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Exploring the growth effects of Artificial Intelligence in developing countries in Africa using a semi-endogenous growth model

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Abstract

In this study, a modified semi-endogenous growth model is employed to assess the impact of AI technology absorption on economic growth in sub-Saharan African countries with limited R&D resources. Utilizing country-level data, the study interprets the ratio of technology-intensive imports as an indicator of both technological engagement and skilled labor growth. It also considers variables representing AI-technology absorptive capacity, readiness, Industrial Activity Index, and ICT. Contrary to traditional views, the research emphasizes the importance of targeted investments in AI-ready sectors. It underscores the need for reorienting investment strategies towards technology-supportive sectors and infrastructure. Furthermore, the positive correlation between technology-intensive imports and per capita income growth underscores the pivotal role of skilled labor in harnessing AI technology benefits. This finding suggests that in environments where AI acts as a complement to skilled labor, economies can boost productivity and income growth by focusing on upskilling the workforce. Investing in education and training, particularly in skills compatible with AI and technology, emerges as a key strategy. This approach not only enhances the capacity to adopt and innovate with imported technologies but also positions these economies to capitalize on AI-driven growth opportunities more effectively. Moreover, the study also stresses the importance of demographic advantages and educational reforms, particularly in STEM and digital literacy, to prepare the workforce for an AI-centric economy.

1.Introduction

The burgeoning field of artificial intelligence (AI) has profoundly impacted global economic landscapes, heralding a new era of technological progress. However, its diffusion and consequent growth effects are not uniformly experienced across the world's economic strata. A new era of technical improvement has been brought about by the creation of artificial intelligence (AI), which has drastically changed the environment for economic growth and development. Particularly, countries such as those in Sub-Saharan Africa have historically had limited resources for research and development (R&D. This focus on African countries presents a significant knowledge gap. These countries face unique challenges, including limited infrastructure, a scarcity of human capital in tech-related fields, and underdeveloped data ecosystems, all of which can significantly influence the adoption and adaptation of AI technologies. As Hall and Jones (1999) pointed out, these factors are crucial determinants of productivity and economic growth.

The role of AI in either exacerbating or ameliorating economic disparities in developing African countries is an underexplored area of inquiry, especially critical aspects such as the substitution and complementarity between AI technology and labor. Previous research has often highlighted the potential of AI to replace human labor, particularly in routine and manual tasks, as discussed by Autor et al (2003). However, there is also potential for AI to complement human labor, especially in tasks that require complex problem-solving and creativity, a perspective supported by Bessen (2019).

Given the significant role of institutional quality and governance in economic development, as explored by Acemoglu et al. (2001), this study also investigates how these factors moderate the impact of AI on economic growth in African regions. The quality of institutions, which includes aspects such as regulatory frameworks, property rights, and the rule of law, can greatly influence the capacity of a country to adopt and benefit from new technologies. Additionally, the study considers the influence of human capital and education on the effectiveness of AI in driving economic growth. Lucas (1988) emphasizes the role of human capital in economic growth, suggesting that the level of education and skills within a country can significantly impact the ability to leverage AI technologies effectively. This is particularly relevant in the African context, where the educational system's alignment with the demands of an increasingly digitized and AI-integrated global economy is crucial.

The significance of technology-intensive imports as a driver of economic growth has been underscored by Coe and Helpman (1995). They argue that imports, particularly those rich in technology, play a crucial role in facilitating technological spillovers, a concept particularly relevant for regions with constrained R&D resources like sub-Saharan Africa. This study extends this concept by interpreting these imports not just as a medium of technology transfer but as a reflection of the skilled labor.

This study aims to assess the potential economic growth effects of proxy indicators for AI-technology absorptive capacity and readiness in the context of the developing country of sub-Saharan African countries, based on a modified semi-endogenous growth model. According to Jones (1995) in "R&D-Based Models of Economic Growth," semi-endogenous growth theories offer a framework for comprehending how innovation supports long-term economic growth, especially in settings with differing levels of R&D capability. To capture a more nuanced picture of AI technology absorption in sub-Saharan African countries, our approach departs from the typical focus on domestic R&D by considering the ratio of technology-intensive imports as a combined indicator of technological engagement and skilled labor growth. To empirically investigate this, we employ a panel data Generalized Method of Moments (GMM) approach, analyzing data from 48 sub-Saharan African countries. This methodology allows us to account for potential endogeneity and omitted variable biases, providing robust insights into how AI adoption in the absence of substantial R&D activities can influence economic growth in these countries.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 outlines the theoretical framework, delving into the semi-endogenous growth model and its application in our context. Section 4 details our methodology, explaining the choice of the GMM approach. Section 5 presents the empirical analysis while Section 6 discusses the findings. The paper concludes with Section 7.

2. Literature Review

Traditional economic growth models have generally viewed AI as a form of automation, essentially acting as a capital-augmenting factor that replaces less efficient labor (Kotlikoff and Sachs, 2012; Graetz and Michaels, 2015; Nordhaus, 2015). However, this perspective is evolving, with some researchers advocating for AI as a labor-augmenting factor due to its synergistic effects with human labor (Bessen, 2018). Increasingly, scholars are conceptualizing AI as a unique factor of production, highlighting its roles in research (Acemoglu and Restrepo, 2018a; Aghion et al., 2018), robotic cooperation (De Canio, 2016), and commercial decision-making (Calvano et al., 2018; Athey et al., 2018). While there is consensus that AI will significantly affect employment and social welfare, the specific implication for developing countries remains unclear, with various theories and viewpoints being put forth.

For instance, Gonzales (2023) underscores a positive correlation between AI innovation and economic growth. Moreover, the Nelson and Phelps model, which initially emphasized the role of human capital in technological diffusion, has been a foundational piece in the study of economic growth. Subsequent works by Lucas (1988) and Romer (1990) have also stressed the importance of human capital and technology in explaining growth differentials among countries. Furthermore, the integration of AI technologies in the production process is expected to lead to substantial gains in productivity and economic development. Notably, the advancement of AI has the potential to enhance economic growth along transitional dynamics paths (Lu, 2021) Despite the positive outlook, the role and place of AI in economic development (ED) remain fragmented and require deeper understanding. The discourse on recent trends in aggregate productivity growth presents a paradox (Brynjolfsson, E., et al., 2019).

Despite its potential in significantly boosting productivity and economic growth , advances in artificial intelligence, empirical data suggests otherwise (Brynjolfsson and McAfee, 2014). Over the past decade, measured productivity growth has slowed down considerably, halving or more compared to the previous decade. This slowdown is not confined to a particular region but is observed across Organization for Economic Co-operation and Development (OECD) countries and even in many large emerging economies (Syverson, 2017). Additionally, AI also holds the promise of boosting economic development in developing nations. However, the implications of AI on global economic growth are highly uncertain, and forecasting its long-term impact remains a challenge.

Research suggests that AI can contribute to economic development, resource conservation, and environmental protection by increasing efficiency (Fujii & Managi, 2018). Additionally, AI technology has been found to positively influence economic growth rates in the manufacturing industry through deep learning and robot-assisted industry, while also impacting labor employment, income distribution, capital accumulation, and production efficiency (Xu, 2022).

Furthermore, studies have shown that information and communication technology (ICT), including AI components, significantly affects income levels and growth per worker in both developed and developing countries (Papaioannou & Dimelis, 2007). Moreover, the integration of AI with the real economy is considered a driving force for technological revolution and industrial change, which can enhance national power and promote sustainable economic development (Li, 2021). The impact of AI on economic growth is not only limited to scientific breakthroughs but also extends to its influence on human society and economies (Lu & Zhou, 2021). Additionally, AI has been identified as a potential driver of economic growth in the Asia-Pacific region (Haseeb et al., 2019).

Furthermore, AI applications have already demonstrated considerable economic and social impacts in developing countries, with a significant proportion of low-skilled jobs in the AI industry being performed in these countries (Kshetri, 2021). It is also important to consider the role of AI in facilitating economic growth and competitiveness, as well as its potential to contribute to the development of Latin American countries (Veronese & Lemos, 2021). Moreover, investment in ICT, including AI, has been shown to contribute significantly to GDP growth in both developed and developing economies (Yousefi, 2015). Additionally, foreign direct investment (FDI) plays a role in economic growth, and AI development is influenced by the economic growth of developing countries (Safarolievich, 2022; Ahmed & Ibrahim, 2019).

Overall, the impact of AI on economic growth in developing countries is multifaceted, encompassing various aspects such as labor employment, income distribution, capital accumulation, production efficiency, and the overall development of the real economy. Despite the potential benefits, advances in AI and automation also pose risks of increasing inequality and poverty, particularly if the digital divide between developed and developing countries widens Korinek et al., 2021). Notably, Studies on AI’s impact in low-income regions, specifically in Sub-Saharan Africa, are less prevalent. However, Alaganthiran et al. (2022) provide insights into economic growth influences in these regions, albeit in the context of carbon dioxide emissions, suggesting a need for further exploration of AI's role in similar economic environments.

Much of the literature on technological progress has moved from the exogenously driven process (e.g., Solow, 1956) to embrace the endogenously generated technological progress (e.g., Romer, 1986 & 1994; Lucas, 1988 & 1993; Jones, 1995). However, the dominant variant of endogenous growth models has been those focusing on R&D and the related innovation. as Jones (2003) points it out, this is not consistent with the context of middle to low-income developing countries. These economies are "small" in the sense that the impact of their individual research on the global technological frontier is negligible. In this context, it makes sense to assume that technology to expand at an exogenous rate from the perspective of an individual small economy. At the global stage, AI-technology is considered as public goods. Once a technology is invented, particularly in advanced economies like those in the OECD, developing countries can adopt these technologies without having to pay for the invention. However, they do need to acquire the skills necessary to utilize these technologies effectively (Jones; 2003; Maswana, 2015). Particularly insightful, in his seminal work, Jones (2006) elaborates on the semi-endogenous growth theory, proposing that long-term economic growth can be sustained without continuously escalating research efforts. Jones argues that sustainable growth can be achieved through the adoption and adaptation of existing technologies rather than relying solely on indigenous innovation. Supporting this, Bernard and Jones (1999) discuss technology-led convergence in productivity and economic growth, indicating that developing countries can achieve sustainable growth by integrating globally available technologies. This approach is especially relevant in the context of AI technology, where developing countries can leverage global technological advancements for growth, bypassing the need for large-scale R&D investments.

The concept of technological progress emerging as a by-product of other economic activities is pivotal in environments with limited or no R&D infrastructure. Aghion and Howitt (1992) in their work on creative destruction, while not directly addressing semi-endogenous growth, lay the groundwork for understanding how technological advancement can occur outside traditional R&D frameworks. Their model suggests that economic activities, such as technology transfer and adaptation, can serve as catalysts for technological progress. This perspective is crucial for developing countries, where AI technology might not evolve through indigenous innovation but rather through the absorption and adaptation of imported technologies. Such a viewpoint shifts the focus from domestic R&D to alternative avenues of technological advancement, like foreign direct investment, trade, and learning-by-doing.

Grossman and Helpman (1991) emphasize the importance of human capital and knowledge spillovers in the growth process. Their analysis underscores how countries can grow economically by absorbing and improving upon existing technologies. This aspect is critical for developing countries with limited R&D capabilities, where the focus shifts to enhancing human capital's ability to adopt, adapt, and utilize AI technologies effectively. Additionally, Acemoglu and Robinson (2012) provide insights into how political and economic institutions shape the way countries engage with technological progress. Their work highlights the significance of creating an environment conducive to technology adoption and adaptation, underlining the role of institutional quality and human capital in maximizing the benefits of AI and other advanced technologies.

3. Methodological Considerations

The previous section underscores the relevance of semi-endogenous growth models in understanding how developing countries, particularly those in sub-Saharan Africa, can leverage technological progress for economic growth despite limitations in their R&D capabilities. Hence, the present paper starts with a semi-endogenous growth model that incorporates AI technology, taking into account the dynamics of skilled and unskilled labor, and the role of technology diffusion through international trade.

3.1. Model Framework

We start by considering that the economy produces a single final good Y using capital K, skilled labor L_s, unskilled labor L_u, and Al technology T. We also assume a

1. Cobb-Douglas production function, which is extended to include Al technology:

   $$Y = AK^{\alpha}(L_sT)^{\beta}(L_u)^{\gamma} \tag{1}$$

   where $0 < \alpha, \beta, \gamma < 1$ and A represents total factor productivity (TFP).

It is also assumed that Al technology is a substitute for unskilled labor and a complement to skilled labor. This can be modeled as:

$$L_sT = L_s^{\delta}T^{\epsilon} \quad \text{and} \quad L_u = L_u^{\eta}T^{\theta} \tag{2}$$

where $\delta, \epsilon, \eta, \theta$ are parameters capturing the interaction between labor types and Al technology.

For technology diffusion, there is no domestic R&D, but technology diffuses through international trade channels. The diffusion rate is a function of the level of skilled labor, modeled as:

$$\dot{T} = \phi(L_s)T \tag{3}$$

where $\phi(L_s)$ captures the absorptive capacity of skilled labor.

For simplicity, capital accumulation can be written as:

$$\dot{K} = sY - \delta_K K \tag{4}$$

where s is the savings rate and δ_K is the depreciation rate of capital.

Before moving any further, let the production function (Equation 1) be expressed in per worker term. Let's denote $L = L_s + L_u$ as the total labor force. The per-worker production function becomes:

The per-worker production function becomes:

$$y = Ak^{\alpha} \left(\frac{L_s}{L}\right)^{\beta} T^{\beta} \left(\frac{L_u}{L}\right)^{\gamma} \tag{5}$$

where $y = \frac{Y}{L}$ and $k = \frac{K}{L}$.

The dynamics of capital accumulation per worker, taking into account labor growth n and depreciation δ_K, are given by:

$$\dot{k} = sk^{\alpha} \left(\frac{L_s}{L}\right)^{\beta} T^{\beta} \left(\frac{L_u}{L}\right)^{\gamma} - (n + \delta_K)k$$

(6)

In the steady state, $\dot{k} = 0$. Solving for k^* involves setting $\dot{k} = 0$ and rearranging the equation:

$$sk^{\alpha^*} \left(\frac{L_s^*}{L^*}\right)^{\beta} T^{*\beta} \left(\frac{L_u^*}{L^*}\right)^{\gamma} = (n + \delta_K)k^* \tag{7}$$

Solving for k^* gives:

$$k^* = \left[\frac{s}{n+\delta_K} \left(\frac{L_s^*}{L^*}\right)^{\beta} T^{*\beta} \left(\frac{L_u^*}{L^*}\right)^{\gamma}\right]^{1/(1-\alpha)} \tag{8}$$

This equation represents the steady-state capital per worker. It depends on the savings rate s, the labor growth rate n, the depreciation rate δ_K, the distribution of skilled and unskilled labor, and the level of technology T^*. Note that this derivation assumes that the parameters α, β, γ, and the growth rate of technology $\phi(L_s)$ are constant in the steady state.

This formulation also incorporates the interactions of AI technology with skilled and unskilled labor as well as the role of technology diffusion, although these are more implicit in the relationships between T, L_s, and L_u. The model thus highlights the impact of these factors on the accumulation of capital per worker, a key determinant of economic growth in this framework.

Substituting this expression for $k*$ into the per worker income equation gives:

$$y^* = A\left[\frac{s}{n+\delta_K}\left(\frac{L_s^*}{L^*}\right)^{\beta} T^{*\beta}\left(\frac{L_u^*}{L^*}\right)^{\gamma}\right]^{\alpha/(1-\alpha)}\left(\frac{L_s^*}{L^*}\right)^{\beta} T^{*\beta}\left(\frac{L_u^*}{L^*}\right)^{\gamma}$$

(9)

This equation represents the steady-state per worker income, illustrating how it is influenced by the savings rate s, the labor growth rate n, the depreciation rate δ_K, and the distribution and technology levels of skilled (L_s^*) and unskilled (L_u^*) labor. Note that this model specifically highlights the role of Al technology and its interactions with different types of labor in determining economic outcomes.

The predictions drawn from the steady-state per worker income highlight the impact of Technology (Al) on income per worker. The presence of T^* in the equation highlights the critical role of technology, particularly Al, in determining per worker income. A higher level of technology T^* should lead to increased per worker income, holding other factors constant. This is consistent with the broader economic understanding that technological advancements boost productivity and, consequently, income levels.

Interplay Between Skilled and Unskilled Labor: The model differentiates between skilled (L_s^*) and unskilled labor (L_u^*), with Al technology being a substitute for unskilled labor and a complement to skilled labor. This distinction implies that an increase in the proportion of skilled labor relative to unskilled labor would lead to higher per worker income, due to the enhanced complementarity with Al technology. Conversely, an economy overly reliant on unskilled labor might not fully leverage the benefits of Al, potentially leading to lower growth in per worker income. Furthermore, Depreciation and Labor Growth Rate: The model incorporates the effects of capital depreciation (δ_K) and labor growth rate (n). Higher rates of either would necessitate greater investment to maintain the same level of capital per worker, potentially dampening the growth in per worker income. This implies that economies with rapid population growth or high capital depreciation might face challenges in sustaining income growth.

3.2. Comparative statics

To illustrate the impacts using derivatives, we'll consider the partial derivatives of the steady-state per worker income with respect to the growth rates of unskilled and skilled labor. Let's start with the steady-state per worker income function:

Impact of Higher Growth Rate of Unskilled Labor $\left(g_{L_u}\right)$:

The impact of g_{L_u} on y^* can be assessed by differentiating y^* with respect to g_{L_u}. This derivative essentially captures the sensitivity of per worker income to changes in the growth rate of unskilled labor. Given the complexity of the function, we'll focus on the critical component, the ratio $\frac{L_u^*}{L^*}$:

$$\frac{\partial y^*}{\partial g_{L_u}} \propto \frac{\partial}{\partial g_{L_u}} \left(\frac{L_u^*}{L^*}\right)^{\gamma} \tag{10}$$

As g_{L_u} increases, $\frac{L_u^*}{L^*}$ increases (assuming g_{L_s} and g_T are constant), which leads to an increase in the unskilled labor component of the production function. However, since Al is a substitute for unskilled labor, this may not positively impact y^*. The exact sign of this derivative will depend on the overall structure and parameters of the model, particularly the substitutability effect.

Impact of Slower Growth Rate of Skilled Labor $\left(g_{L_s}\right)$:

For the impact of g_{L_s} on y^*, we differentiate y^* with respect to g_{L_s}. Again, focusing on the critical component:

$$\frac{\partial y^*}{\partial g_{L_s}} \propto \frac{\partial}{\partial g_{L_s}} \left(\frac{L_\varepsilon^*}{L^*}\right)^{\beta} \tag{11}$$

If g_{L_s} decreases, $\frac{L_s^*}{L^*}$ decreases, assuming g_{L_u} and g_T are constant. This leads to a reduction in the skilled labor component, which in turn, could decrease y^*, considering the complementarity between skilled labor and Al technology. Clearly, the derivatives indicate that an increase in g_{L_u} (relative to g_{L_s} and g_T) could potentially have a negative impact on per worker income due to the substitution effect with Al technology. Conversely, a decrease in g_{L_s} could also negatively impact per worker income due to reduced complementarity with Al technology.

From these comparative statics can be drawn the empirically testable hypothesis that an increase in the ratio of technology-intensive imports, indicative of higher skilled labor growth, will positively correlate with per capita income growth. This correlation is due to AI technology acting as a complement to skilled labor and a substitute for unskilled labor, enhancing overall productivity. Conversely, an increase in unskilled labor growth, relative to skilled labor and AI technology growth, may negatively impact per capita income due to substitution effects with AI technology.

4. Econometrics Model Specification

To convert the given steady-state per worker income function into an econometric model suitable for panel data analysis, we need to reframe it in a way that aligns with econometric practices. This involves expressing the model in a linear or log-linear form, incorporating error terms, and specifying the necessary assumptions for panel data analysis.

Given the steady-state per worker income function:

$$y^* = A\left[\frac{s}{n+\delta_K}\left(\frac{L_s^*}{L^*}\right)^{\beta} T^{*\beta}\left(\frac{L_u^*}{L^*}\right)^{\gamma}\right]^{\alpha/(1-\alpha)}\left(\frac{L_s^*}{L^*}\right)^{\beta} T^{*\beta}\left(\frac{L_u^*}{L^*}\right)^{\gamma} \tag{12}$$

Converting to a log-linear form, we get:

$$\ln(y^*) = \ln(A) + \frac{\alpha}{1-\alpha}\left[\ln(s) - \ln(n+\delta_K) + \beta\ln\left(\frac{L_s^*}{L^*}\right) + \beta\ln(T^*) + \gamma\ln\left(\frac{L_u^*}{L^*}\right)\right] + \beta\ln\left(\frac{L_s^*}{L^*}\right) + \beta\ln(T^*) + \gamma\ln\left(\frac{L_u^*}{L^*}\right) \tag{13}$$

As it is usually the case in empirical studies, it is assumed that $\ln(A)$ has two components-a constant term and a random error term. This accounts for both the average effect of total factor productivity (TFP) across all countries and the individual deviations from this average for each country at each time period. Specifically, $\ln(A)$ is expressed as the sum of α_0 and ϵ_{it}, where α_0 captures the average level of TFP across all countries and all time periods, and ϵ_{it} captures the country-specific and time-varying deviations from the average TFP. The econometric model with this assumption for a panel of countries becomes:

$$\ln(y_{it}) = \alpha_0 + \alpha_1\ln(s_{it}) - \alpha_2\ln\left(n_{it} + \delta_{K,it}\right) + \alpha_3\ln\left(\frac{L_{s,it}}{L_{it}}\right) + \alpha_4\ln(T_{it}) + \alpha_5\ln\left(\frac{L_{u,it}}{L_{it}}\right) + \varepsilon_{it} \tag{14}$$

It should be noted that **g**iven the definition of technology diffusion as $\dot{T} = \phi(L_s)T$, where $\phi(L_s)$ captures the absorptive capacity of skilled labor, we can incorporate this into the econometric model by replacing T with its components related to skilled labor and the diffusion process.

The technology diffusion rate $\phi(L_s)$ implies that the level of technology T in a country is a function of its skilled labor's absorptive capacity. Let's express $\phi(L_s)$ as a separate term that influences T. In an econometric context, we can model this as:

$$\ln(T_{it}) = \delta_1\ln\left(\phi\left(L_{s,it}\right)\right) + \delta_2 \tag{15}$$

Where:

- δ_1 and δ_2 are parameters to be estimated.
- $\phi(L_{s,it})$ is the absorptive capacity related to the skilled labor in country i at time t.
- We assume that $\phi(L_s)$ can be directly related to observable characteristics of skilled labor, such as education level, skill intensity in industries, or other proxies.

With this change, the revised econometric model becomes:

$$\ln(y_{i,t}) = \alpha_0 + \alpha_1 \ln(k_{i,t}) - \alpha_2 \ln(n_{i,t} + \delta_{K,it}) + \alpha_3 \ln\left(\frac{L_{s,it}}{L_{i,t}}\right) + \alpha_4 \left(\delta_1 \ln\left(\emptyset(L_{s,it})\right)\right.$$
$$\left. + \delta_2\right) + \alpha_5 \ln\left(\left(\frac{L_{u,it}}{L_{it}}\right) + \varepsilon_{it}\right. \qquad (16)$$

Where:

- y_{it} is the per worker income of country i at time t.
- $s_{it}, n_{it}, \delta_{K,it}, L_{s,it}, L_{u,it}, T_{it}$ are the corresponding country-year observations of the savings rate, population growth rate, depreciation rate, skilled labor, unskilled labor, and technology level.
- $\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5$ are parameters to be estimated.
- ε_{it} is the error term capturing unobserved factors and measurement errors.

Given Equation (10), the following points should be kept in mind:

1. This model now directly links the technology level in a country to the absorptive capacity of its skilled labor, reflecting the role of skilled labor in adopting and utilizing technology diffused through international trade.

2. The parameters δ_1 and δ_2 capture how changes in skilled labor's absorptive capacity $\left(\phi(L_{s,it})\right)$ affect the level of technology in a country.

3. We assume that the relationship between technology and skilled labor's absorptive capacity is log-linear and that we can suitably quantify or proxy $\phi(L_s)$.

4. Econometrics model and data considerations

4.1. Econometrics model

In our empirical analysis, we employ the System Generalized Method of Moments (System GMM) estimator, a powerful tool for dynamic panel data models, particularly suitable for examining the growth effects of trade and technological progress. This approach, as outlined by Arellano and Bover (1995) and further developed by Blundell and Bond (1998) and Blundell et al. (2000), is advantageous for addressing biases inherent in dynamic panel models, controlling unobserved country-specific effects, and correcting potential endogeneity in explanatory variables.

$$y_{i,t} = \delta y_{i,t-1} + \beta X_{it} + \alpha_i + u_{i,t} \tag{17}$$

$$E(\alpha_i) = E(u_{it}) = E(\alpha_i u_{it}) = 0,$$

Here, $y_{i,t}$ represents the economic growth for country i in year t, X includes all other explanatory variables, α_i is the country-specific unobserved heterogeneity, and $u_{i,t}$ is the idiosyncratic error term. The unobserved heterogeneity α_i varies across countries but is constant over time for any given country, and it may be correlated with explanatory variables. Moreover, Ordinary Least Squares (OLS) estimation of equation (17) is problematic due to the endogeneity of the lagged dependent variable. For instance, a positive growth shock in a country not accounted for in the model will be absorbed into the error term, causing a bias in OLS estimates. A standard approach to address this issue is differencing the data, which leads to the following first-differenced equation:

$$\Delta y_{i,t} = \delta \Delta y_{i,t-1} + \Delta X_{it}\beta + \Delta u_{i,t} \tag{18}$$

However, differencing does not completely resolve the issue of endogenous regressors, such as the lagged dependent variable. In this context, lagged levels of the variables serve as instruments in the differenced equations.

Blundell and Bond (1998) note that first-differenced GMM estimators perform poorly in cases of persistent time series and limited time periods, as lagged levels are weak instruments in such scenarios. System GMM, as proposed by Arellano and Bover (1995) and Blundell and Bond (1998), addresses this by combining moment conditions from the differenced equation with additional conditions derived from the level equation, assuming that the differenced explanatory variables are uncorrelated with individual effects, even though the levels of these variables may be correlated. The additional moment conditions for the level equation in the System GMM can be expressed as:

$$E\left[\Delta X_{i,t-j} \cdot \left(\alpha_i + u_{i,t}\right)\right] = 0 \text{ for } t = 3, \ldots, T \text{ and } j \geq 1 \tag{19}$$

This condition assumes that the lagged differences of the explanatory variables (*ΔX*) are valid instruments for the equation in levels, meaning that these lagged differences are not correlated with the fixed effects (α) or the idiosyncratic errors (u) in the level equation.

To validate System GMM estimates, several tests are usually conducted. The Arellano-Bond AR(2) test checks for second-order serial correlation in the differenced residuals, with a high p-value indicating the absence of autocorrelation. Additionally, we perform the Hansen J-test and the Difference-in-Hansen test to assess the validity of our instruments and the additional exclusion restrictions inherent in the System GMM model, as per the methodology described by Roodman (2009b). These tests, including the Arellano-Bond test for serial correlation and the Sargan-Hansen test for over-identifying restrictions, are crucial to ensure the validity of our instruments and the consistency of the GMM estimator. The Sargan-Hansen test, which extends the original Sargan test to nonlinear GMM settings, evaluates the exogeneity of the instruments under the null hypothesis. By utilizing the System GMM estimator and rigorously testing for serial correlation and instrument validity, we ensure a robust and reliable analysis of the dynamic relationships within our panel data.

4.2. Variables and Data

The primary outcome variable in our study is the Growth Rate of Annual Per Capita GDP (GDPPC_GR), obtained from the World Development Indicators (WDI) of the World Bank. Complementing this is the Import variable, sourced from UN COMTRADE, which measures Science and Technology based imports as a percentage of total imports. This variable not only indicates a country's engagement with new technologies but also serves as a proxy for skilled-labor growth. The rationale for using technology-intensive imports (based on the Standard International Trade Classification: SITC) as a skilled labor proxy is twofold. Firstly, our model posits that technology diffusion primarily occurs through international trade, with skilled labor playing a critical role in assimilating and utilizing this technology. A high ratio of such imports suggests an integration of advanced technologies, implying a skilled and educated workforce. Secondly, the import of high-tech goods often aligns with domestic skilled labor demand since these goods generally require skilled operation and innovation. This correlation suggests that economies with substantial high-tech imports are likely to have a larger proportion of skilled labor, further supported by investments in education and skill development to stay competitive in the global high-tech market.

Likewise, the study uses proxy variables of AI-technology absorptive capacity and readiness (e.g., Frontier Tech Index, R&D index, Skills index). Related indices from the United Nations Conference on Trade and Development (UNCTAD) are included to provide a comprehensive view of a country's technology landscape. The Frontier Tech Index, adjusted to a 0-100 scale to manage coefficient size, measures preparedness to adopt leading-edge technologies. The Industrial Activity Index gauges high-tech exports and industrial activities, while the Research & Development (R&D) Index captures spending, patents, and researcher numbers. These indices are complemented by the Skills Index, which assesses human capital in terms of its capacity for innovation and technology use, and the Financial Access Index, indicating the availability and ease of finance for innovative ventures. Additionally, the Information and Communication Technology (ICT) Index measures the availability and usage of ICT infrastructure, a critical component in today's technology-driven world.

Gross Capital Formation (GCF), representing investment intensity, and Population Growth Rate (POPGR), both from WDI, offer insights into economic activity and demographic trends, respectively. Also, the study also includes the Human Capital variable, denoting tertiary education enrollment rates from WDI, to gauge the educational level of the workforce. The Public Sector Corruption Index from the V-Dem Dataset provides a perspective on governance quality, and Financial Institutions Efficiency, from the IMF’s Financial Development database, reflects the efficiency of financial institutions in supporting economic growth and technological innovation. Ultimately, the quality of a country's institutions, good governance, absence of corruption, etc, can significantly enhance the productivity of available resources (TFP).

Table 1. Variable Description and Sources

Variable	Description/Definition	Source
GDPPC_GR	Growth rate of annual per capita GDP	WDI, WB
Import_Tech	Science and Technology based import as a percentage of total import.	UN_Comtrade
Frontier Tech Index	Index of preparedness to adopt leading technologies (0-1)*	UNCTAD
Industrial activity index	Measures industrial activities include high tech export.	UNCTAD
R&D index	R&D index capturing R&D spending, patents, and number of researchers.	UNCTAD
Skills index	Measures the extent of human capital capable of innovating, adopting, and using leading technologies.	UNCTAD
Financial access index	Measures the availability of finance, include cost and ease of access, for innovative ventures.	UNCTAD
ICT index	Measures the availability of ICT infrastructure and users.	
GCF (%)	Gross capital formation as a percentage of GDP	WDI, WB
POPGR	Annual population growth rate (%)	WDI, WB
Human Capital	Tertiary school enrollment rate, % of gross	WDI, WB
Public sector corruption	Public sector corruption index, low to high (0 – 1)	VDem Dataset
Financial inst. efficiency	Total natural resources rents (% of GDP)	FD, IMF

***Note: The Frontier technology readiness index is adjusted to 0-100 from 0-1 to avoid the problem of large coefficients.**

The descriptive statistics for the panel on economic growth and its determinants, spanning from 2007 to 2020, reveal several intriguing aspects. The Gross Domestic Product Per Capita Growth Rate (GDPPC_GR) shows a substantial variation with a mean of 1.16 and a standard deviation of 4.47, indicating significant disparities in economic performance across observations. The Frontier Tech Index and Skills Index both exhibit wide ranges (0 to 60) and considerable standard deviations (11.8 and 12.7, respectively), suggesting heterogeneous levels of technological advancement and skills development. The Financial Access Index averages 51.78, with a relatively high standard deviation of 14.77, reflecting varying degrees of financial inclusion. Interestingly, the R&D Index, with a mean of 7.6 and a high standard deviation of 9.16, underscores the uneven focus on research and development. The Population Growth Rate maintains a moderate mean of 2.38 but with minimal fluctuation (standard deviation of 0.86), implying a relatively consistent demographic trend.

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
GDPPC_GR	434	1.16	4.47	-36.78	19.94
Import_UNCOMTRADE	434	8.83	3.25	3.03	31.81
Frontier Tech Index	400	20.35	11.8	0	60
Industrial activity index	400	44.05	12.88	0	80
R&D index	400	7.6	9.16	0	50
Skills index	400	22.08	12.7	0	60
Financial access index	400	51.78	14.77	10	90
ICT index	400	19.5	13.29	0	60
GCF (% of GDP)	408	24.65	10.91	0	79.4
Population growth rate	434	2.38	.86	-.08	3.87
Corruption (public sector)	434	.61	.23	.09	.96
Financial Inst. Efficiency (FIE)	421	.49	.12	.18	.77
Education	353	10.51	7.96	.57	42.78

Note: Data is from 2007 to 2020

4. **Empirical results**

Empirical estimations started with the fixed-effects before resorting to the System-GMM estimation technique. The use of this estimation technique is justified by the pairwise correlations (Table A2) among the variables. First, Endogeneity and Dynamic Relationships: Several variables show low to moderate correlations with GDPPC_GR (Gross Domestic Product Per Capita Growth Rate), such as Financial Access (0.08), Population Growth Rate (0.06), and Financial Institutions Efficiency (0.08). These correlations might hint at endogeneity issues, where these explanatory variables are potentially influenced by past values of GDPPC_GR. System-GMM effectively addresses this by using lagged values as instruments. Next, serial Correlation: Variables like the Frontier Tech Index, Skills Index, and Education display significant correlations with each other (e.g., Skills and Frontier Tech with a correlation of 0.73). This suggests potential serial correlation in these variables, a condition where System-GMM can provide robust estimates by differentiating out unobserved individual effects. Moreover, heteroskedasticity and Cross-Sectional Dependence: The varying degrees of correlation across different variables (e.g., R&D with Import at 0.29, ICT Index with Corruption at -0.21) indicate potential heteroskedasticity and cross-sectional dependence. System-GMM, with its capability to handle such complexities, becomes a suitable estimation technique.

Table 3 presents the results from the fixed-effect models. First, the coefficient of technology-intensive imports is positive and significant across all models, suggesting that an increase in the percentage of Science and Technology based imports (as a part of total imports) is associated with higher GDP per capita growth rates. The significance of this variable indicates the potential impact of technology absorption on economic growth. Next, GCF (%): The Gross Capital Formation percentage shows a positive but mostly insignificant effect on GDP per capita growth rate. This could suggest that while investment is important, its impact might be overshadowed by other factors or may not be linear. Third, Population Growth Rate (Pop. GR): This variable becomes significant and positive in model (3) but loses its significance in the subsequent models. The fluctuating significance might indicate an unstable relationship or omitted variable bias. Interestingly, Corruption and Financial Institutions Efficiency (FIE): Corruption shows a significant negative impact, indicating that higher corruption levels are detrimental to economic growth. FIE shows a significant positive impact, suggesting that efficient financial institutions contribute positively to economic growth. Going forward, economic growth is a dynamic process, likely influenced by its past values. System-GMM, with its ability to incorporate lagged dependent variables and differentiate out fixed effects, is better suited for capturing these dynamics.

The system-GMM results are presented in two models, the first with regression with SITC import data from UNCOMTRADE as one of the key independent variables (Table 3) and the second regression with the Frontier Technology Readiness Index from UNCTAD. Firstly, from Table 3, the validity of the System-GMM as used in the present analysis. As can be seen in models (7) to (12), the AR2 test does not show significance in any model, indicating no second-order autocorrelation and supporting the model specification. Also, Hansen Test of Overidentifying Restrictions: The Hansen test p-values are above conventional significance levels in all models, suggesting that the instruments used are valid and not over-identifying the model.

On the coefficients of interest, the lagged GDP per Capita Growth Rate (GDPPCGRt-1) shows a significant and positive coefficient across all models; indicating the dynamic nature of GDP growth, where past growth rates influence current growth. Next, the results of the Regression with SITC Import Data from UNCOMTRADE (% of total import) using the System-GMM shows that technology-intensive imports variable is consistently significant positive coefficients; suggesting a strong positive relationship between the percentage of Science and Technology based imports (as a part of total imports) and GDP per capita growth rate. This implies that technological import is a crucial factor in driving economic growth. Next, GCF (%) and Population Growth Rate (Pop. GR): The Gross Capital Formation percentage and Population Growth Rate show varied significance across models. This suggests that their impact on economic growth may depend on other factors or specific country contexts. Additionally, Corruption and Financial Institutions Efficiency (FIE): Corruption negatively affects GDP growth in most models, indicating that lower corruption levels are conducive to economic growth. FIE shows a generally positive impact, underscoring the importance of efficient financial institutions. Also noteworthy, the negative coefficient in model (12) suggests a complex relationship between education and GDP growth, warranting further investigation.

Overall, these results demonstrate the importance of technological imports, institutional quality, and financial efficiency in influencing economic growth. The significant and consistent coefficient of the lagged dependent variable across models validates the dynamic nature of the growth process.

Secondly, the results of the regression with Frontier Technology Readiness Index confirm the validity of the System-GMM estimation. The AR2 test (second-order autocorrelation) p-values are not significant in any model, which is crucial as it indicates no autocorrelation in the differenced errors at the second lag. This supports the validity of the model specification. Hansen Test of Overidentifying Restrictions: The Hansen test p-values are well above the conventional thresholds (e.g., 0.05), indicating that we cannot reject the null hypothesis of the instrument's validity. This suggests that the instruments used in the models are appropriate. Importantly, lagged Dependent Variable (GDPPCGRt-1): The coefficient of the lagged GDP per capita growth rate is consistently significant across all models, indicating the importance of past economic performance in predicting current growth. This persistence highlights the dynamic nature of economic growth.

Table 3. Regression with SITC Import Data from UNCOMTRADE (% of total import)

	Fixed Effect Models						Two-Step System GMM Models					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent Variable: GDP per capita growth rate											
$GDPPCGR_{t-1}$							.291***	.29***	.183***	.203***	.134***	.324***
							(.018)	(.042)	(.053)	(.037)	(.044)	(.043)
Import_comtrade	.229***	.226***	.209**	.201**	.16**	.129*	.31***	.577**	.782**	.454***	.639***	.224*
	(.084)	(.087)	(.088)	(.087)	(.079)	(.066)	(.087)	(.214)	(.321)	(.104)	(.167)	(.12)
GCF (%)		.053	.051	.047	.017	.013		.034	.023	.028*	-.008	-.017
		(.033)	(.033)	(.033)	(.03)	(.026)		(.025)	(.029)	(.015)	(.021)	(.015)
Pop. GR			1.117	1.193	1.767**	.629			-1.095**	-.371	-.577	-.27
			(.74)	(.737)	(.699)	(.683)			(.471)	(.325)	(.499)	(.273)
Corruption				-6.678**	-7.13***	-5.074**				-2.712***	-2.353**	-2.772***
				(2.974)	(2.719)	(2.571)				(.774)	(1.027)	(.642)
FIE					7.101**	6.424**					5.157*	2.811**
					(3.307)	(2.836)					(2.698)	(1.331)
Education						-.069						-.076***
						(.08)						(.027)
Constant	2.759	1.272	-1.026	2.778	-.988	1.262	-1.821**	-4.975**	-3.737	-1.102	-3.744	.509
	(2.425)	(2.593)	(3.003)	(3.433)	(3.452)	(3.25)	(.736)	(2.071)	(2.857)	(1.023)	(2.336)	(1.712)
Observations	434	408	408	408	395	320	434	408	408	408	395	320
No. of Countries	42	40	40	40	39	37	42	40	40	40	39	37
Instruments							39	26	27	32	31	37
ar1p							.039	.028	.018	.029	.036	.002
ar2p							.781	.793	.658	.641	.799	.986
Hansen Statistics							30.578	9.361	8.252	18.007	13.044	18.317
Hansen P-value							.134	.405	.509	.157	.29	.306
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

*Standard errors are in parentheses; *** p<.01, ** p<.05, * p<.1*

Indeed, the results from the Frontier Technology Index indicates in model (1) that this index has a significant positive effect on GDP per capita growth rate, suggesting that readiness to adopt frontier technologies is crucial for economic growth. Additionally, Access to Finance, ICT, Industrial Activities, R&D, and Skills Indices: The significant positive coefficients of ICT index (model (3)), R&D index (model (5)), and Skills index (model (6)) indicate the positive impact of these factors on economic growth. Conversely, the Industrial Activities Index in model (4) shows a significant negative effect, which might need further investigation to understand the underlying reasons.

Table 4. Regression with Frontier Technology Readiness Index from UNCTAD
(Two-Step System GMM Models)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: GDP per capita growth rate					
$GDPPCGR_{t-1}$	.114**	.224***	.171*	.119***	.193***	.199***
	(.046)	(.052)	(.095)	(.041)	(.044)	(.058)
Front_technology index	.394***					
	(.121)					
Access to finance index		.085				
		(.171)				
ICT index			.434**			
			(.164)			
Industrial activities index				-.254**		
				(.096)		
R&D index					.15**	
					(.067)	
Skills index						.273***
						(.086)
Constant	7.782	18.899**	15.567	30.199***	36.745***	-11.665
	(10.144)	(8.092)	(19.331)	(6.131)	(9.193)	(8.927)
Observations	380	391	380	380	380	380
No. of Countries	34	35	34	34	34	34
Instruments	27	28	26	30	29	27
ar1p	.001	.000	.000	.000	.002	.000
ar2p	.406	.251	.078	.115	.151	.212
Hansen Statistics	10.754	6.749	3.26	7.029	8.387	6.256
Hansen P-value	.15	.663	.776	.723	.496	.51
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

*Standard errors are in parentheses; *** $p<.01$, ** $p<.05$, * $p<.1$*

5. Discussions

Our empirical results provide a comprehensive understanding of how sub-Saharan African countries can capitalize on AI technology for economic growth. For instance, on the role of Technology-Intensive Imports reflects the significant impact of science and technology imports on GDP per capita growth for countries with low innovation capacity. This finding confirms our theoretical prediction of a positive correlation between skilled-labor (proxy by the ratio of technology-intensive imports) and per capita income growth. This confirmation highlights the crucial role of skilled labor in maximizing the benefits of AI technology. Given that AI substitutes for unskilled labor, this correlation implies that economies focusing on upgrading their workforce's skills can better integrate AI technologies, leading to higher productivity and income growth. This shift emphasizes the need for policies and investments in education and training, specifically targeting skills that complement AI, to transform the labor force in a way that aligns with technological advancements and the evolving demands of the AI-driven economy.

This finding showing a positive impact of technology-intensive imports on economic growth also suggests that technology transfer through imports is a key driver of economic growth. Other studies also support this notion. For instance, studies by Acemoglu et al. (2014) and Aghion et al. (2019) have emphasized the role of technology diffusion, primarily through imports, in enhancing productivity and growth. However, some studies caution about the dependency risk and the need for domestic innovation alongside technology importation. This being said, it is still relevant to consider that sub-Saharan African countries could enhance their economic growth by increasing their engagement with global technological advancements. Importing technology-intensive goods may be a vital pathway for technology transfer, contributing to productivity improvements and economic diversification.

Interestingly, the mostly insignificant effect of investment (GCF ratio) indicates that merely increasing investment is not sufficient for economic growth. Although this finding contradict those in papers like Jorgenson and Vu (2016) suggesting that investments, especially in ICT, have a significant positive effect on economic growth, in our case, the insignificant results could be interpreted to mean that the quality and focus of the investment, particularly towards sectors that can absorb and leverage AI technology, might be more crucial. This suggests a need for targeted investment strategies that align with technological advancement goals.

Noteworthy, the fluctuating significance of population growth rate across models may reflect varying demographic impacts on economic growth. It could be argued that in the context of sub-Saharan Africa, a young and growing population could be a potential asset only if aligned with skill development in AI and technology-related fields. Relatedly, the complex relationship between education and GDP growth suggests the need for education systems that are more attuned to the skills required in an AI-driven economy. Focusing on STEM education and digital literacy could be key to enhancing the absorptive capacity for AI technology.

Need not restate it, the findings highlight the importance of good governance and efficient financial institutions. This aligns with findings in the literature (e.g., studies by Knack and Keefer, 1997; La Porta et al., 1997), which underscore the role of institutional quality in economic development. However, the specific focus on AI and technology as a growth factor in the context of institutional quality is relatively novel in African studies. Meaning that reducing corruption can create a more conducive environment for AI-technological investment, while efficient financial institutions can facilitate the necessary funding and support for tech-driven enterprises.

Notably, the significant positive effect of the Frontier Tech Index underscores the importance of readiness to adopt leading-edge technologies. For sub-Saharan African countries, investing in infrastructure, policy frameworks, and partnerships that foster technology adoption can be instrumental in harnessing the potential of AI.

Furthermore, the positive impacts of ICT, R&D, and skills on economic growth point towards the importance of developing robust ICT infrastructure, encouraging R&D activities (even if initially limited), and enhancing skills that are relevant to the digital economy. Fostering a culture of innovation and technological experimentation could be particularly beneficial. Interestingly, an eye opening is given by the negative impact of Industrial Activities Index. This may reflect a transition phase where traditional industrial sectors are being disrupted by new technologies, highlighting a need for strategic policy interventions to manage this transition.

Taken together, human Capital (Education, Skills, R&D) reflects complex relationships between education, skills, R&D, and growth, emphasizing the need for skills and education systems aligned with AI and technology readiness. This resonates with the growing body of research (e.g., studies by Autor et al., 2014; Brynjolfsson and McAfee, 2014) which posits that education and skills, particularly in STEM and digital literacy, are crucial in maximizing the benefits of AI and technology on economic growth. The literature also emphasizes the importance of R&D, though your study finds that in regions with limited R&D, other factors like skills and technology imports become more critical.

Lastly, it is important to note, however, that while using technology-intensive imports as a proxy for skilled labor can be insightful, it might not fully capture the complex dynamics of skilled labor in the economy. This approach should be complemented with other data and contextual understanding of the specific economies being studied. Moreover, the direct impact of AI-technology could not be assessed because of data limitations. Hopefully, both data and more relevant proxy indicators will be available for future studies.

6. Conclusion

This study aims to assess the potential economic growth effects of proxy indicators for AI-technology absorptive capacity and readiness in the context of the developing country of sub-Saharan African countries, using a semi-endogenous growth framework. Overall, our findings offer an illuminating perspective on the pathways through which sub-Saharan African countries can harness AI technology for economic growth, despite the challenges posed by limited R&D capabilities. The significant and positive impact of technology-intensive imports on economic growth underscores the vital role of technology transfer through imports in these economies. A significant interpretation of this finding is that in environments where AI acts as a complement to skilled labor, economies can boost productivity and income growth by focusing on upskilling the workforce. Investing in education and training, particularly in skills compatible with AI and technology, emerges as a key strategy. This approach not only enhances the capacity to adopt and innovate with imported technologies but also positions these economies to more effectively capitalize on AI-driven growth opportunities.

One of our findings interestingly diverge from the traditional emphasis on investment (GCF ratio) as a primary growth driver. Instead, they suggest that the nature and focus of investments, particularly towards sectors poised to absorb and leverage AI technology, are more critical. This calls for a reorientation of investment strategies towards technology-friendly sectors and infrastructure.

The study also sheds light on the multifaceted role of human capital. The fluctuating significance of population growth rate and the complex relationship between education and economic growth imply that demographic advantages and educational reforms, especially in STEM and digital literacy, are paramount in building a workforce ready for an AI-driven economy. This aligns with the broader literature that underscores the importance of aligning education and skills development with the demands of the digital age.

Moreover, our research highlights the crucial role of good governance and efficient financial institutions. In the context of AI technology adoption, reducing corruption and enhancing financial institution efficiency become even more significant. Moreover, the unexpected negative impact of industrial activities on economic growth suggests a disruptive transition phase, indicating the need for strategic policy interventions to navigate the shift towards a more technology-centric economy.

Our study, while insightful, also acknowledges certain limitations, such as the proxy use of technology-intensive imports for skilled labor and the lack of direct measures of AI technology impact due to data constraints. Future research in this area would benefit immensely from more nuanced data and analysis to further elucidate the complex dynamics at play. Nevertheless, in essence, this study serves as a clarion call for sub-Saharan African countries to embrace AI technology not just as a tool but as a catalyst for sustainable and inclusive economic growth. By aligning investments, policy frameworks, and educational systems with the demands of a rapidly evolving technological landscape, these nations can unlock unprecedented growth potentials and chart a path towards a prosperous and technologically empowered future.

Selected References

1. Acemoglu, D., Johnson, S., & Robinson, J. A. (2001). The Colonial Origins of Comparative Development: An Empirical Investigation. American Economic Review, 91(5), 1369-1401.
2. Ahmed, Y., & Ibrahim, R. (2019). The impact of FDI inflows and outflows on economic growth: an empirical study of some developed and developing countries. Journal of Raparin University, 6(1), 129-157. https://doi.org/10.26750/vol(6).no(1).paper9
3. Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. Journal of Econometrics, 68, 29-51.
4. Autor, D. H., Levy, F., & Murnane, R. J. (2003). The Skill Content Of Recent Technological Change: An Empirical Exploration. Quarterly Journal of Economics, 118(4), 1279–1333.
5. Benzell, S. G., Kotlikoff, L. J., LaGarda, G., & Sachs, J. D. (2015). Robots Are Us: Some Economics of Human Replacement. National Bureau of Economic Research. DOI: 10.3386
6. Bessen, J. E. (2019). AI and Jobs: The Role of Demand. NBER Working Paper No. 24235. National Bureau of Economic Research.
7. Blundell, R. W., Bond, S. R., & Windmeijer, F. (2000). Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator. In B. Baltagi (Ed.), Nonstationary Panels, Panel Cointegration, and Dynamic Panels, Advances in Econometrics, Volume 15 (pp. 53-91). New York: JAI Press, Elsevier Science.
8. Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87, 115-143.
9. Brynjolfsson, E., et al. (2019). Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics. In A. Agrawal et al. (Eds.), The Economics of Artificial Intelligence. degruyter.com.
10. Coe, D., & Helpman, E. (1995). International R&D Spillovers. European Economic Review, 39, 859–887.
11. Fujii, H., & Managi, S. (2018). Trends and priority shifts in artificial intelligence technology invention: a global patent analysis. Economic Analysis and Policy, 58, 60-69. https://doi.org/10.1016/j.eap.2017.12.006
12. Hall, R. E., & Jones, C. I. (1999). Why Do Some Countries Produce So Much More Output per Worker than Others. Quarterly Journal of Economics, 114, 83-116.Haseeb, M., Mihardjo, L., Gill, A., & Jermsittiparsert, K. (2019). Economic impact of artificial intelligence: new look for the macroeconomic assessment in Asia-Pacific region. International Journal of Computational Intelligence Systems, 12(2), 1295. https://doi.org/10.2991/ijcis.d.191025.001
13. Jones, C. I. (1995). R&D-Based Models of Economic Growth. Journal of Political Economy, 103, 759-783.
14. Jones, C. I. (2003). Human Capital, Ideas and Economic Growth. In L. Paganetto & E. S. Phelps (Eds.), Finance, Research, Education and Growth (pp. 51-74). Palgrave Macmillan.
15. Jones, C. I. (2003). Population and Ideas: A Theory of Endogenous Growth. In P. Aghion, R. Frydman, J. Stiglitz, & M. Woodford (Eds.), Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps. Princeton University Press.
16. Korinek, A., Schindler, M., & Stiglitz, J. (2021). Technological Progress, Artificial Intelligence, and Inclusive Growth. IMF Working Paper WP 21/166.
17. Kshetri, N. (2021). Data labeling for the artificial intelligence industry: economic impacts in developing countries. IT Professional, 23(2), 96-99. https://doi.org/10.1109/mitp.2020.2967905
18. Li, B. (2021). Dynamic evaluation and system coordination degree of the integration of artificial intelligence and real economy. Complexity, 2021, 1-9. https://doi.org/10.1155/2021/5539793
19. Lu, C.-H. (2021). The impact of artificial intelligence on economic growth and welfare. Journal of Macroeconomics, 10, 33-42.
20. Lu, Y., & Zhou, Y. (2021). A review on the economics of artificial intelligence. Journal of Economic Surveys, 35(4), 1045-1072. https://doi.org/10.1111/joes.12422
21. Lucas, R. (1988). On the Mechanics of Economic Development. Journal of Monetary Economics, 22,

3-42.

22. Lucas, R. E. Jr. (1993). Making a miracle. Econometrica, 61(2), 251–272.
23. Maswana, J.-C. (2015). Assessing the Effects of Trade-induced Technology Imitation on Economic Growth in Africa. Procedia Economics and Finance, 30, 543-549. https://doi.org/10.1016/S2212-5671(15)01266-6
24. Papaioannou, S., & Dimelis, S. (2007). Information technology as a factor of economic development: evidence from developed and developing countries. Economics of Innovation and New Technology, 16(3), 179-194. https://doi.org/10.1080/10438590600661889
25. Romer, P. M. (1986). Increasing Returns and Long-Run Growth. Journal of Political Economy, 94, 1003.
26. Romer, P. M. (1994). The origins of endogenous growth. Journal of Economic Perspectives, 8(1), 3–22.
27. Safarolievich, D. (2022). The impact of wages, unemployment and economic growth on artificial intelligence: evidence from countries divided into three groups in the government artificial intelligence readiness index. Review of Economics and Finance, 20, 797-804. https://doi.org/10.55365/1923.x2022.20.90
28. Veronese, A., & Lemos, A. (2021). Regulatory paths for artificial intelligence in Latin American countries with data protection law frameworks: limits and possibilities of integrating policies. Revista Latinoamericana De Economía Y Sociedad Digital, (2). https://doi.org/10.53857/cjfb4918
29. Xu, Z. (2022). The influence of robot-assisted industry using deep learning on the economic growth rate of manufacturing industry in the era of artificial intelligence. Wireless Communications and Mobile Computing, 2022, 1-12. https://doi.org/10.1155/2022/4594858
30. Yousefi, A. (2015). A panel Granger causality test of investment in ICT capital and economic growth: evidence from developed and developing countries. Economics World, 3(3). https://doi.org/10.17265/2328-7144/2015.0506.001

Appendixes

Table A1. List of Countries (48 countries)

Angola	Madagascar
Benin	Malawi
Botswana	Mali
Burkina Faso	Mauritania
Burundi	Mauritius
Cabo Verde	Mozambique
Cameroon	Namibia
Central African Republic	Niger
Comoros	Nigeria
Congo, Dem. Rep.	Rwanda
Congo, Rep.	Sao Tome and Principe
Cote d'Ivoire	Senegal
Eswatini	Seychelles
Ethiopia	Sierra Leone
Gabon	South Africa
Gambia, The	Sudan
Ghana	Tanzania
Guinea	Togo
Guinea-Bissau	Uganda
Kenya	Zambia
Lesotho	Zimbabwe

Table A2. Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) GDPPC_GR	1.00												
(2) Import	0.06	1.00											
(3) Front_Tech	-0.11	0.10	1.00										
(4) Ind_acitivity	-0.01	-0.06	0.55	1.00									
(5) R&D	-0.09	0.29	0.56	0.24	1.00								
(6) Skills	-0.07	0.08	0.73	0.25	0.29	1.00							
(7) Fin_access	0.08	0.07	0.63	0.25	0.31	0.55	1.00						
(8) ICT	-0.21	0.09	0.60	0.19	0.40	0.37	0.24	1.00					
(9) GCF(%)	0.02	-0.05	-0.06	0.01	-0.10	-0.13	0.04	-0.07	1.00				
(10) Pop_GR	0.06	0.10	-0.62	-0.35	-0.16	-0.61	-0.53	-0.37	0.15	1.00			
(11) Corruption	-0.11	0.11	-0.31	-0.30	-0.05	-0.18	-0.40	-0.21	-0.30	0.28	1.00		
(12) FIE	0.08	-0.08	0.34	0.14	0.35	0.19	0.48	0.21	0.14	-0.16	-0.21	1.00	
(13) Education	-0.10	-0.10	0.71	0.29	0.34	0.70	0.54	0.46	-0.09	-0.66	-0.38	0.35	1.00