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## Cover Page Footnote

The authors thanks Dr. Ngozi Adeleye from Lincoln University, the creator and tutor of Crunch Econometrix online teaching.

RESEARCH ARTICLE

# Human Capital Development and Industrial Sector Growth in Sub-Saharan African Countries. An Augmented Pooled Mean Group Estimator

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**Abstract**

**Human capital is considered a vital catalyst for industrial sector growth. However, the lack of relevant skills and technical expertise can be a great setback to industrial growth. Thus, this study aimed to examine the effect of human capital development on industrial sector growth in Sub-Saharan African (SSA) countries. The study makes use of World Bank data from 1972 to 2021 using heterogeneous dynamic panel modeling. Due to cross-sectional dependence, both the first and second-generation unit root tests were examined in the study showing evidence of mixed order of integration. The study employed other econometric methods in the study such as mean group (MG), pooled mean group (PMG), and dynamic fixed effect (DFE) estimator but the Hausman test indicates the PMG as the most efficient method of estimation. To solve the cross-sectional dependence and account for unobserved common factors, the CS-ARDL common correlation effect pool mean group (CCEPMG) was examined. The result indicates that government expenditure on education has a negative and significant effect on industrial sector growth while life expectancy has a positive and significant effect in the short run. Tertiary school enrolment is positive but insignificant in the short run. However, in the long run, tertiary school enrolment and life expectancy have a positive and significant effect while government expenditure on education has a negative but insignificant effect on industrial sector growth. The results further indicate that there exists a long-run asymmetry nexus between human capital and industrial sector growth. The study recommends that SSA member countries should initiate strategies to improve the quality of human capital such as school enrolment and curriculum that are in line with industrial sector growth to improve the industrial value added.**

*Keywords:* Human capital, Industrial sector growth, Life expectancy, Educational enrolment, SSA, Value-added

## 1. Introduction

Human capital development is broadly considered a vital factor in industrial sector development particularly those attained through education and skills (Lucas, 1988; Mankiw et al., 1992). This is because a well-educated labor force is a focal point for industrial development, unemployment reduction, and an increase in entrepreneurial activities (Adejumo et al., 2013). Hence, greater human capabilities acquired through modern technology facilitate structural growth (Lee, 2020; Squicciarini & Voigtländer, 2015). Saka and Olanipekun (2021) indicate that the educational knowledge or skills acquired by the labor force boost production. However, the lack of relevant skills and technical know-how to drive technology has made industries in advanced countries perform better than those in developing countries in terms of human capital development (Abdul, 2011). In support of this fact, the United Nations Development Program (UNDP) argues that human capital investment should be the focus of development (Okumoko et al., 2018).

In the Sub-Saharan African (SSA) region with a vast population and low skill acquisition,

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development in human capital is low which has hindered the development of the industrial sector (Oyinlola et al., 2019). Taiwo et al. (2021) indicate that human capital is anticipated to be a primary driver of industrial productivity in SSA since industrial innovation might be promoted through a well-equipped human capital base for development in the long run. However, human capital development remains relatively low as compared to peer countries. For instance, in 2020, SSA failed to attain the tertiary education global average of 38% as she had only a 9.4% gross tertiary education enrollment ratio (The World Bank, 2020). Nevertheless, the enrolment percentage differs amongst countries in the region. For instance, the World Bank reports revealed that the latest value of gross enrolment ratio in tertiary education in 2020 for Senegal was 14%, Burundi 5%, and 6% for the democratic republic of Congo. This is quite low compared to advanced countries in 2020 such as Australia at 114%, Canada at 80%, and Denmark at 83%. The regional gross enrolment ratio in tertiary education in Table 1 revealed that the SSA region incurred the lowest expenditure in tertiary education as compared to other regions of the world. The deficiency of vital skills to boost technology has been the reason behind the poor industrial performance. According to the competitive industrial performance (CIP) index indicated in Table 1, SSA member countries are rank at the bottom of the scale with poor CIP scores. This is an indication that their industrial sector performance is inadequate. The World Bank reports indicate that the share of manufacturing value added as a percentage of GDP in SSA was 11% in 2021 while industrial activities made up the second-leading sector with a GDP contribution of approximately 27 percent.

*Table 1. Competitive industrial performance index (CIP) in 2020 for some SSA countries.*

| Country | CIP score | Rank |
|---|---|---|
| Gabon | 0.011 | 110 |
| Cameroon | 0.007 | 121 |
| Congo | 0.007 | 123 |
| Central Africa republic | 0.002 | 144 |
| Ghana | 0.009 | 116 |
| Angola | 0.006 | 129 |
| Kenya | 0.01 | 118 |
| Gambia | 0.001 | 151 |
| Zimbabwe | 0.009 | 114 |
| Uganda | 0.007 | 122 |
| Zambia | 0.006 | 126 |
| Burundi | 0.001 | 148 |
| Ivory Coast | 0.016 | 93 |
| Namibia | 0.012 | 114 |
| Senegal | 0.012 | 102 |
| Malawi | 0.002 | 143 |
| Ethiopia | 0.003 | 141 |
| Libya | 0.005 | 131 |

Source: Computed by authors from UNIDO (2020).
Notes: A Higher rank indicates poor industrial sector growth.

Previous empirical investigations have indicated that human capital development acts as a catalyst to boost productivity and growth (Okumoko et al., 2018). Thus, it is paramount for SSA countries to invest in tertiary education and health sectors considered the engines of industrial sector growth. However, the SSA region spends more on primary and secondary education than tertiary education. For instance, in 2020, she spent 43% on primary education, 27% on secondary education, and 21% on tertiary education (The World Bank, 2020).

Though policies in skills development, vocational and technical education, and training vary across countries in this region, they face similar problems in terms of access to education, lack of resources, power failure, and qualified personnel to upgrade their skills (UNIDO, 2005). These factors are a binding constraint to exalt industrial sector growth. Thus, it is imperative to upgrade and expand human capital to boost employment, productivity, and growth.

Human capital, comprising the knowledge, skills, and expertise of a workforce, is widely recognized as a vital catalyst for driving growth and progress within the industrial sector. However, in the context of SSA countries, the lack of relevant skills and technical proficiency among the population can pose a significant challenge to the sustained development of the industrial landscape. Numerous empirical studies have explored the relationship between human capital and industrial sector growth, providing valuable insights into this crucial economic dynamic. However, the impact of human capital on long-term growth in SSA has not received the attention it deserves. This research seeks to establish the key determinants of industrial sector growth, with a particular focus on the role of education and health. This is particularly timely, given the recent improvements in educational levels observed in the region (Akinlo & Oyeleke, 2020). We also aim to explore the potential asymmetric impact that various human capital indicators may have on the growth of industrial sectors. This is a significant area of inquiry, as previous research has not addressed this relationship. Through a more comprehensive examination of these dynamics, we can expand the current understanding and provide valuable guidance for policymakers and industrial leaders seeking to strategically leverage human capital to drive industrial growth.

The rest of the paper will focus on the literature review (both theoretical and empirical literature), data and methodology used in the study, presentation and discussion of findings, conclusion, and recommendations.

## 2. Literature review

### 2.1. Theoretical literature

The understanding of growth theories is based on the Solow model which indicates that changes in savings rate, population growth rate, and technological progress bring about changes in the level of output in an economy over time. However, the shortcomings of the model augment a new version specified by Mankiw et al. (1992) with the assumption of the Cobb-Douglas production function. This new amplification embodies the addition of human capital, which is a significant factor in growth as shown below;

$$y_t = k_t^{\alpha} H_t^{\beta} (A_t L_t)^{1-\alpha-\beta}$$

Where A is an index of technical change, K is capital, L is the labor supply and H is human capital while $(1 - \alpha - \beta)$ is the elasticity of income per unit of effective work. They revealed that improvement in human capital is paramount in industrial growth.

This study also rests on the endogenous growth theory, which argues that faster innovation and investment in human capital are significant ingredients to boost productivity. One such prominent theory is the Romer (1990) theory. Romer believes that investment in knowledge and innovation through Research and development is paramount for long-term growth. Similarly, Connolly (2004) indicates that human capital acquired through formal education or learning by doing are key factors that drive growth. In addition, Nkoa Emmanuel et al. (2014) indicate that based on the endogenous growth theory, human and physical capital remain the key sources of growth. An example of endogenous growth specifications is that of Barro (1997). The mathematical equation is expressed thus:

$$\Delta t = f(t, t^*)$$

$$t^* = f(W)$$

Where $\Delta t$ is the per capita output growth rate, t is the per capita output at the current level, and $t^*$ is the per capita output at steady state. For a specified value of t, the rise in growth rate is proportionate to $t^*$, which is determined by economic and environmental factors defined by W. Though these factors vary across studies, they are often measured in terms of factors such as population, government expenditure, investment, and educational variables (Ihensekhien & Soriweli, 2023).

Barro (1997) revealed that in a transition period, any increase in long-term growth rate $t^*$ is proportionate to per capita growth rate t. For instance, if the government improves the business climate by increasing spending on the tertiary education enrolment ratio, the target level $t^*$ will increase and so will t also increase proportionately. This adopted policy does not only have a long-term impact on growth rate but also per capita output level.

### 2.2. Empirical literature

The nexus between human capital development and industrial sector growth is heterogeneous. Some authors found a positive link. For instance, Ciccone and Papaioannou (2009) posit that a country will have better-developed knowledge and intensive industries when the residents of a country or region have a higher educational level. They further indicate that countries will have a more advanced industrial structure when human capital accumulates faster. Similarly, Karim and Shabbir (2012) also revealed that human capital played a significant role in the development of the manufacturing sector in Malaysia from 1981 to 2010. Equally, Chen (2011) revealed that human capital has a direct relationship with industrial clusters. Ossadzifo (2019) finds that manufacturing sectors in SSA are promoted by the quality of human capital through value-added which boosts growth in the region. Likewise, Das and Drine (2020) conclude that the most significant obstacle to industrial growth in SSA is the poor performance of human capital development and depreciated infrastructure. However, the absorption of new technology will be a significant panacea for economic growth. Suliaman et al. (2015) found a significant positive effect between human capital in secondary and tertiary school enrollments and economic growth for a period of 35years in Nigeria. They also consider technology as an important parameter for long-term growth.

A study conducted by Oyinlola et al. (2019) postulates that the challenges of sub-Saharan Africa's industrial development are poor human capital development and low health expenditure. Hence, SSA should utilize its revenues obtained from the sales of natural resources to boost human capital and industrial development. Similarly, Wonyra (2018) using SSA countries from 1990 to 2015, shows that the value added in the manufacturing sector positively impacts economic growth. Taiwo et al. (2021) found that human capital contributes to industrial development in SSA from 1986 to 2018. The study also found that physical capital exerts a negative impact on industrial development while the impact of trade openness is mixed.

Anyawu et al. (2015) using ARDL revealed a positive but insignificant effect of human capital on the growth of Nigeria's economy. However, Saka and Olanipekun (2021) found that the industrialization process affected economic growth positively in Nigeria from 1980 to 2016 using two-stage least squares. Shuaibu and Oladayo (2016) using 33 African countries from 2000 to 2013 found government expenditure on health and education as key determinants of human capital. Also, Gao (2021) indicates that human capital has a positive effect on low-carbon growth and upgrading of China's industrial structure.

Fang and Chao (2015) using China's Shandong Province found that the average years of schooling positively and significantly affected the development of the tertiary industry from 1996 to 2010. Their findings are consistent with that of Olarewaju et al. (2021) who examined the impact of human capital on manufacturing value-added in Nigerian companies. Using the Spearman Correlation, they revealed that formal training, high school education, and research significantly affect industrial production. Max (2021) found that growth in education boosts human capital and as a result stimulates industrial investment. This lowers prices and increases output due intensive use of human capital. Similarly, Gruzina et al. (2021) also found that economic growth is a result of human capital innovations. They further indicate that human capital is a key factor that causes a difference in growth between developed and developing countries. Samouel and Aram (2016) revealed that human capital was a key determinant of industrialization in 33 African countries from 1970 to 2012. However, it varies among regions in the continent. Dinkneh and Yushi (2015) studied the effect of human capital on economic growth in Ethiopia from 1980 to 2013. They found out that expenditure on public health, and primary and secondary education positively and significantly affect economic growth in both the short and long run while tertiary school enrolment was found to be insignificant. Wirajing et al. (2023) used 48 African countries to examine the effect of human capital on economic growth from 2000 to 2019. They deployed the system GMM technique which revealed that human capital plays a positive role in African economic growth. They also indicate both the female and male gender play a significant role in economic growth.

Contrarily, other studies have confirmed a negative relationship between human capital and industrial growth. Okumoko et al. (2018) show that educational expenditure and health negatively affected industrial growth in Nigeria from 1976 to 2016 using time series data. Their findings are consistent with Ojewumi and Olademeji (2016) who found that recurrent expenditure on education correlates negatively with growth from 1981 to 2013 in Nigeria. Similarly, Day and Ellis (2013) also found that average years of schooling negatively and significantly affect manufacturing value-added in a variety of industries in Indonesia, particularly in the areas of electric machinery, paper and goods, and printing and publishing. In addition, Shaddady (2022) investigates the role of government spending on growth in EECA from 1995 to 2019 using a panel of 19 countries. The linear model reveals a negative linear nexus between government spending and economic growth. Ihensekhien and Soriweli (2023) using Nigeria as a case study examined the relationship between human capital and industrial sector growth from 1986 to 2020. They used ARDL in their analysis and found that recurrent investment in education by the government negatively and significantly has a short-run impact on industrial sector growth but has a positive and significant long-run effect. In addition, they found government expenditure on health to be positive and significant in the short run while in the long run, it was found to be negative and insignificant.

For an insignificant relationship, Akpoghelie et al. (2024) analyzed the connection between human development and industrial sector performance across the selected SSA and OECD countries. The study found that changes in the Human Development Index (HDI) were not statistically significant in explaining variations in industrial sector performance in either the SSA or OECD contexts. This suggests that the relationship between human development and industrial performance may be more complex and multifaceted.

## 3. Data and methodology

The study makes use of data from world development indicators (WDI) using Panel estimation. The analysis focuses on 34 countries in the SSA for 49 years (1972–2021) giving 1666 observations. Tertiary education enrolment, life expectancy, and government expenditure on education are used to capture human capital while industrial sector growth was captured using industrial value added as a percentage of GDP. These variables have been used in previous studies: government spending (Okumoko et al., 2018; Shaddady, 2022; Shuaibu & Oladayo, 2016), school enrolment (Fang & Chao, 2015), and life expectancy (Okumoko et al., 2018).

The choice of data was based on the availability of data with respect to the variables used in the study.

This study rests on the study of Asteriou et al. (2021) who revealed that when T is greater than N, the ARDL is the appropriate technique of estimation. Thus, in this study, since T = 49 years is greater than N = 34 countries, the panel ARDL is preferable for the analysis. The method is also more efficient in the case of I(0), I(1), or a mixture of both (Pesaran & Shin, 1998). The unit root tests result in Appendix 2 show evidence of a mixed order of integration where some variables are stationary at levels and others at first difference which meets the condition of panel ARDL. The choice of the lag length was based on the AIC information criteria. Thus, the study makes use of panel ARDL introduced by Pesaran et al. (1999) and Pesaran and Smith (1995). The generalized format of panel ARDL appears as follows;

$$y_{it=}\sum_{j=1}^{p}\alpha_i y_{i,t-j}+\sum_{j=o}^{q}\beta'_{ij}x_{i,t-j}+\omega_i+\mu_{ie} \quad (1)$$

Where $y_{it}$ is the outcome variable; $(x'_{it})'$ is a k ×1 vector which is expected to be purely I(0) or I(1) series or cointegrated; $\alpha_{ij}$ is the coefficient of lagged outcome variables called scallers; $\beta'_{ij}$ are kx1 coefficient vector; $\omega_i$ is the specific fixed effect unit; i = 1,… ….N; t = 1,2 ….,T; p and q are the optimal lag; $\mu_{ie}$ is the error correction term.

The key significant demonstration is the re-parameterized ARDL(p,q) error correction model (ECM) which is specified accordingly;

$$\nabla y_{it=}\theta_i\left[y_{i,t-1}-\gamma'_i x_{i,t}\right]+\sum_{j=1}^{p-1}\alpha_{ij}\nabla y_{i,t-j}+\sum_{j=o}^{q-1}\beta'_{ij}\nabla x_{i,t-j}+\varphi_i+\mu_{ie} \quad (2)$$

To obtain the effect of human capital development on industrial sector growth, the re-parameterized model can be transformed thus;

$$\nabla HCD_{it=}\theta_i\left[IVA_{1,t-1}-\varnothing_1\partial_{i,t-1}-\varnothing_2 x_{i,t-1}\right]+\sum_{j=1}^{p-1}\alpha_{ij}\nabla HCD_{i,t-j}+\sum_{j=o}^{q-1}x_{ij}\nabla x_{i,t-j}+\varphi_i+\mu_{ie} \quad (3)$$

Where: IVA is industrial value added which is the dependent variable; $\theta_i$ is the speed of adjustment coefficient for the specific group; $\gamma'_i$ is the vector of long run relationship; $\alpha$ and $x$ are short-run coefficient; $[y_{i,t-1}-\gamma'_i x_{i,t}]$ is the ECM, which captured the long-run representation in the model; p-1 is the optimal lag for the outcome variables; q-1 is the optimal lag for the regressors; Δ is the difference operator; $\varnothing_1$ and $\varnothing_2$ are long-run coefficients for human capital development.

Based on extant literature, equation (3) can be estimated by either pooled mean group (PMG), mean group (MG), or dynamic fixed effect (DFE) estimator which considers the heterogeneity of the dynamic adjustment process (Demetriades & Law, 2006). However, the Hausman test will be a decision-maker.

The MG estimator proposed by Pesaran and Smith (1995) considers parameters heterogeneous across the group in both the short and long run. Hence, it is less informative as it averages the data by calculating the coefficient means. This method is however sensitive to permutations of small models and outliers if N is small. Hence, for the estimate to be stable, the estimator is suitable for a large N (Favara, 2003).

The DFE estimator is not quite different from the PMG estimator but it limits the coefficient of the co-integrating vector to be equal across all panels in the long run (Rafindadi, 2013). For DFE, the intercept and dynamic specification are heterogeneous across the groups while the slope coefficient and error variance are homogenous. Applying this method requires the assumption that in both the short run and long run, countries' reactions are homogenous (Asteriou et al., 2021). For small sample data, this method may suffer from simultaneity bias due to the endogeneity problem among the error term and lagged independent variables (Baltagi et al., 2000).

Contrarily, the PMG estimator proposed by Pesaran et al. (1999) is more informative and acts as an in-between estimator between the MG and DFE. It allows intercepts, short-run coefficients, and error variances to be heterogeneous across the group but the long-run coefficients are homogenous. Deciding between the MG, PMG, and DFE is based on the Hausman (1978) test.

The null hypothesis between the MG and PMG is that; PMG is more efficient against the alternative that the null is not true. If the estimated p-value >0.05, the null hypothesis cannot be rejected. Hence, the PMG is the most appropriate estimator. However, the null hypothesis is rejected when the p-value <0.05 where the MG is the appropriate estimator.

For the MG and DFE, the null hypothesis is that DFE is more efficient which is rejected when the p-value<0.05 stipulating MG as the preferred estimator otherwise the DFE is used while DFE and PMG, test the null hypothesis that PMG is more efficient which is rejected when the p-value<0.05. Hence, the DFE is the appropriate estimator otherwise, the PMG is used.

Since this study takes into account lower-middle-income, upper-middle-income, and low-income countries, their short-run coefficients are expected to be heterogeneous due to countries' specific economic differences but they may display similar behavior in the long run due to unobserved common factors or spillover effects (Wang & Betrand, 2023). Hence, some level of similarity in their human capital and industrial sector development is expected in the long run. Thus, the PMG estimator will be a better estimator for the analysis.

However, to account for contemporaneous correlation, the CS-ARDL common correlation effect pool mean group (CCEPMG), an augmented pooled mean group estimator is utilized in the study. Pesaran (2006) indicates that when common factors are allowed in a model, the use of the (weighted) cross-sectional averages of the regressors is paramount to control for the common factors and individual heterogeneity. Hence, this study will focus on the CCEPMG estimator to account for unobserved common factors that affect coefficient estimates (Bhattacharya et al., 2018).

## 4. Asymmetry panel ARDL

To ascertain if human capital development has an asymmetric effect on industrial sector growth, the nonlinear ARDL of Shin et al. (2014) which accounts for heterogeneity and non-stationarity is adopted. It is specified as follows;

$$IVA_{it} = b_0 + b_1 ISG_{it}^{+} + b_2 ISG_{it}^{-} + \mu_{it} \quad (4)$$

Where IVA is industrial value added, ISG is the industrial sector growth defined in terms of tertiary school enrolment, life expectancy, and government expenditure on education, $b_1 ISG_T^{+}$ and $b_2 ISG_T^{-}$ are the partial sum of positive and negative changes in total ISG derived as follows.

$$ISG_{it}^{+} = \sum_{i=1}^{t} \Delta ISG_j^{+} = \sum_{j=1}^{t} max\left(\Delta ISG_J, O\right) \quad (5)$$

$$ISG_{it}^{-} = \sum_{i=1}^{t} \Delta ISG_j^{-} = \sum_{j=1}^{t} min\left(\Delta ISG_J, O\right) \quad (6)$$

The long-run ECM in equation (4) is given as follows;

$$\Delta IVA_{it} = b_{01} + \sum_{i=1}^{p} b_{1i} \nabla IVA_{it-i} + \sum_{i=1}^{P} b_{2i}^{+} \Delta ISG_{it-1}^{+} + \sum_{i=1}^{P} b_{3i}^{-} \Delta ISG_{it-1}^{-} + \lambda ECT_{it-1} + \mu_{1t} \quad (7)$$

Where $ECT_{t-1}$ is the one-period lagged error correction term. The coefficient $\lambda$ is the adjustment speed which must be negative and significant to show long-run convergence.

## 5. Results and discussions

### 5.1. Unit root and cross-section dependence test

Stationarity is imperative to avoid spurious regression (Gujarati, 2004). It is also paramount in panel ARDL to make sure none of the variables are integrated into order two. However, since time series for different cross-sectional units may be correlated, which may arise due to similarity in political, cultural, and economic cross-sectional units (Wang & Betrand, 2023), it is primordial to conduct cross-sectional dependent tests which help in deciding whether to use the first generation (Im et al., 2003; Levin et al., 2002) or the second generation panel unit root tests (Pesaran, 2003, 2004, 2007, 2015). The first-generation unit root tests are constructed under the assumption of cross-sectional independence while the second-generation unit root test accounts for cross-sectional dependence (Barbieri, 2016). The Pesaran (2015) CD test, which tests the null hypothesis of no cross-section dependence (correlation) in the residuals is used. Table 2 shows evidence of cross-section dependence in the model. Hence, both the first and second-generation unit root tests will be used to ascertain stationarity.

The Hausman test in Table 3 indicates that between the MG and PMG, the PMG is preferred, between the DFE and PMG, the PMG is preferred, and between the MG and DFE, the MG is preferred. Thus, the final options from the three models are PMG and MG. However, the PMG will be the most preferred option since the null hypothesis was rejected between the MG and PMG.

### 5.2. Discussion of results

The results in Table 4 examine the contribution of each variable to industrial sector growth in both the

*Table 2. The CD test for cross-sectional dependence.*

| variables | CD | p-values |
|---|---|---|
| LogIVA | 110.177 | 0.000 |
| schenrol | 143.058 | 0.000 |
| govexp | 127.234 | 0.000 |
| lifeexp | 81.402 | 0.000 |

Source: Computed by authors, 2023.

*Table 3. Hausman test.*

| Test types | p-values | decision | conclusion |
|---|---|---|---|
| MG vs PMG | 0.2493 | Do not reject Ho | PMG preferred |
| DFE vs PMG | 0.3451 | Do not reject Ho | PMG preferred |
| MG vs DFE | 0.9620 | Do not reject Ho | MG preferred |

Source: Computed by authors, 2023.

*Table 4. Panel ARDL estimation.*

| PMG | | | MG | | | DFE | | |
|---|---|---|---|---|---|---|---|---|
| Variables | LR | SR | Variables | LR | SR | Variables | LR | SR |
| ECT | | −0.156***<br>(0.0186) | ECT | | −0.275***<br>(0.0372) | ECT | | −0.122***<br>(0.0113) |
| D.schenrol | | −0.00207<br>(0.00219) | D. schenrol | | 0.00353<br>(0.00473) | D. schenrol | | −0.000841<br>(0.00274) |
| D.goveexp | | −0.0279***<br>(0.00710) | D.gexpedun | | −0.0275**<br>(0.0131) | D.gexpedun | | −0.0330***<br>(0.00862) |
| D.lifeexp | | 0.0440**<br>(0.0173) | D.lifeexp | | 0.0403***<br>(0.0149) | D.lifeexp | | 0.0195***<br>(0.00390) |
| L. schenrol | 0.0279***<br>(0.00262) | | L. schenrol | 0.0253***<br>(0.00961) | | L. schenrol | 0.0391***<br>(0.00528) | |
| L.govexp | −0.0846*<br>(0.0511) | | L.gexpedun | −0.0185<br>(0.0552) | | L.gexpedun | −0.242***<br>(0.0931) | |
| L.lifeexp | 0.0502***<br>(0.00533) | | L.lifeexp | 0.0454<br>(0.0279) | | L.lifeexp | 0.0268**<br>(0.0108) | |
| Constant | | 2.748***<br>(0.327) | Constant | | 5.168***<br>(1.099) | Constant | | 2.378***<br>(0.211) |
| Observations | 1666 | 1666 | Observations | 1666 | 1666 | Observations | . | . |

Note: *** denote 1% significant level, ** denote 5%, and * denote 10%.
Standard errors in parentheses.
Source: Computed by authors, 2023.

short and long run. The estimated result focuses more on PMG where the Hausman test confirms its efficient and consistent performance over MG and DFE models. The PMG results indicate that in the short run, government expenditure on education negatively and significantly affects industrial value added in the short run. This suggests that higher government expenditure on education may actually have a detrimental impact on the growth of the industrial sector. This counterintuitive result underscores the nuanced dynamics at play, where the immediate benefits of educational spending may not directly translate to industrial progress. This is contrary to the study of Max (2021) who found that growth in education boosts human capital and as a result, stimulates industrial investment. However, the findings are consistent with that of Ihensekhien and Soriweli (2023) who revealed that recurrent investment in education by the government negatively and significantly has a short-run impact on industrial sector growth.

Conversely, the study highlights the positive and significant influence of life expectancy on industrial growth in the short run. This indicates that factors contributing to improved health and longevity within the population can have tangible benefits for industrial development, likely by fostering a more productive and resilient workforce. This confirms the findings of Oyinlola et al. (2019) who postulate that the challenges of sub-Saharan Africa's industrial development are poor human capital development and low health expenditure.

In the long term, the research shows that increased tertiary school enrollment and life expectancy exhibit a positive and significant effect on industrial sector growth over time. This suggests that investments in higher education and public health can yield substantial dividends for industrial advancement in the long run, despite the more immediate challenges observed. The findings of the study are in line with those of Samouel and Aram (2016) who provided valuable insight into the crucial role that human capital plays in driving industrialization across 33 African countries.

Also, government investment in education has been shown to have a detrimental and statistically significant impact on the value added by the industrial sector. This finding suggests that the allocation of public funds toward educational initiatives may come at the expense of industrial growth and productivity. This is true with the findings of Okumoko et al. (2018) who revealed that educational expenditure and health negatively affected industrial growth in Nigeria from 1976 to 2016 using time series data.

On the assumption of long-run homogeneity, cointegration will be inferred from the statistical significance of the long-run coefficient and ECT. All the estimation tools indicate that there is cointegration and long-run convergence among the variables based on the significance of the ECT. That is previous years' errors are corrected in the current year. Their respective speed of adjustments to long-run equilibrium is 15.6%, 27.5%, and 12.2% for PMG, MG, and DFE respectively. This is also an indication that all variables in the respective tools of estimation have a causal effect on industrial sector growth in the long run.

The results of CCEPMG in Table 5 indicate that government expenditure on education negatively affects industrial sector growth while life expectancy has a positive effect in the short run and both are significant at 1%. In the long run, tertiary school enrolment and life expectancy positively affect industrial sector growth at a 5% significant level. The results are in line with a priori expectations and true with the findings of Fang and Chao (2015) who confirmed that average years of schooling positively affect industrial sector growth. However, government expenditure on education has a negative and insignificant effect on industrial growth. The high level of corruption prevalent in the educational sector in most SSA countries has made expenditure on education not have a direct relationship with human capital development. Also, most government expenditure and the school curriculum are not structured in the domain of industrial sector growth. This is true with the findings of Ojewumi and Olademeji (2016) who found that recurrent expenditure on education correlates negatively with growth but contrary to the findings of Okumoko et al. (2018) who found government expenditure on education to have a positive effect on industrial sector growth.

The ECT is negative and significant indicating that the speed of adjustment to long-run equilibrium is 59.3% (−0.5934).

*Table 5. CS-ARDL common correlated effects pooled mean group (CCEMG) estimator.*

| VARIABLES | CCEPMG |
|---|---|
| **Shortrun** | |
| govexp | −0.311*** |
| | (0.175) |
| schenrol | 0.0161 |
| | (0.0147) |
| lifeexp | 0.0587*** |
| | (0.0328) |
| **long run** | |
| ECM | −0.5934229 |
| govexp | −0.235 |
| | (0.411) |
| lifeexp | 0.172** |
| | (0.045) |
| schenrol | 0.0622** |
| | (0.0358) |
| Observations | 1532 |
| R-squared | 0.157 |
| RMSE | 0.12 |
| CD Statistic | 1.35 |

Note: *** denote 1% significant level, ** denote 5%, and * denote 10%.
Standard errors in parentheses.
Source: Computed by authors, 2023.

*Table 6. PMG ARDL short-run and long-run asymmetry test.*

| Walt test | p-values | Decision |
|---|---|---|
| Long run asymmetry | 0.006 | Long-run asymmetry nexus exist |
| Short run asymmetry | 0.653 | Short-run asymmetry nexus does not exist |

Source: Computed by authors, 2023.

The Walt test results in Table 6 revealed a long-run asymmetry effect of human capital on industrial sector growth but a short-run asymmetry nexus does not exist. Thus, the alternative hypothesis that the variables in the long run are asymmetric is accepted. The nonlinear ARDL presented in Appendix 4 revealed the positive and negative changes of individual variables and their effect on industrial sector growth.

## 6. Conclusion and recommendation

Human capital is an indispensable and invaluable asset for driving growth and progress within the industrial sector. In fact, the very nature of human capital development is even more crucial in ensuring increased industrial value-added and overall sectoral advancement. However, it is concerning to note that many countries in SSA have unfortunately experienced poor industrial sector growth over the years. Hence, this insightful study examines the crucial relationship between human capital development and the growth of the industrial sector across SSA countries. Utilizing the panel Autoregressive Distributed Lag (ARDL) approach, the researchers employ the Hausman test to determine the Pooled Mean Group (PMG) as the most efficient estimator for this analysis. Notably, the focus is on the Cross-Correlated Effects Pooled Mean Group (CCEPMG) method, which accounts for unobserved common factors that may influence the variables under investigation.

The result indicates that government expenditure on education has a negative and significant effect on industrial sector growth while life expectancy has a positive and significant effect in the short run. However, in the long run, tertiary school enrolment and life expectancy have a positive and significant effect while government expenditure on education has a negative and insignificant effect. Based on this conclusion, the study recommends that SSA member countries should initiate strategies to improve the quality of human capital such as school enrolment by targeting educational spending in favor of industrial sector growth and better health facilities to improve industrial value added. In addition, the study further highlights the critical need for governments in these countries to ensure that funds earmarked for educational investments, such as the procurement of essential materials and supplies, are utilized appropriately and transparently, without any misappropriation or corrupt practices.

## 7. Limitations, recommendations for future research, and implications

While the study was constrained by incomplete and lack of data, this limitation is a common challenge faced when conducting research in SSA countries. The availability of comprehensive and reliable data in this region is often lacking, making it difficult to perform thorough panel evaluations. Additionally, the study was further limited by the issue of multicollinearity, which prevented the inclusion of other human capital development variables such as labor force participation rate that could have provided valuable insights.

To fully comprehend the impact of human capital development on industrial sector growth, research studies need to delve deeper into areas related to other key components of human capital. This includes investigating the effects of training, intelligence, skills, and other employer-valued attributes such as loyalty and punctuality, and how they collectively contribute to driving industrial growth. Additionally, these studies must account for potential structural breaks, as panel series analyses are often susceptible to such discontinuities, which can significantly influence the observed relationships and patterns.

Based on implication, it appears that government expenditure on education does not yield any immediately tangible or substantial impact on industrial value added in the short term. However, the research indicates that the relationship between educational spending and industrial growth is not statistically significant in the near future. Policymakers would be wise to closely monitor these expenditures and explore ways in which educational initiatives can be strategically leveraged to drive industrial development over time. The lack of a clear, immediate correlation between educational funding and industrial value added does not negate the intrinsic value of investing in education. However, Quality education lays the foundation for a skilled and innovative workforce that can fuel economic progress in myriad ways. By taking a more nuanced, long-term view, policymakers can identify opportunities to optimize the synergies between educational initiatives and industrial growth strategies, ultimately benefiting society as a whole.

The study also reveals a significant contributing factor in boosting industrial value added - the life expectancy of the population. This suggests lawmakers will focus on those factors related to the overall health and longevity of the population, as these elements can have a profound impact on enhancing industrial productivity and output. By prioritizing initiatives that promote public well-being and increased lifespans, lawmakers have the opportunity to unlock new avenues for bolstering the strength and vitality of the industrial sector, ultimately leading to greater economic prosperity and growth.

Further, the research findings indicate that while school enrollment may have the potential to exert a meaningful influence over the long term, it does not appear to make a substantial positive contribution in the immediate short term. This revelation presents an important consideration for policymakers as they can work to devise effective strategies and allocate resources towards educational initiatives aimed at driving sustainable, short-term, and long-term industrial growth. The study highlights the need to thoughtfully balance short-term goals with a focus on cultivating lasting and systemic change through investments in the education sector.

## Ethical approval

Not applicable.

## Author's contribution

Betrand Ewane, Enongene: Conceive and design the study, collected data, run the regression plus interpretation, and produce the final draft of the study.

Ivo Ewane, Etah: Wrote the introduction, Literature Review, and methodology of the study.

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## Data availability statement

The data use in this study can be made available upon a reasonable request.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix 1. Summary statistics.

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| logIVA | 1636 | 20.717 | 1.88 | 15.404 | 25.676 |
| schenrol | 1700 | 34.652 | 14.087 | 10.956 | 60.18 |
| govexp | 1700 | 4.447 | 00.678 | 3.194 | 7.825 |
| lifeexp | 1666 | 54.929 | 8.405 | 14.098 | 76.593 |

Source: Computed by authors, 2023.

*Appendix 2. Unit root test.*

| First generation unit root test | | | | | | | Second generation unit root test | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Test type | variables | Test statistics at levels | p-values | Test statistic at first difference | P-value | Decision | Test types | variable | statistic at levels | statistics at first difference | Decision |
| IPS | logIVA | 0.5678 | 0.7149 | −21.8817 | 0.0000 | I(1) | CIPS | logIVA | 1.234 | −3.873 | I(1) |
| | Schenrol | 5.7086 | 1.0000 | −37.4480 | 0.0000 | I(1) | | Sch enrol | 2.610 | – | I(0) |
| | Govexp | −9.9893 | 0.0000 | – | – | I(0) | | Gov exp | 2.610 | – | I(0) |
| | lifeexp | −3.0029 | 0.0013 | – | – | I(0) | | lifeexp | −1.825 | −3.976 | I(1) |
| | | | | | | | 5% CV = −2.110 | | | | |

Source: Computed by authors, 2023.

*Appendix 3. Correlation matrix table.*

### Pairwise correlations

| Variables | logIVA | schenro | govexp | lifeexp |
|---|---|---|---|---|
| logIVA | 1.000 | | | |
| schenrol | 0.498 | 1.000 | | |
| govexp | −0.138 | −0.324 | 1.000 | |
| Lifeexp | 0.465 | 0.474 | −0.148 | 1.000 |

Source: Computed by authors, 2023.

*Appendix 4. Nonlinear ARDL estimates.*

| Variables | coefficient | Std.error |
|---|---|---|
| **shortrun** | | |
| ECM | −0.111*** | (0.00915) |
| Schenrol_pos | 0.00557*** | (0.00169) |
| Schenrol_nega | −0.0457*** | (0.0128) |
| Lifeexp_pos | 0.000121 | (0.000298) |
| Lifeexp_nega | 0.000203 | (0.000313) |
| Govexp_pos | 0.0239*** | (0.00882) |
| Govexp_neg | 0.0286*** | (0.00672) |
| **long run** | | |
| Schenrol_pos | 0.0150*** | (0.00507) |
| Schenrol_nega | 0.0947*** | (0.0136) |
| Lifexp_pos | 0.00264 | (0.00165) |
| Lifexp_neg | 0.00183 | (0.00177) |
| Govexp_pos | −0.0441*** | (0.00823) |
| Govexp_nega | −0.0287*** | (0.00513) |
| Constant | 2.238*** | (0.176) |
| Observations | 1598 | |
| R-squared | 0.377 | |

Note: *** denote 1% significant level, ** denote 5%, and * denote 10%.
Source: Computed by authors, 2023.

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