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Spring 4-10-2019

Measuring Efficiency and Productivity of ICT Infrastructure Utilization

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MEASURING EFFICIENCY AND PRODUCTIVITY OF ICT INFRASTRUCTURE UTILIZATION

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The paper discusses how Data Analytics can be used to investigate how ICT infrastructure is being utilized within the educational component of the human development index using non parametric methods. It is particularly aimed towards any of the following topic areas for the conference:

- Bridging the Digital Divide: emancipatory IS
- Business Intelligence and Decision Support
- IS Innovation, Adoption and Diffusion

MEASURING EFFICIENCY AND PRODUCTIVITY OF ICT INFRASTRUCTURE UTILIZATION

Abstract

Several researches have been carried out with respect to ICT Infrastructure Investments made by nations in a bid to bridge the digital divide and improve quality of life and the Human Development Index (HDI). With a strong argument being made in the literature for continued investments in ICT Infrastructure, this research investigated the relative efficiency and productivity of ICT Infrastructure Utilization in Education. The research employed the Data Envelopment Analysis (DEA) and Malmquist Index (MI) non-parametric research methodology with Arab States, Europe, Sub-Saharan Africa and World regions forming the Decision-Making Units. With Data collected from the United Nations Educational, Scientific and Cultural Organization (UNESCO) and the International Telecommunications Union (ITU), findings show a relatively efficient utilization and steady increase in productivity for the regions but with only Europe and Arab States currently operating in a state of positive growth in productivity.

Keywords: Data Analytics, Data Envelopment Analysis, Malmquist Index, ICT4D, Learning Analytics

1.0 Introduction

The growth of Information and Communication Technology (ICT) in recent years has been remarkable in all countries and sectors throughout the world because of it's transformational power that favours productivity and efficiency (Kayisire & Wei, 2016). Many governments have heeded the call for increased investments in ICT with the aim to improve national development with respect to the Human Development Index (HDI). This is based on the assumption that increasing investments in ICT will lead to improvements in productivity and other aspects of development at the organizational and national levels (Samoilenko & Osei-Bryson, 2017a). With Educational Attainment being one of the core indices for measuring Development with respect to the Human Development Index (UNDP, 2006; Bankole et al., 2011a; Bankole & Mimbi, 2017), and the overwhelming successes gained from Data Analytics in decision making, it is little wonder that Data Analytics has found its way into the Education Sector especially in ICT4D research. This field of Data Analytics in Education, otherwise known as Learning Analytics (LA) is fast gaining grounds in terms of research interests and advancement in technology (Oyerinde & Chia, 2017).

National development is said to encapsulate the notion of human development as the means of enlarging people's choices to acquire knowledge, amongst other things, in order to have access to the resources needed for a decent standard of living (UNDP, 2006; Bankole & Mimbi, 2017). The need to understand the relevance of education in Human Development is well known and adequately acknowledged as it is important for social and economic development (Bankole & Assefa, 2017). It is therefore not a surprise that over the last three decades, research in national development has been expanded to certain intervening variables and social factors such as education and some other aspects of human welfare. (Desai, 1991; Anand & Ravallion, 1993; Bankole & Mimbi, 2017). This is ever more evident considering that countries have defined policies that show an emphasis on creating support mechanisms for the use of ICT, including for example, technical and pedagogical support as well as putting special attention on the use of ICT in teaching and learning (Hinostroza, 2018). However, the opinions on the bearings of ICT Infrastructure for development are in two perspectives vis a vis national development: The adoption of ICTs has the potential to empower communities and countries while secondly, the

ICT revolution can lead to imbalances and inequalities through lack of ICT adoption, access and usage (Bankole, 2015).

With the levels of ICT Infrastructure currently available, there is a need to understand the potentials of these nations to improve national development by investigating whether these ICT infrastructures are being utilized efficiently. Consequently, we can then measure their productivity levels over time with respect to the educational component of the HDI. In doing this, we take into consideration the standardized ICT indicators as determined by the World Summit on the Information Society (WSIS) and the United Nations Conference on Trade and Development (UNCTAD) in June 2004. In order to explore the utilization efficiency of these ICT infrastructure indicators, we use the following region groupings; Arab States; Europe; Sub-Saharan Africa; World and measure their productivity with respect to these indicators.

In this paper, we measure the efficiency and productivity of ICT Infrastructure utilization in education with respect to national development vis a vis adult literacy rates. We employ the Data Envelopment Analysis (DEA) and Malmquist Index (MI) approaches to carry out this research. The Malmquist Productivity Index is considered the most appropriate tool for measuring changes in efficiency and productivity (Arjomandi et al., 2015). This paper explores further findings from Oyerinde & Bankole, (2018) research which investigated the relative efficiency of ICT infrastructure utilization in education with data collected for 2010-2016. The rest of the article is organized as follows: section two provides the background, section three discusses the theoretical framework, section four provides the research methodology, section fives provides the data analysis, section six provides the discussion of findings, section seven the limitations and section 8 the conclusion.

2.0 Background

There has been a rapid expansion during the last few decades in the use of non-parametric approaches in measuring the efficiency and productivity changes in education albeit mostly in education institutions (Arjomandi et al., 2015). A large number of these studies have been undertaken in developed countries (e.g., Athanassapoulos and Shale 1997; Abbott and Doucouliagos 2003; Emrouznejad and Thanassoulis 2005; Johnes 2006). However, only a small, but growing, number of studies have so far attempted to use the Malmquist Index for this purpose, among them are Flegg et al., (2004); Carrington et al., (2005); Johnes (2008); Worthington and Lee (2008); Agasisti and Johnes (2009); and Bradley et al., (2010). Most of these studies have found productivity progress in different sectors, but this is mainly attributed to changes in technology and/or efficiency.

DEA has been used to measure efficiency for well over 3 decades and its applications spread over a wide range of thematic areas (Liu et al., 2013a). Some applications such as education and health care blossomed in the early days of DEA, while other applications, on the other hand, have just begun to apply DEA fairly recently (Liu et al., 2013b). A systematic survey on DEA applications was carried out by Liu et al., (2013b) and the results identified education as being one of the top five major application areas of DEA and prominent in its grand development. This is seen in Bessent & Bessent (1980), Charnes et al. (1981), Bessent et al. (1982), and Bessent et al. (1983). Liu et al., (2013b) discovered that historically, there have been two major groups of DEA applications in education in the literature. There is the one that studies the efficiency of higher education and that for basic education. The group for higher education includes Bessent et al. (1983), Sinuany-stern et al. (1994), Arcelus and Coleman (1997), Johnes (2006), and Johnes and Li (2008). The recent trend of efficiency studies in the education category clearly focuses on the higher education sector as articles mostly evaluate the performance of universities (Liu et al., 2013b).

There have been some studies that have used DEA to measure efficiency in education with respect to Human Development. Gupta & Verhoeven (2001) measured the efficiency of education in Africa and Clements (2002) measured efficiency of education in Europe. St. Aubyn (2002) and Afonso and St. Aubyn (2005, 2006a, 2006b) measured with respect to OECD countries. Tondeur et al., (2007) and Gulbahar, (2008) have examined the efficiency of countries in utilising their ICT resources for educational outputs and the Impact of ICT on education. Recently, Aristovnik, (2012) did a study on the impact of ICT on educational performance and its efficiency in select EU and OECD countries using DEA while Oyerinde & Bankole, (2018) investigated the relative efficiency of ICT infrastructure utilization in education using both the CRS and VRS models of the DEA methodology.

With the potential of educational technologies to positively improve educational quality and attainment, there is great optimism that efficient ICT infrastructure utilization in education can greatly increase both average literacy rates and educational attainment levels in developing economies (Oyerinde and Bankole, 2018). However, despite these promises being included in education policies that are related towards achieving a positive impact of ICTs on students' achievements, there is no conclusive evidence to support this (Hinostroza et al., 2014). It is against this backdrop that we carry out this research to investigate the productivity of ICT infrastructure utilization in education over time using the Data Envelopment Analysis and Malmquist Index approaches.

3.0 Theoretical Framework

This research builds upon the Oyerinde & Bankole (2018) conceptual model for measuring the efficiency of ICT Infrastructure on Education. This model considers ICT infrastructure available for utilization. This conceptual model takes the form of a linear equation derived from Bankole et al., (2011b) model for measuring impact on education within the Human Development Index and expressed as:

$$Log(\boldsymbol{E})=\alpha_o+\alpha_{HS}log(H)*log(S)+\alpha_{TH}log(T)*log(H)+\alpha_{TS}log(T)*log(S)+\xi$$

Where:

E - the educational component of the human development index (HDI), H - the Hardware Infrastructure,

S - the Software Infrastructure,

T - the Telecommunication Infrastructure

It can be considered to have similarity to another linear model, the translog production function framework (Ko and Osei-Bryson, 2004), in that it allows for pairwise interactions between the components of ICT. Therefore, the model for this study which reflects the above logarithmic expression is:

The impact on Education (Adult Literacy rates) = f[Internet Infrastructure (II) + Computer Infrastructure (CI) + Mobile Phone Infrastructure (MPI)].

In investigating the productivity, we use the classic Malmquist Index calculation model defined by Färe et al., (1994) and expressed as:

$$MI = EC * TC = PC * SC * TC$$

where:

MI - Malmquist Index

EC – Efficiency Change

TC - Technical Change

PC - Pure efficiency Change

SC - Scale efficiency Change

4.0 Research Methodology

For this study, time series data from the United Nations Educational, Scientific and Cultural Organization (UNESCO); adult literacy rates and the International Telecommunication Union (ITU); individuals using internet and mobile phones, house-holds with computers and internet were obtained. Available data was collected for Arab States, Europe, Sub-Saharan Africa and World regional aggregates. These formed the four Decision Making Units (DMU's). Data for the past 7 years, 2010-2016 was collected in percentages of the country population, with the ratio values computed annually as shown in Table 1. We employed Data Envelopment Analysis and Malmquist Index methodologies to calculate the relative efficiency and productivity of the regions respectively.

DEA is a well-known non-parametric linear programming method for measuring the relative efficiency (Thanassoulis et al., 2011; Bankole et al., 2011a). DEA is a data-oriented method for evaluating the performance (efficiency) of entities known as Decision Making Units (DMUs) (Bankole et al., 2011a) which uses input-output data to compute an efficient production frontier produced by the most efficient DMU's (Bollou, 2006). DEA, unlike a parametric method, is context specific with respect to the interpretations of the results of the analysis, which are restricted to the sample and should not be generalized beyond the sample (Samoilenko & Osei-Bryson, 2017b). DEA, therefore, can then be viewed as a multiple-criteria evaluation methodology where DMUs are alternatives, and DEA inputs and outputs are two sets of performance criteria where one set (inputs) is to be minimized and the other (outputs) is to be maximized (Cook et al., 2014). In DEA, these multiple criteria are generally modelled as in a ratio form, e.g., the CCR ratio model (Charnes et al., 1978; Cook et al., 2014) which is expressed as:

max e_{jo}

subject to $e_j < 1$
where

$$\frac{\sum_{r=1}^{s} u_r y_{fj}}{\sum_{i=1}^{m} v_i x_{ij}}$$

where x_{ij} and y_{rj} represents DEA inputs and outputs, and v_i and u_r are unknown weights.

DMU	Year	Individuals Using Internet	Individuals Using Mobile Phones	House Holds with Computers	House Holds with Internet	Adult Literacy Rates
Arab States	2010	0.243851	0.878879	0.29001	0.232158	0.705886
	2011	0.264767	0.992095	0.32822	0.285053	0.723635
	2012	0.301176	1.053982	0.34799	0.317884	0.735101
	2013	0.328239	1.10441	0.385256	0.352699	0.737778
	2014	0.362787	1.103706	0.416368	0.393087	0.743747
	2015	0.396576	1.093104	0.429814	0.438926	0.748119
	2016	0.417966	1.071321	0.432594	0.452841	0.752468
Europe	2010	0.66571	1.15018	0.718962	0.677246	0.991259
	2011	0.6777	1.16929	0.74234	0.705838	0.99195
	2012	0.69977	1.186281	0.760531	0.735699	0.992161
	2013	0.717408	1.198177	0.776394	0.760604	0.99236
	2014	0.738128	1.188474	0.777583	0.777855	0.992507
	2015	0.753289	1.181677	0.784886	0.800177	0.992685
	2016	0.779112	1.180181	0.795946	0.824782	0.992968
Sub Saharan Africa	2010	0.066549	0.453982	0.054487	0.038642	0.594201
	2011	0.082019	0.52484	0.061122	0.056485	0.610416
	2012	0.100362	0.590977	0.067181	0.074492	0.621054
	2013	0.121372	0.655498	0.069966	0.088046	0.626017
	2014	0.145319	0.707791	0.079257	0.113966	0.633275
	2015	0.175895	0.763712	0.086832	0.142042	0.63893
	2016	0.198949	0.745745	0.096419	0.162793	0.646231
World	2010	0.337062	0.906232	0.37934	0.323642	0.845641
	2011	0.363531	0.956908	0.408511	0.360708	0.845974
	2012	0.404172	0.999815	0.434492	0.405763	0.853639
	2013	0.430326	1.045377	0.458936	0.444529	0.854905
	2014	0.459529	1.070316	0.477992	0.477404	0.858093
	2015	0.491648	1.082437	0.492167	0.511062	0.860172
	2016	0.517076	1.089909	0.50448	0.534683	0.862478

Table 1. Regional Data in Ratios to Population

Malmquist Productivity Index (MPI) measures the productivity changes along with time variations and can be decomposed into changes in efficiency and technology with DEA like non-parametric approach. Productivity decomposition into technical change and efficiency catch-up necessitates the use of a contemporaneous version of the data and the time variants of technology in the study period. The MPI can be expressed in terms of distance function (E) as Equation (1) and Equation (2) using the observations at time t and t+1.

$$MPI_I^t = \frac{E_I^t(x^{t+1}, y^{t+1})}{E_I^t(x^t, y^t)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$$MPI_I^{t+1} = \frac{E_I^{t+1}(x^{t+1}, y^{t+1})}{E_I^{t+1}(x^t, y^t)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots . (2)$$

where I denotes the orientation of MPI model.

The geometric mean of two MPI in Equation (1) and Equation (2) gives the Equation

$$MPI_I^G = (MPI_I^t MPI_I^{t+1})^{1/2} = [\left(\frac{E_I^t(x^{t+1}, y^{t+1})}{E_I^t(x^t, y^t)}\right) . \left(\frac{E_I^{t+1}(x^{t+1}, y^{t+1})}{E_I^{t+1}(x^t, y^t)}\right)]^{1/2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

The input oriented geometric mean of MPI can be decomposed using the concept of input oriented technical change (TC) and input oriented efficiency change (EC) as given in the Equation

$$MPI_I^G = (EC_I).(TC_I^G) = \left(\frac{E_I^{t+1}(x^{t+1}, y^{t+1})}{E_I^t(x^t, y^t)}\right) . \left[\left(\frac{E_I^t(x^t, y^t)}{E_I^{t+1}(x^t, y^t)}\right) . \left(\frac{E_I^t(x^{t+1}, y^{t+1})}{E_I^{t+1}(x^{t+1}, y^{t+1})}\right)\right]^{1/2} \ldots\ldots . (4)$$

The first and second terms represent the efficiency change (EC) and the technology change (TC) respectively. MPI given by Equation (3) and Equation (4) can be defined using DEA like distance function. That is, the components of MPI can be derived from the estimation of distance functions defined on a frontier technology. Färe et al., (1994) provided the formal derivation of MPI and it is the most popular method among the various methods that have been developed to estimate a production technology (Coelli et al., 2005; Thanassoulis 2001). By utilizing both CRS and VRS DEA frontiers to estimate the distance functions in Equation (4), the TC can be decomposed into scale efficiency (SC) and pure technical efficiency (PC) components. SC is given in equation (5) and PC is given in equation (6) (Lee et al., 2011).

$$SC = [\frac{E_{vrs}^{t+1}(x^{t+1}, y^{t+1})/E_{crs}^{t+1}(x^{t+1}, y^{t+1})}{E_{vrs}^{t+1}(x^{t}, y^{t})/E_{crs}^{t+1}(x^{t}, y^{t})} \cdot \frac{E_{vrs}^{t}(x^{t+1}, y^{t+1})/E_{crs}^{t}(x^{t+1}, y^{t+1})}{E_{vrs}^{t}(x^{t}, y^{t})/E_{crs}^{t}(x^{t}, y^{t})}]^{1/2} \quad \ldots \ldots (5)$$

$$PC = \frac{E_{vrs}^{t+1}(x^{t+1}, y^{t+1})}{E_{crs}^{t}(x^{t}, y^{t})} \ldots \ldots \ldots \ldots \ldots (6)$$

Conceptually, however, the mechanism for estimating changes in a DMU using DEA is intuitive as the position of a DMU changes over time and is thus measured by means of MI. The change in the position of a DMU, and the corresponding value of MI, is comprised of two components, the changes in Efficiency (EC) and changes in Technology (TC). With regards to the changes in MI, a value equal to 1 means no change in productivity, while a value of greater than 1 or less than 1 reflects a growth or decline in productivity respectively (Samoilenko & Osei-Bryson, 2017b).

5.0 Analysis

The Input-Oriented Data Envelopment Analysis was carried out to determine the relative efficiency of ICT Utilization. The Analysis was run for each year to determine the relative efficiency for each of the DMU's. Table 2 shows the summary of the results for both the Variable Returns to Scale and Constant Returns to Scale models.

DMU	RTS	2010	2011	2012	2013	2014	2015	2016
Arab States	VRS	0.7657	0.8208	0.8279	0.8294	0.8261	0.8407	0.8523
	CRS	0.6136	0.6271	0.6637	0.6995	0.7532	0.817	0.8105
Europe	VRS	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	CRS	0.6585	0.7294	0.7959	0.8672	0.9334	1.0000	0.9709
Sub-Saharan Africa	VRS	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	CRS	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
World	VRS	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	CRS	0.7129	0.7601	0.8124	0.8563	0.8961	0.9477	0.9132

Table 2. Data Envelopment Analysis Results

The choice of an Input-Oriented model is based on the theoretical assumption that the ICT Infrastructure (Input) indices are controllable and an increase or decrease in the levels of these inputs is expected to bring about a corresponding increase or decrease in the Adult Literacy levels (Output) indices respectively (Oyerinde and Bankole, 2018). Practically, however this may not be the case as effective utilization of the Inputs may or may not be properly controlled and therefore become subjective to particular users and participants. Therefore, we use both the Constant Returns to Scale (CRS) and the Variable Returns to Scale (VRS) methods to enable us measure the relative efficiency without assuming the inputs are controllable (Oyerinde and Bankole, 2018) and catering for both scenarios. Table 3 gives a more detailed DEA result where:

t-1 – Base time moment

t – New time moment

CRS (t-1) – CRS efficiency in base moment relative to base frontier

CRS (t) – CRS efficiency in analyzed moment relative to new frontier

CRSMix (t,t-1) – CRS efficiency in analyzed moment relative to base frontier

CRSMix2 (t-1,t) – CRS efficiency in base moment relative to new frontier

VRS (t-1) – VRS efficiency in base moment relative to base frontier

VRS (t) – VRS efficiency in analyzed moment relative to new frontier

The Malmquist Index Analysis was carried out using the KonSi Malmquist Index Software. Table 4 shows the outcome of the MI calculation. This software allows us to calculate Malmquist index using three calculation methods:

i. Fixed base
ii. Adjacent base
iii. Seasonal calculation

DMU	t-1	t	CRS (t-1)	CRS(t)	CRSMix (t,t-1)	CRSMix2 (t-1,t)	VRS (t-1)	VRS(t)
Arab States	2010	2011	0.6136	0.6271	0.5573	0.6906	0.7657	0.8208
	2011	2012	0.6271	0.6637	0.5997	0.6941	0.8208	0.8279
	2012	2013	0.6637	0.6995	0.6357	0.7303	0.8279	0.8294
	2013	2014	0.6995	0.7532	0.7056	0.7466	0.8294	0.8261
	2014	2015	0.7532	0.817	0.7649	0.8047	0.8261	0.8407
	2015	2016	0.817	0.8105	0.8382	0.7898	0.8407	0.8523
Europe	2010	2011	0.6585	0.7294	0.6481	0.741	1	1
	2011	2012	0.7294	0.7959	0.7191	0.8073	1	1
	2012	2013	0.7959	0.8672	0.7881	0.8757	1	1
	2013	2014	0.8672	0.9334	0.8744	0.9257	1	1
	2014	2015	0.9334	1	0.9389	0.9943	1	1
	2015	2016	1	0.9709	1.0016	0.9694	1	1
Sub Saharan Africa	2010	2011	1	1	0.9158	1.4229	1	1
	2011	2012	1	1	0.9257	1.2962	1	1
	2012	2013	1	1	0.9679	1.1998	1	1
	2013	2014	1	1	0.9369	1.2796	1	1
	2014	2015	1	1	0.9351	1.2353	1	1
	2015	2016	1	1	1.0357	1.1331	1	1
World	2010	2011	0.7129	0.7601	0.6754	0.8023	1	1
	2011	2012	0.7601	0.8124	0.7341	0.8413	1	1
	2012	2013	0.8124	0.8563	0.7782	0.894	1	1
	2013	2014	0.8563	0.8961	0.8395	0.914	1	1
	2014	2015	0.8961	0.9477	0.8882	0.9564	1	1
	2015	2016	0.9477	0.9132	0.9435	0.917	1	1

Table 3. Detailed CRS and VRS DEA Results

For this research we use the Adjacent base method. This method assumes that each time moment is selected as the base moment and the moment next to base is considered as the analyzed time moment. Each moment is subsequently selected as the base moment and the one next to it the analyzed moment and so on. Calculations are performed for the following time moment pairs:

t_1 *and* t_2

t_2 and t_3

...

t_{n-1} and t_n

Which can further be represented as:

$$MI(t_1t_2)\ MI(t_2t_3)\ \dots\ MI(t_{n-1}t_n)$$

DMU	Base Time Moment (t - 1)	Analyzed Time Moment (t)	Efficiency Change (EC)	Pure Efficiency Change (PC)	Scale Efficiency Change (SC)	Technology Change (TC)	Malmquist Index (MI)
Arab States	2010	2011	1.022	1.072	0.953	0.889	0.908
	2011	2012	1.058	1.009	1.049	0.904	0.956
	2012	2013	1.054	1.002	1.052	0.909	0.958
	2013	2014	1.077	0.996	1.081	0.937	1.009
	2014	2015	1.085	1.018	1.066	0.936	1.015
	2015	2016	0.992	1.014	0.979	1.034	1.026
Europe	2010	2011	1.108	1	1.108	0.889	0.984
	2011	2012	1.091	1	1.091	0.904	0.986
	2012	2013	1.09	1	1.09	0.909	0.99
	2013	2014	1.076	1	1.076	0.937	1.008
	2014	2015	1.071	1	1.071	0.939	1.006
	2015	2016	0.971	1	0.971	1.032	1.002
Sub Saharan Africa	2010	2011	1	1	1	0.802	0.802
	2011	2012	1	1	1	0.845	0.845
	2012	2013	1	1	1	0.898	0.898
	2013	2014	1	1	1	0.856	0.856
	2014	2015	1	1	1	0.87	0.87
	2015	2016	1	1	1	0.956	0.956
World	2010	2011	1.066	1	1.066	0.889	0.947
	2011	2012	1.069	1	1.069	0.904	0.966
	2012	2013	1.054	1	1.054	0.909	0.958
	2013	2014	1.046	1	1.046	0.937	0.98
	2014	2015	1.058	1	1.058	0.937	0.991
	2015	2016	0.964	1	0.964	1.033	0.996

Table 4. Malmquist Index Analysis Results

6.0 Discussion of Findings

The result of the analysis shows that using both the CRS and VRS methods of the Input Oriented Data Analysis Model, the regions are relatively efficiently using their ICT infrastructure with respect to the educational component of the HDI. There has been a marginal increase from 2010 to 2016 in the relative efficiencies of ICT infrastructure utilization in education for the regions being investigated. Europe, Sub-Saharan Africa and World regions show an optimal relative efficiency score using the VRS model with Arab States being least relatively efficient. With the CRS however only Sub-Saharan Africa has optimal relative efficiency with the others still having a decent relative efficiency score. It is however also important to note that from 2010 to 2016 all regions being investigated show a steady increase in relative efficiency from year to year as seen in Table 3. This can mean that there is a steady growth in the ICT infrastructure utilization efforts for education in the regions. This supports the notion that should there be in increase in ICT infrastructure in these regions, whether properly controlled or not, there should be a corresponding increase in adult literacy rates. An increase in adult literacy rates will bring about an increase in quality of life and human development with respect to the Nations HDI (Oyerinde and Bankole, 2018). Table 5 shows the average Relative Efficiency and MI values for the years of study.

DMU	Relative Efficiency		Malmquist Index
	VRS	CRS	
Arab States	0.8233	0.7121	0.9787
Europe	1.0000	0.8508	0.9960
Sub-Saharan Africa	1.0000	1.0000	0.8712
World	1.0000	0.8427	0.9730

Table 5. Average Relative Efficiency and Malmquist Index Values

In measuring Productivity, this research has been able to show that during the years of study there has also been a steady increase in productivity yearly across all regions. On the average however, there is still opportunity for continuous growth in productivity as the average values show that all regions are still operating in a declining state of productivity. However, from Table 4 we see that Arab states and Europe have moved into a state of growth in productivity from 2013, with Sub-Saharan Africa and World still yet to score above 1.0000 MI productivity values although showing a steady increase in productivity scores.

This may prove useful for policy makers and potential donors to the Sub-Saharan region for example, as we can see that the region is optimally relatively efficient in its utilization of ICT infrastructure for education. However, there is a big opportunity here for growth in its productivity in order to increase its HDI. Calls for increase in investments in ICT for education can therefore be justified and a strong case made for digital inclusion in education. Sustained investments and educational policies with regards to ICT infrastructure utilization in Europe for example can be justified and more digital inclusive models be developed and employed.

7.0 Limitations

The main limitation of this study is the availability of the data for the dataset. The data was collected from the United Nations Educational, Scientific and Cultural Organization (UNESCO) - educational attainments; World bank - literacy rates and the International Telecommunication Union (ITU) - individuals with computers, internet and mobile phones. Considering that the years being investigated are the most recent and the sources of the data are credible and well cited sources for scientific data collection, some countries within each region did not have data available for one or more years being investigated. This necessitated collecting the data in the regional groupings as was available. Having the raw data for the individual countries within the regions would have allowed for a more individualistic analysis and will allow us see not only how the regions compare amongst themselves, but also how constituent countries fare in relation to each other.

8.0 Conclusion

The research has been able to show that Learning Analytics is not limited to use of data analytics to facilitate teaching and learning. Data Analytics in education can be used to measure efficiency and productivity of ICT infrastructure utilization within this sector and also enable decision makers and policy makers make more informed decisions and policies regarding the educational component of the HDI vis a vis ICT infrastructure investments and utilizations. While acknowledging that that DEA as a methodology is context specific and by its very nature of being non-parametric does not allow for generalization, the research has been able to provide a means of not only measuring the relative efficiency but also being able to investigate productivity as well.

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