Fuller (CADF) and Cross-sectional Im, Pesaran and Shin (CIPS) Panel Unit Root Test.

| Variable     | CADF          | CIPS          | Inference |
|--------------|---------------|---------------|-----------|
|              | Level | ∆Level | Level | ∆Level          |          |
| lnRGDP       |   -0.228 | -5.288*** | -0.238 | -4.288*** | I(1) |
| lnID         |   -0.495 | -4.836*** | -0.593 | 6.139***  | I(1) |
| lnICT        |   -0.558 | -4.896*** | -0.457 | -5.375*** | I(1) |
| Overall Sample of SSA |          |             |         |           |          |
| lnRGDP       |   -0.178 | -4.737*** | -0.168 | -5.031*** | I(1) |
| lnID         |   -0.280 | -5.437*** | -0.422 | 5.422***  | I(1) |
| lnICT        |   -0.287 | -5.731*** | -0.398 | -5.027*** | I(1) |
| Upper Middle-Income Countries (UMIC) |          |             |         |           |          |
| lnRGDP       |   -0.123 | -3.082*** | -0.152 | -4.437*** | I(1) |
| lnID         |   -0.198 | -4.300*** | -0.190 | -4.829*** | I(1) |
| lnICT        |   -0.218 | -4.638*** | -0.289 | -4.192*** | I(1) |
| Low-Income Countries (LIC) |          |             |         |           |          |
| lnRGDP       |   -0.152 | -3.817*** | -0.102 | -3.927*** | I(1) |
| lnID         |   -0.122 | -3.920*** | -0.281 | 5.029***  | I(1) |
| lnICT        |   -0.188 | -4.489*** | -0.192 | -4.427*** | I(1) |

Source. Authors computation.

Note. RGDP = real per capita GDP; ID = innovation diffusion; ICT = information and communication technology.

***Denotes statistically significant at the 1% level.

Table B2. Pedroni Panel Cointegration Test Results.

| Test statistics | No intercept | With intercept | With intercept & trend |
|-----------------|--------------|----------------|------------------------|
| Overall Sample of SSA |             |                |                        |
| Alternative hypothesis (AH): common AR coefficients (within-dimension) |             |                |                        |
| Pv-s            | -1.352 [0.475] | -1.275 [0.642] | -1.723 [0.79]           |
| Pτ-s            | -2.494 [0.032]** | -2.133 [0.081]* | -0.754 [0.07]*          |
| PPP-s           | -6.151 [0.000]*** | -3.243 [0.000]*** | -5.611 [0.000]***        |
| PADF-s          | -4.363 [0.011]*** | -4.172 [0.000]*** | -2.743 [0.02]**          |
| AH: common AR coefficients (between-dimension) |             |                |                        |
| Gp-s            | -3.542 [0.000]*** | -5.015 [0.000]*** | -2.012 [0.08]***         |
| GPP-s           | -7.353 [0.000]*** | -4.343 [0.000]*** | -4.154 [0.000]***        |
| GADF-s          | -6.071 [0.000]*** | -5.051 [0.000]*** | -4.023 [0.00]***         |
| Upper Middle-Income Countries (UMIC) |             |                |                        |
| AH: common AR coefficients (within-dimension) |             |                |                        |
| Pv-s            | -1.253 [0.684] | -1.283 [0.753] | -1.165 [0.813]           |
| Pτ-s            | -1.891 [0.062]* | -4.841 [0.000]*** | -1.964 [0.091]*          |
| PPP-s           | -4.312 [0.000]*** | -4.324 [0.010]*** | -6.952 [0.000]***        |
| PADF-s          | -2.921 [0.032]** | -5.392 [0.010]*** | -4.625 [0.000]**         |
| AH: common AR coefficients (between-dimension) |             |                |                        |
| Gp-s            | -2.063 [0.091]* | -2.535 [0.043]** | -2.216 [0.065]**         |
| GPP-s           | -7.604 [0.000]*** | -7.461 [0.000]*** | -7.674 [0.000]***        |
| GADF-s          | -7.462 [0.000]*** | -5.653 [0.000]*** | -5.252 [0.000]***        |
| Lower Middle-Income Countries (LMIC) |             |                |                        |
| AH: common AR coefficients (within-dimension) |             |                |                        |
| Pv-s            | -1.592 [0.634] | -1.382 [0.692] | -1.364 [0.595]           |
| Pτ-s            | -5.501 [0.000]*** | -2.097 [0.074]* | -3.421 [0.024]**         |
| PPP-s           | -5.586 [0.000]*** | -4.433 [0.010]*** | -4.525 [0.000]***        |
| PADF-s          | -4.922 [0.000]*** | -3.561 [0.023]** | -3.633 [0.010]***        |

(continued)
Table B2. (continued)

| Test statistics | No intercept | With intercept | With intercept & trend |
|------------------|--------------|----------------|------------------------|
| **AH: common AR coefficients (between-dimension)** | | | |
| Gρ-s             | −4.184 [0.000]*** | −3.146 [0.034]*** | 2.051 [0.081]* |
| GPP-s            | −8.901 [0.000]*** | −7.372 [0.000]*** | −7.834 [0.000]*** |
| GADF-s           | −7.652 [0.000]*** | −5.763 [0.000]*** | −4.585 [0.000]*** |
| **Low-Income Countries (LIC)** | | | |
| PV-s             | −1.651 [0.293] | −1.622 [0.653] | −1.434 [0.724] |
| Pρ-s             | −1.963 [0.081]* | −2.512 [0.021]** | −1.953 [0.073]* |
| PPP-s            | −4.682 [0.000]*** | −4.172 [0.000]*** | −6.394 [0.000]*** |
| PADF-s           | −6.324 [0.000]*** | −5.593 [0.000]*** | −5.831 [0.000]*** |
| **AH: common AR coefficients (within-dimension)** | | | |
| Gρ-s             | −4.795 [0.000]*** | −5.752 [0.000]*** | −4.535 [0.000]*** |
| GPP-s            | −7.336 [0.000]*** | −5.831 [0.000]*** | −5.536 [0.000]*** |
| GADF-s           | −5.592 [0.000]*** | −4.612 [0.000]*** | −5.732 [0.000]*** |

Source. Authors computation.

Note. PV-S = Panel v-statistics; Pρ-s = Panel ρ-statistics; PPP-S = Panel PP-statistics; PADF-S = Panel ADF-statistics; Gρ-s = Group ρ-statistics; GPP-s = Group PP-statistics; GADF-s = Group ADF-statistics; AR = Auto regression. Probability values are in parenthesis.

***Denotes significant at the 1% level; **denotes significant at the 5% level; *denotes significant at the 10% level.

Authors Contribution
Mugabe Roger, Shu Lin Liu, and Brima Sesay substantially contributed to the conception or design of the manuscript, analysis and interpretation of data for the work. The authors equally contributed in drafting the work or revising it critically for important intellectual content. All the authors are accountable for all aspects of the work in ensuring that questions related to the accuracy and integrity of any part of the work are appropriately investigated and resolved. All the authors approved the final version to be published.

Acknowledgments
The authors would like to acknowledge Byiringiro Enock for his guide in writing this manuscript.

Availability of Data and Material
Data are available upon reasonable request from the corresponding author.

Consent for Publication
Upon acceptance, the authors consent publication of the article.

Declaration of Conflicting Interests
The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding
The author(s) received no financial support for the research, authorship, and/or publication of this article.

Ethical Approval and Consent to Participate.
There is no ethical issue in this manuscript.

ORCID iDs
Mugabe Roger https://orcid.org/0000-0002-0880-6055 Brima Sesay https://orcid.org/0000-0002-1353-1383

References
Adeleye, N., & Eboagu, C. (2019). Evaluation of ICT development and economic growth in Africa. NETNOMICS Economic Research and Electronic Networking, 20(1), 31–53.
Agbemabiese, L., Nkomo, J., & Sokona, Y. (2012). Enabling innovations in energy access: An African perspective. Energy Policy, 47(1), 38–47.
Akerkar, S., Joshi, P. C., & Fordham, M. (2016). Cultures of entitlement and social protection: Evidence from flood prone Bahraich, Uttar Pradesh, India. World Development, 86, 46–58.
Akkemik, K. A. (2015). Rapid economic growth and its sustainability in China. Perceptions, 20, 133–158.
Alimi, A. S., & Adediran, I. A. (2020). ICT diffusion and the finance–growth nexus: A panel analysis on ECOWAS countries. Future Business Journal, 6(1), 1–10.
Arvin, M., & Pradhan, R. (2014). Broadband penetration and economic growth nexus: Evidence from cross-country panel data. Applied Economics, 2014, 4360–4369.
Asongu, S. A., & Le Roux, S. (2017). Enhancing ICT for inclusive human development in Sub-Saharan Africa. Technological Forecasting and Social Change, 118, 44–54.
Asongu, S. A., & Odhiambo, N. M. (2019). How enhancing information and communication technology has affected inequality in Africa for sustainable development: An empirical investigation. Sustainable Development, 27, 647–656.
Asongu, S. A., & Tchamyou, V. S. (2020). Human capital, knowledge creation, knowledge diffusion, institutions and economic incentives: South Korea versus Africa. Contemporary Social Science, 15(1), 26–47.
Belloumi, M., & Alshehry, A. (2020). The impact of international trade on sustainable development in Saudi Arabia. Sustainability, 12, 5421. https://doi.org/10.3390/su12135421
Booij, A. W. A., & Marin, M. (2010). Financial innovation: Economic growth versus instability in bank-based versus financial market-driven economies. International Journal of Business and Commerce, 2(1), 1–32.
Cetin, M. (2013). The hypothesis of innovation-based economic growth: A causal relationship. *International Journal of Economic and Administrative Studies, 6*(11), 1–16.

Chawla, D. (2020). Economic growth and R&D expenditures in selected OECD countries: Is there any convergence? *African Journal of Science, Technology, Innovation and Development, 2020*, 13–25.

Cheng, C. Y., Chien, M. S., & Lee, C. C. (2021). ICT diffusion, financial development, and economic growth: An international crosscountry analysis. *Economic Modelling, 94*, 662–671. https://doi.org/10.1016/j.econmod.2020.02.008

Choi, C., & Yi, M. H. (2018). The Internet, R&D expenditure and economic growth. *Applied Economics Letters, 25*(4), 264–267.

Daniele, V. (2006). Information Technologies and the Italian Economic Growth, 1980-2004. SSRN. https://ssrn.com/abstract=898600 or http://doi.org/10.2139/ssrn.898600

Din, S. U., Khan, M. Y., Khan, M. J., & Nilofar, M. (2021). Nexus between sustainable development, adjusted net saving, economic growth, and financial development in South Asian emerging economies. *Journal of the Knowledge Economy*, 1–14.

Edquist, H., & Henrekson, M. (2017). Do R&D and ICT affect total factor productivity growth differently? *Telecommunications Policy, 41*(2), 106–119.

Ejemeyovwi, J., Adiat, Q., & Ekong, E. (2019). Energy usage, internet usage and human development in selected Western African countries. *International Journal of Energy Economics and Policy, 9*(5), 316–321. https://doi.org/10.32479/ijiep.7611

Ejemeyovwi, J. O., Gershon, O., & Doyah, T. (2018). Carbon dioxide emissions and crop production: Finding a sustainable balance. *International Journal of Energy Economics and Policy, 8*(4), 303–309.

Ejemeyovwi, J. O., & Osabuohien, E. S. (2020). Investigating the relevance of mobile technology adoption on inclusive growth in West Africa. *Contemporary Social Science, 15*, 48–61. https://doi.org/10.1080/21582041.2018.1503320

Ejemeyovwi, J. O., Osabuohien, E. S., & Bowale, E. I. K. (2021). ICT adoption, innovation and financial development in a digital world: empirical analysis from Africa. *Transnational Corporation Review, 13*(1), 16–31. https://doi.org/10.1080/19186444.2020.1851124

Ejemeyovwi, J. O., Osabuohien, E. S., Bowale, E. K., Ahub, O., Adedoyin, J. P., & Ayanda, B. (2019). Information and communication technology adoption and innovation for sustainable entrepreneurship. *Journal of Physics Conference Series, 1378*(2), 022085.

Fei, L., Dong, S., Xue, L., Liang, Q., & Yang, W. (2011). Energy consumption-economic growth relationship and carbon dioxide emissions in China. *Energy Policy, 39*(2), 568–574.

Furman, J. L., Porter, M. E., & Stern, S. (2002). The determinants of national innovative capacity. *Research Policy, 31*, 899–933.

Granger, C. W. (1988). Some recent development in a concept of causality. *Journal of Econometrics, 39*(1-2), 199–211.

Gretton, P., Gali, J., & Parham, D. (2002, December). *Uptake and impacts of ICTs in the Australian economy: Evidence from aggregate, sectoral and firm levels [Paper presentation]. Workshop on ICT and Business Performance, OECD, Paris.*

Herreras, M. J., Joyeux, R., & Girardin, E. (2013). Short- and long-run causality between energy consumption and economic growth: Evidence across regions in China. *Applied Energy, 112*, 1483–1492.

Hickel, J. (2020). The sustainable development index: Measuring the ecological efficiency of human development in the anthropocene. *Ecological Economics, 167*, 106331.

Iscan, E. (2012). The impact of information and communication technology on economic growth: Turkish case. *International Journal of Ebusiness and Egovernment Studies, 4*, 2146–0744.

Ishida, H. (2015). The effect of ICT development on economic growth and energy consumption in Japan. *Telematics and Informatics, 32*, 79–88.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control, 12*(1), 231–254.

Jung, J., & López-Bazo, E. (2019). On the regional impact of broadband on productivity: The case of Brazil. *Telecommunications Policy, 5*, 2.

Kacprzyk, A., & Świeczewska, I. (2019). Is R&D always growth-enhancing? Empirical evidence from the EU countries. *Applied Economics Letters*, 26(2), 163–167.

Kao, C. D., & Chiang, M. H. (2000). On the estimation and inference of a cointegrated regression in panel data. *Advances in Econometrics: Nonstationary Panels, Panel Cointegration and Dynamic Panels, 15*, 179–222.

Kararakara, A. A., & Osabuohien, E. S. (2019). Households’ ICT access and bank patronage in West Africa: Empirical insights from Burkina Faso and Ghana. *Technology and Society, 56*, 116–125. https://doi.org/10.1016/j.techsoc.2018.09.010

Koutroumpis, P. (2019). The economic impact of broadband: Evidence from OECD countries. *Technological Forecasting and Social Change, 148*, 119719. https://www.sciencedirect.com/science/article/pii/S004016251930112X

Koutroumpis, P., Leiponen, A., & Thomas, L. D. W. (2020). Small is big in ICT: The impact of R&D on productivity. *Telecommunications Policy, 44*(1), 101833. https://www.sciencedirect.com/science/article/pii/S0308596119301004

Kumar, V., & Kumar, U. (2017). Introduction: Technology, innovation and sustainable development. *Transnational Corporation Review, 9*, 243–247. https://doi.org/10.1016/j.trc.2017.11.005

Kurniawati, M. A. (2020). “The role of ICT infrastructure, innovation and globalization on economic growth in OECD countries, 1996-2017. *Journal of Science and Technology Policy Management, 11*(2), 193–215.

Leamer, E. E. (1983). Let’s take the con out of econometrics. *American Economic Review, 73*, 31–43.

Manejeuk, P., & Yamaka, W. (2020). An analysis of the impacts of telecommunications technology and innovation on economic growth. *Telecommunications Policy, 44*(10), 102038.

Maradana, R. P., Pradhan, R. P., Dash, S., Gaurav, K., Jayakumar, M., & Chatterjee, D. (2017). Does innovation promote economic growth? Evidence from European countries. *Journal of Innovation and Entrepreneurship, 6*(1), 1. https://doi.org/10.1186/s13731-016-0061-9

Myovella, G., Karacuka, M., & Haucap, J. (2020). Digitalization and economic growth: A comparative analysis of Sub-Saharan Africa and OECD economies. *Telecommunications Policy, 44*(2), 101856.

Narayan, P. K., & Smyth, R. (2007). A panel cointegration analysis of the demand for oil in the Middle East. *Energy Policy, 35*(12), 6258–6265.
Nazir, M. R., Tan, Y., & Nazir, M. I. (2021). Financial innovation and economic growth: Empirical evidence from China, India and Pakistan. *International Journal of Finance & Economics, 26*, 6036–6059. https://doi.org/10.1002/ijfe.2107

Nguyen, T. T., Pham, T. A. T., & Tran, H. T. X. (2020). Role of information and communication technologies and innovation in driving carbon emissions and economic growth in selected G-20 countries. *Journal of Environmental Management, 261*, 110162.

Ofori, I., & Asongu, S. A. (2021, May 26). ICT diffusion, foreign direct investment and inclusive growth in Sub-Saharan Africa (MPRA Paper No. 107757). UTC. https://mpra.ub.uni-muenchen.de/107757/

Oluwatobi, S., Efobi, U., Olurinola, I., & Alege, P. (2015). Innovation in Africa: Why institutions matter. *South African Journal of Economics, 83*(3), 390–410.

Oluwatobi, S. O. (2015). Innovation-driven economic development model: A way to enable competitiveness in Nigeria. In L. Leonard & M. A. Gonzalez-Perez (Eds.), *Beyond the UN global compact: Institutions and regulations* (pp. 197–218). Emerald.

Pedroni, P. (2000). Fully modified OLS for heterogeneous cointegrated panels. *Advanced in Econometrics, 15*(1), 93–130.

Pedroni, P. (2001). Purchasing power parity tests in cointegrated panels. *The Review of Economics and Statistics, 83*(4), 727–731.

Pedroni, P. (2004). Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Economic Theory, 20*(03), 597–625.

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association, 94*(446), 621–634.

Pradhan, R. P., Arvin, M., Nair, M., Bennett, S., & Bahmani, S. (2017). ICT-finance-growth nexus: Empirical evidence from the next-11 countries. *Cuadernos de Econom, 40*, 115–134.

Pradhan, R. P., Arvin, M. B., Bahmani, S., & Bennett, S. E. (2017). The innovation- growth link in OECD countries: Could other macro-economic variables matter? *Technology and Society, 51*, 113–123.

Pradhan, R. P., Arvin, M. B., Bahmani, S., & Norman, N. R. (2014). Telecommunications Infrastructure and economic growth: comparative policy analysis for the G-20 developed and developing countries. *Journal of Comparative Policy Analysis Research and Practice, 16*(5), 401–423.

Pradhan, R. P., Arvin, M. B., Hall, J. H., & Nair, M. (2016). Innovation, financial development and economic growth in eurozone countries. *Applied Economics Letters, 23*(16), 1141–1144.

Pradhan, R. P., Arvin, M. B., Nair, M., Sara, E. (2020). Bennett, sustainable economic growth in the European Union: The role of ICT, venture capital, and innovation. *Review of Financial Economics, 38*, 34–62.

Pradhan, R. P., Mallik, G., & Bagchi, T. P. (2018). Information communication technology (ICT) infrastructure and economic growth: A causality evinced by cross-country panel data. *IIMB Management Review, 30*(1), 91–103.

Rahman, H. U., Ali, G., Zaman, U., & Pugnetti, C. (2021). Role of ICT investment and diffusion in the economic growth: A threshold approach for the empirical evidence from Pakistan. *International Journal of Financial Studies, 9*, 14. https://doi.org/10.3390/ijfs9010014

Reddy, A. A. (2018). Electronic national agricultural markets: The way forward. *Current Science, 115*(5), 826–837.

Reddy, A. A., & Mehjabeen, L. N. U. (2019). Electronic national agricultural markets, impacts, problems and way forward. *IIM Kozhikode Society & Management Review, 8*(2), 143–155.

Romer, P. M. (1994). The origins of endogenous growth. *Journal of Economic Perspectives, 8*, 3–22.

Saidi, K., & Mongi, C. (2018). The effect of education, R&D and ICT on economic growth in high income countries. *Economics Bulletin, 38*(2), 810–825.

Schumpeter, J. (1942). *Capitalism, socialism, and Democracy*. Harper.

Shehzad, K., Zaman, U., Josè, A. E., Koçak, E., & Ferreira, P. (2021). An officious impact of financial innovations and ICT on economic evolution in China: Revealing the substantial role of BRI. *Sustainability, 13*, 8962. https://doi.org/10.3390/su13168962

Sokolov-Mladenović, S., Cvetanović, S., & Mladenović, I. (2016). R&D expenditure and economic growth: EU28 evidence for the period 2002–2012. *Economic Research, 29*(1), 1005–1020.

Solomon, E. M., & van Klyton, A. (2020). The impact of digital technology usage on economic growth in Africa. *Utilities Policy, 67*, 101104.

Tchamyou, V. S. (2017). The role of knowledge economy in African business. *Journal of the Knowledge Economy, 8*(4), 1189–1228.

Teh, P. L., Adebanjo, D., & Kong, D. L. Y. (2021). Key enablers and barriers of solar paver technologies for the advancement of environmental sustainability. *Heliyon, 7*(10), e08189.

Toader, E., Firtescu, B., Roman, A., & Anton, S. (2018). Impact of information and communication technology infrastructure on economic growth: An empirical assessment for the EU countries. *Sustainability, 10*(10), 3750.

Tsakanikas, A., Dimas, P., & Stamopoulos, D. (2021). The Greek ICT sector and its contribution to innovation and Economic Growth. In V. lachos, V. Bitzenis, & A. B. S Sergi. (Eds.), *Modeling economic growth in contemporary Greece (Entrepreneurship and global economic growth)* (pp. 281–300). Emerald Publishing Limited.

Vu, K., Hanafizadeh, P., & Bohlin, E. (2020). ICT as a driver of economic growth: A survey of the literature and directions for future research. *Telecommunications Policy, 44*(2), 101922.

Whitacre, B., Roberto, G., & Sharoh, S. (2014). Broadband’ s contribution to economic growth in rural areas: Moving towards a causal relationship. *Telecommunications Policy, 38*(11), 1011–1023.

Yang, C. H. (2006). Is innovation the story of Taiwan’s economic growth? *Asian Economic Journal, 17*(5), 867–878.

Yousefi, A. (2011). The impact of information and communication technology on economic growth: Evidence from developed and developing countries. *Economics of Innovation and New Technology, 20*(6), 581–596. https://doi.org/10.1080/10438599.2010.544470

Zhao, Y., Ramzan, M., Adebayo, T. S., Oladipupo, S. D., Adeshola, I., & Agyeum, E. B. (2021). Role of renewable energy consumption and technological innovation to achieve carbon neutrality in Spain: Fresh Insights from wavelet coherence and spectral causality approaches. *Frontiers in Environmental Science, 9*, 769067. https://doi.org/10.3389/fenvs.2021.769067