A Theoretical Framework for Assessing the Productivity of ICT Infrastructure Utilization in Human Development Policy Formulation

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Abstract

A lot of research has 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 proposed a novel framework for measuring the productivity of the utilization of ICT Infrastructure with respect to the educational component of the HDI. This theoretical framework was tested using Structural Equation Modelling (SEM). The research also 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 countries grouped into clusters or regions with each region becoming a Decision-Making Unit. Findings show a relatively efficient utilization and marginal growth in productivity for some regions and a marginal decline in others.

Keywords: Human Development Index, Digital Opportunity Index, ICT Development Index, Data Envelopment Analysis, Malmquist Index

1 Introduction

Realistic Sustainable Development requires the balancing of how individual human needs are satisfied and how well nature and its resources are preserved while satisfying these needs. Consequently, Information and Communication Technologies (ICTs) have emerged as an essential tool for sustainable development, offering numerous benefits and opportunities to improve the quality of life for people around the world (Oyerinde & Odinkaru, 2023). A fundamental concern to ICT supporting sustainable development is the recognition of the existing challenges in ICT itself and how well these demands can be resolved to socio-economic growth and sustainable development. As new findings and outcomes of research crop up daily, it is evident that successes in ICT's research and implementations can have overwhelmingly positive impacts on the Human Development Index (HDI). With Educational Attainment being one of the core indices for measuring Development with respect to the Human Development Index (UNDP, 2006; Bankole et al., 2011; Bankole & Mimbi, 2016), there is need to determine the productivity and efficiency of ICTs and their implementations with respect to achieving SDG's and improving on HDI.

With regards to ICT4D, national development encapsulates the notion of human development as the means of enlarging people's choices to acquire knowledge, amongst others, in order to have access to the resources needed for a decent standard of living (UNDP, 2006; Bankole et al., 2015). Over the last three decades, the lexicon of 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, 2016). In line with this, 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).

Increasing investments in ICT is often premised on the assumption that such investments will lead to improvements in productivity and other aspects of development at the organizational and national levels (Samoilenko & Osei-Bryson, 2017b). With the levels of ICT Infrastructure currently available, there is a need to understand the potentials of these nations to improve national development by assessing the Digital Opportunity Index (DOI) while investigating whether these ICT Infrastructure are efficiently being utilized. Consequently, we can then measure their productivity levels over time with respect to the educational component of the HDI. Taking 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, which showed that mobile readiness; computer penetration; and internet access are indicators of the Infrastructural component of the DOI, we explore the utilization efficiency of a select group of regions and measure their productivity with respect to these indicators.

In this paper, we propose a novel framework for measuring and understanding the productivity of ICT Infrastructure utilization and apply this framework to the educational component of the

HDI. We investigate the Infrastructure component of the DOI using the mobile subscribers; computer penetration; and internet access indicators as well as measure the efficiency and productivity of ICT Infrastructure utilization in Education with respect to National Development vis a vis national literacy rates and educational attainment for post-secondary and tertiary education levels. We employ the Data Envelopment Analysis and Malmquist Index approaches to carry out this research and use Structural Equation Modeling to test the constructs of the proposed framework. The Malmquist productivity index is considered the most appropriate tool for measuring changes in efficiency and productivity (Arjomandi, Salleh, & Mohammadzadeh, 2015).

2 Background

There has been a rapid expansion during the last few decades in the use of nonparametric 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, Coelli, and Rao (2005), Johnes (2008), Worthington and Lee (2008), Agasisti and Johnes (2009), and Bradle, Johnes, and Little (2010). Most of these studies have found productivity progress in different sectors, but this is mainly attributed to changes in technology and/or efficiency.

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 the efficiency of education with respect to OECD countries. However, only 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 (2019a and 2019b) investigated the efficiency and productivity respectively of ICT Infrastructure Utilization on the educational component of the HDI.

The need to understand the relevance of education in Human Development is well known and adequately acknowledged. With the potential of educational technologies to positively improve educational quality and attainment, there is great optimism that ICT in education can greatly increase both average literacy rates and educational attainment levels in developing economies (Oyerinde and Bankole, 2021). 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, Isaacs, & Bougroum, 2014). In this paper, we employ the theory of replication in Information Systems as a means of strengthening validated theory (Palvia, 2006, 2013; Olbrich et al., 2015; Bankole & Bankole, 2017) in our proposed framework aimed at measuring and understanding the productivity of ICT utilization in education and how it affects the HDI.

The ICT Development Index (IDI) and the Digital Opportunity Index (DOI), developed and commissioned by the United Nations and the International Telecommunications Union (ITU) respectively, present core ICT indicators that can be used to measure various aspects of human development (Ayanso, Cho, & Lertwachara, 2014). The IDI represents a single ICT measurement that is designed to capture "the level of advancement of information and communication technologies" in 154 nations worldwide and compares the progress made by these countries between the years 2002 and 2007 (ITU, 2009). The Digital Opportunity Index is a composite index that measures digital opportunity or the possibility for the citizens of a particular country to benefit from access to information (ITU, 2011). The main objective of IDI is to provide policy-makers with a useful instrument to benchmark and assess the progress that each country has made toward becoming an information society (ITU, 2009) while the DOI can be used to enrich policy and inform policymakers of the latest trends and impact analysis of ICT policies to identify successful policies and replicate them elsewhere (ITU, 2011).

While previous researches, mentioned earlier in this section, have employed non-parametric methods in order to investigate the relative efficiency of ICT infrastructure utilization and productivity measurements there is still a need to understand how policy and decision makers can utilize this information adequately. While the IDI and DOI provide broad models for measuring economic and developmental indices with respect to ICT utilization, this research proposes a new conceptual model based on prevailing IS theories of replication as shown by

Bankole & Bankole, (2017) and Unified Theory of Acceptance and Use of Technology (UTAUT) as defined by Venkatesh et al., (2003) to provide an empirically tested framework for measuring and understanding the efficiency and productivity of ICT infrastructure utilization with particular emphasis on education and it's resultant impact on national development and the HDI. Even though the last decade has seen an explosion in the use of ICTs in developing countries (Walsham, 2017), governments, donors, policy and decision makers require an appropriate benchmarking model as the literature is abound with research which postulates that increase in ICT investments and penetration will bring about a corresponding increase in Human Development (Akpan, 2000; Neumayer, 2001;) especially in developing and underdeveloped economies.

This research falls within the progressive perspective of ICT-enabled development as postulated and defined by Avgerou (2010). The theory behind this perspective is that it considers ICT as an enabler of transformations in multiple domains of human activities. ICT-enabled developmental transformations are assumed to be achieved within the existing international and local social order (Avgerou, 2010). Central in this theoretical perspective is the view that investment in ICT and effective use do matter for the economic development of a country (Mann, 2004). It is however acknowledged that ICT needs to be accompanied by organizational or national restructuring, as the case may be, to deliver productivity gains (Dedrick et al., 2003; Draca et al., 2007) hence the need for an empirical basis to allow for decisions to be made in order to bring about the much-needed restructuring which this proposed framework aims to provide.

3 Theoretical Framework

This research proposes a framework for determining the ICT Utilization productivity for the educational component of the HDI, hereafter referred to as the Digital Productivity Index (EPI). The framework is conceptualized on the theory of replication in IS as shown by Bankole and Bankole, (2017) and its model is derived from the DOI and ICT Development Index (IDI) frameworks, consisting of seven composite indicators grouped in three clusters as shown in figure 1. Central to this conceptual framework is the premise that one must first use a technology before one can achieve desired outcomes (Venkatesh, Thong, & Xu, 2016), which is as a result of several researches in the literature on technology adoption by groups and organizations (e.g., Sarker & Valacich, 2010; Sarker, Valacich, & Sarker, 2005; Sia, Lee, Teo, & Wei, 2001; Sia, Teo, Tan, & Wei, 2004). For validation of this framework, this research uses macroeconomic data that falls within the educational component of the HDI. These indicators form the Skill-Set component of the DPI.

The Digital Opportunity Index is an e-index based on internationally-agreed ICT indicators. This makes it a valuable tool for benchmarking the most important indicators for measuring the Information Society. The DOI is a standard tool that governments, operators, development agencies, researchers and others can use to measure the digital divide and compare ICT performance within and across countries (Ayanso et al., 2014). The IDI represents a single ICT measurement that is designed to capture "the level of advancement of information and communication technologies" in 154 nations worldwide and compares the progress made by these countries between the years 2002 and 2007 (ITU, 2009; Ayanso, Cho, & Lertwachara, 2014). The main objective of this composite index is to provide policy-makers with a useful instrument to benchmark and assess the progress that each country has made toward becoming an information society (ITU, 2009).

SKILL-SET INDICATORS	ICT INFRASTRUCTURE INDICATORS	ICT UTILIZATION INDICATORS
Educational Attainment (Post-Secondary)	Percentage of Individuals with a Computer	Relative Efficiency
Educational Attainment (Short-Cycle Tertiary)	Percentage of Individuals with Internet Access	Productivity
Educational Attainment (Bachelors)	Percentage of Individuals with Mobile Phones	
Adult Literacy Rates		

Table 1. DPI Components and Indicators

The proposed framework, just like the IDI model, is constructed based on a conceptual framework which involves a three-stage information society model. However, in this case, the three stages for the proposed model and their composite constructs or indicators are derived from Bankole et al., (2011a); Oyerinde and Bankole, (2019a and 2019b); Oyerinde and Bankole, (2021). These are skill-set; ICT Infrastructure; and ICT Utilization as shown in Table 1. The proposed framework follows the same accepted methodology as the DOI and HDI, arguably the benchmark for composite indices, as it is one of the longest-standing and most referenced models of all (ITU, 2010). However, it does not have equal weights amongst the three clusters as the IDI and DOI do. The third cluster, ICT Utilization, is weighted more than the first two as they form the composite indices for calculating the ICT Utilization index with ICT Infrastructure being the Input variables and Skill-Set the Output. Data Envelopment Analysis and Malmquist Index methodologies are used to calculate the Relative Efficiency and Productivity values respectively which give the ICT Utilization index. The three clusters are then weighted with Skill-Set and ICT Infrastructure carrying 25% each and ICT Utilization carrying 50%. The weighted score gives the EPI and ranges from 0 to 1.

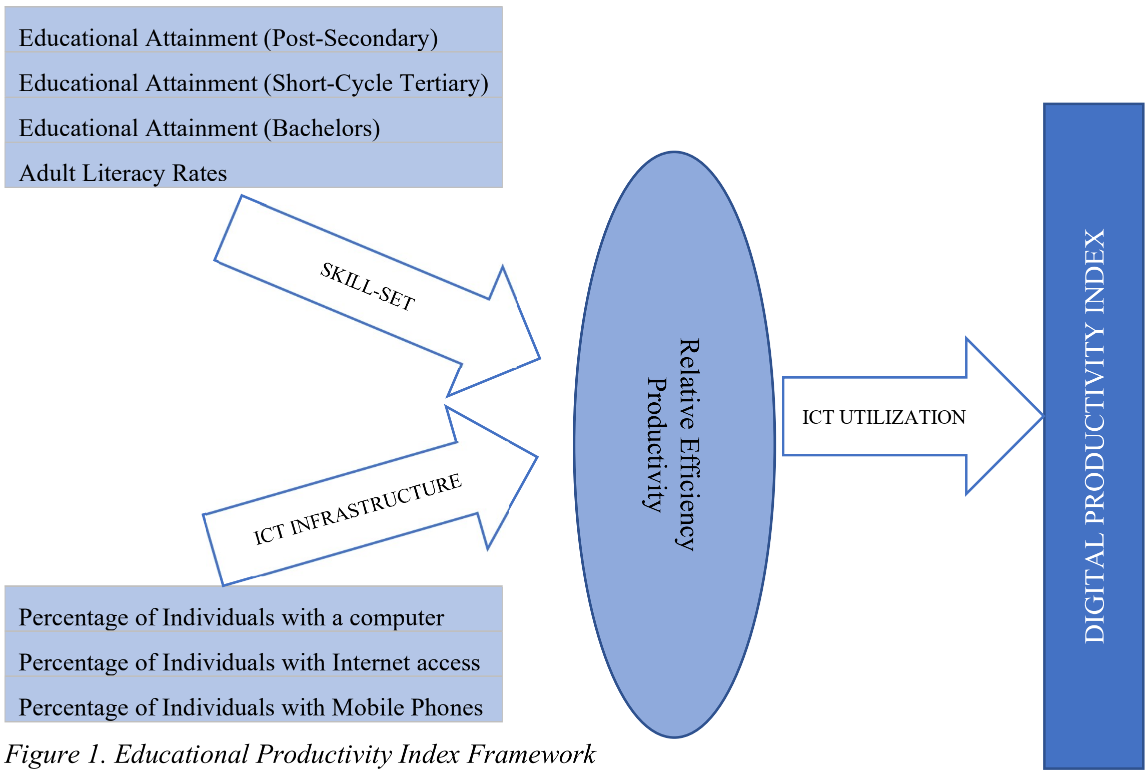

Figure 1. Educational Productivity Index Framework

4 Research Methodology

For this study, time series data from the United Nations Educational, Scientific and Cultural Organization (UNESCO); educational attainments; World bank; literacy rates for the Skill-Set Cluster and the International Telecommunication Union (ITU); individuals with computers, internet and mobile phones were obtained for the ICT Infrastructure Cluster. Available data was collected for all countries in Sub-Saharan Africa, Northern Africa, and select countries in Europe and Northern America. These formed three categories or regions with World percentages forming the fourth. Data for the years 2010-2016 was collected in percentages of the country population, with the ratio values computed annually as shown in Table 2. These groupings were necessitated by the lack of availability of data in certain countries for certain years, therefore the average percentages of was calculated with missing data inferred by means of extrapolation and used for the research to represent each region. For the ICT Utilization Cluster, we employed Data Envelopment Analysis and Malmquist Index methodologies to calculate the Relative Efficiency and Productivity of the regions respectively.

DMU	Year	Individuals Using Computers	Individuals Using Internet	Individuals Using Mobile Phones	Educational Attainment (Post-Secondary)	Educational Attainment (Short-Cycle Tertiary)	Educational Attainment (Bachelors)	Adult Literacy Rates
Sub-Saharan Africa	2010	0.0482	0.0815	0.6086	0.0791	0.0276	0.0168	0.5992
	2011	0.0674	0.0952	0.6262	0.0918	0.0344	0.0205	0.6098
	2012	0.0866	0.1114	0.6438	0.0808	0.0504	0.0261	0.6204
	2013	0.1058	0.135	0.6614	0.0953	0.0484	0.0243	0.6254
	2014	0.125	0.1591	0.679	0.1099	0.046	0.018	0.6326
	2015	0.2017	0.1882	0.7495	0.152	0.0656	0.0488	0.6383
	2016	0.2783	0.2093	0.82	0.1804	0.0912	0.0348	0.6455
Northern Africa	2010	0.144	0.2348	0.7336	0.0905	0.1162	0.10335	0.6834
	2011	0.1778	0.2403	0.7391	0.107	0.1327	0.11985	0.6999
	2012	0.2116	0.2929	0.7917	0.1235	0.1492	0.13635	0.7164
	2013	0.2454	0.2907	0.7895	0.1312	0.1569	0.14405	0.7241
	2014	0.2792	0.3247	0.8235	0.1343	0.16	0.14715	0.7272
	2015	0.313	0.3564	0.8552	0.1408	0.1665	0.15365	0.7337
	2016	0.482	0.3839	0.8827	0.1472	0.1729	0.16005	0.7401
Europe & North America	2010	0.9872	0.6349	0.9948	0.2808	0.2506	0.1719	0.9911
	2011	0.9859	0.6544	0.9906	0.2876	0.2501	0.1907	0.9912
	2012	0.9846	0.69	0.9864	0.2944	0.2496	0.2095	0.9913
	2013	0.9833	0.712	0.9822	0.3037	0.2581	0.2378	0.9915
	2014	0.982	0.7332	0.978	0.2884	0.2591	0.2199	0.9916
	2015	0.863	0.7529	0.9446	0.3066	0.2524	0.226	0.9917
	2016	0.7327	0.774	0.9111	0.3248	0.2457	0.2321	0.9919
World	2010	0.2875	0.3393	0.8755	0.2467	0.1979	0.1334	0.8384
	2011	0.3004	0.3522	0.8884	0.2506	0.2065	0.1409	0.846
	2012	0.329	0.3808	0.917	0.2545	0.2151	0.1145	0.8536
	2013	0.3489	0.4007	0.8333	0.2642	0.2359	0.1709	0.8549
	2014	0.3723	0.4241	0.7495	0.277	0.2432	0.1896	0.8581
	2015	0.7896	0.4492	0.945	0.3014	0.2584	0.1971	0.8602
	2016	0.5565	0.4708	0.8773	0.3258	0.2736	0.2046	0.8625

Table 2: Regional Data in Ratios to Population

DEA is a well-known non-parametric linear programming method for measuring the relative efficiency (Thanassoulis et al., 2011; Bankole et al., 2011c). DEA is a data-oriented method for evaluating the performance (efficiency) of entities known as Decision Making Units (DMUs) (Bankole et al., 2011c) 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, 2017a). 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:

Maximise:

$$h_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$$

Subject to:

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

Where:

$$j = 1, \dots, n, v_r v_i \geq 0; r = 1, \dots, s; i = 1, \dots, m.$$

where x_{ij} and y_{rj} represents DEA inputs and outputs of the jth DMU, and u_r ,$v_i \geq 0$ are unknown variable weights to be determined by the solution of the problem (Charnes et al., 1978).

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 nonparametric 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 (Lee & Lee, 2010).

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

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

where I denotes the orientation of MPI model.
The geometric mean of two MPI in Equation (1) and Equation (2) gives the Equation

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

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, 2017a).

In testing the proposed model with respect to its constructs and indicators, we make use of the Structural Equation Model (SEM). SEMs are multi-equation regression models (Fox, 2002) that extends beyond linear modelling such as ANOVA and multiple regression. SEMs incorporate multiple independent and dependent variables, as well as theoretical latent constructs that the observed variables might represent (Hoe, 2008). The use of SEM therefore allows researchers to posit the presence of relationships between these latent constructs (Samoilenko & Osei-Bryson, 2017a). Figure 2 shows the outcome of the SEM model run on our proposed framework constructs. The ICT infrastructure and Skill Set Indices take up a reflective model as their composite indicators can be removed and added without adversely affecting the Index itself. However, the ICT Utilization Index takes upon a formative model as its two indicators are required for the index to maintain its viability and have any meaning as ICT Utilization in this context is measured by the relative efficiency and productivity assessment analyses carried out.

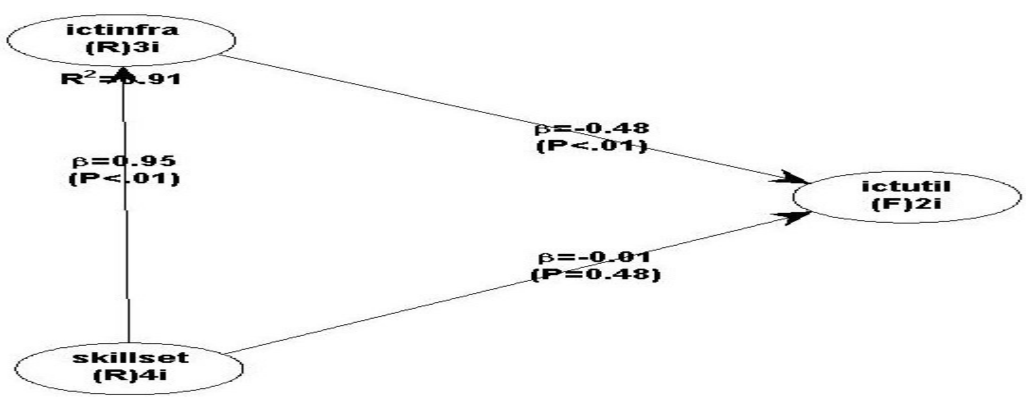

Figure 2. Outcome of Structural Equational Model

The methodology and approach to theory implemented in this research is based on an exploratory data analysis methodology for abducting hypotheses that was presented in Osei-Bryson & Ngwenyama (2011). This Hypothetico-Deductive (H-D) approach to theory development has been presented as a cyclo-iterative process comprising of empirical observation; theory formulation (being that in most cases Information Systems theories are annexed from other disciplines); hypotheses generation; and hypotheses testing (Grimes, 1990; Chalmers, 1994; Palys, 2003). However, no amount of testing can ever fully guarantee the truth value of a theory about phenomena (Chalmers, 1994), and so what is actually attained by using the scientific method(s) to build upon and test a theory, in this case DEA, MI and SEM, is gradually increasing confirmation of the theory (Osei-Bryson & Ngwenyama, 2011).

5 Analysis

The Input-Oriented Data Envelopment Analysis was carried out using the DEAFrontier Software. This was used to determine the Relative efficiency indicator for the ICT Utilization Cluster. The Analysis was run for each year to determine the relative efficiency for each of the DMU's. Table 3 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
Sub-Saharan Africa	VRS	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
	CRS	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
Northern Africa	VRS	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
	CRS	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
Europe & North America	VRS	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
	CRS	1.00000	1.00000	1.00000	1.00000	0.88883	1.00000	1.00000
World	VRS	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000
	CRS	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000	1.00000

Table 3: 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 levels of the Skill-Set (Output) indices respectively (Oyerinde and Banlole, 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).

The Malmquist Index Analysis was carried out using the KonSi Malmquist Index Software. Table 4 shows the outcome of the MI calculation:

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

where:

MI - Malmquist Index
EC – Efficiency Change
TC - Technical Change
PC - Pure efficiency Change
SC - Scale efficiency Change

This software allows us to calculate Malmquist index using three calculation methods:

- Fixed base
- Adjacent base
- Seasonal calculation

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)
Sub-Saharan Africa	2010	2011	1	1	1	0.87	0.87
	2011	2012	1	1	1	0.853	0.853
	2012	2013	1	1	1	0.9	0.9
	2013	2014	1	1	1	0.905	0.905
	2014	2015	1	1	1	0.862	0.862
	2015	2016	1	1	1	0.874	0.874
Northern Africa	2010	2011	1	1	1	1.017	1.017
	2011	2012	1	1	1	0.977	0.977
	2012	2013	1	1	1	0.977	0.977
	2013	2014	1	1	1	0.921	0.921
	2014	2015	1	1	1	0.933	0.933
	2015	2016	1	1	1	0.818	0.818
Europe & North America	2010	2011	1	1	1	1.053	1.053
	2011	2012	1	1	1	1.046	1.046
	2012	2013	1	1	1	1.076	1.076
	2013	2014	0.889	1	0.889	1.083	0.962
	2014	2015	1.125	1	1.125	0.923	1.038
	2015	2016	1	1	1	1.098	1.098
World	2010	2011	1	1	1	1.009	1.009
	2011	2012	1	1	1	0.927	0.927
	2012	2013	1	1	1	1.151	1.151
	2013	2014	1	1	1	1.075	1.075
	2014	2015	1	1	1	0.787	0.787
	2015	2016	1	1	1	1.167	1.167

Table 4: Malmquist Index Analysis Results

For this research we use the adjacent-base calculation method. Usage of the adjacent-base calculation 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:

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

In calculating the DPI, according to our proposed model, each index in the Skill-Set Cluster has a 25% weight, each index in the ICT Infrastructure cluster has a 33% weight and each index in the ICT Utilization cluster has a 50% weight. This is in line with the DOI and IDI methodology which set a goalpost of 100% for the indicators i.e. per 100 population or percent of population. To find each DMU's respective score for each index in the Skill-Set and ICT Infrastructure cluster, the score gotten from the data was divided by 100 (being that it was in percentages) then multiplied by the respective cluster weight. For example, to find out the value for the Adult literacy rate index within the Skill-Set cluster for Sub-Saharan Africa, we take the average values from the data for that indicator (2010 – 2016), divide it by 100 and multiply the outcome by 25 (since each indicator has a weight of 25%). However, for calculating the Productivity weight of the ICT Utilization Cluster, after the MI scores for the years are averaged, the highest MI value in the grouping sets the benchmark for the other DMU's and is therefore given the full 50% score. The other scores are calculated relative to this benchmark. Table 5 shows each region's calculated cluster weights and overall EPI.

DMU	Skill-Set Cluster Weight (25%)	ICT Infrastructure Cluster Weight (25%)	ICT Utilization Cluster Weight (50%)	Aggregated score (100%)	DPI
Sub-Saharan Africa	5.1013	7.8743	45.9780	58.9535	0.5895
Northern Africa	7.0698	11.3049	47.4893	65.8639	0.6586
Europe and North America	10.9644	21.5181	49.8025	82.2850	0.8228
World	9.5317	14.0100	49.3735	72.9152	0.7292

Table 5: Analysis Outcome Showing Digital Productivity Index Calculation

6 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 utilizing their ICT Infrastructure with respect to the educational component of the HDI. This supports the notion that should there be in increase in ICT Infrastructure in this region, whether properly controlled or not, there will be a corresponding increase in educational attainment and Adult Literacy rates. This will bring about an increase in quality of life and Human Development with respect to the

Nations HDI (Oyerinde and Bankole, 2018). Table 6 shows the average Relative Efficiency and MI values for the years of study.

In measuring Productivity, this research has been able to show that during the years of study there has been a marginal growth in productivity for Europe and North America and for the world as well. However, there has been a marginal decline in productivity in Sub-Saharan Africa and Northern Africa. The DPI calculated also shows Sub-Saharan Africa having the lowest value of 0.5895 with Europe and North America having the highest of 0.8228. Even though Europe and North America had a relative efficiency value of 0.9921, the lowest in the grouping with the others being optimally relatively efficient, Europe and North America have the highest average growth in productivity.

DMU	Relative Efficiency	Malmquist Index
Sub-Saharan Africa	1	0.8773
Northern Africa	1	0.9405
Europe and North America	0.9921	1.0455
World	1	1.0193

Table 6: Average Relative Efficiency and Malmquist Index

With a TC averaging less than 1 for Sub-Saharan Africa and Northern Africa, an increase and/or improvement in ICT Infrastructure will yield a growth in productivity of the utilization in education. This is proven by both averaging an EC of 1. This means that both regions are relatively efficient in their ICT Infrastructure utilization but the technology available is inadequate. This may prove useful for policy makers and potential donors to the Sub-Saharan region 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 in these regions can therefore be justified and a strong case made for increased digital inclusion in education.

Interestingly, Europe and North America have a slightly lower relative efficiency average, but a superior level of growth in productivity than the other regions. This means that even though this region has a marginally relative inefficiency score, the superior technology and availability of ICT Infrastructure yields a growth in productivity levels. Policy makers and decision makers in this region may decide to make a stronger case for educational attainments especially with respect to post-secondary and tertiary education. The availability of ICT Infrastructure is not the question here but whether more people can utilize this Infrastructure for education.

The results of our SEM testing on the constructs of the proposed model show a very high level of correlation between the ICT Infrastructure and Skill-Set indices. These can be seen in table 7. However, there is a high level of collinearity experienced amongst the constructs themselves resulting in an unfavorable p value result of 0.48 on the hypothesis that the reflective model of Skill-Set has an impact on the formative model of ICT Utilization as shown in figure 2. Our assumption here in this model is made on the basis that a certain level of educational attainment is required for efficient utilization of ICT Infrastructure. The constructs of the model themselves, however, can be tweaked and individual components added or removed as may be desired by the researchers in line with the overall objective of the model to be implemented. For this research, we are looking at the educational component of the HDI and as such use the educational indices built upon from previous researches (Bankole et al., 2011a; Bankole et al., 2011b; Oyerinde & Bankole, 2019a; Oyerinde & Bankole 2019b; Oyerinde & Bankole, 2021).

ICT Infrastructure/Skill Set Indicators	Individuals using Computers	Individuals using Mobile Phones	Individuals using Internet
Educational Attainment (Post-Secondary)	0.825	0.839	0.865
Educational Attainment (Short-Cycle Tertiary)	0.816	0.890	0.884
Educational Attainment (Bachelors)	0.815	0.841	0.908
Adult Literacy Rates	0.915	0.897	0.967

Table 7: Correlation between ICT Infrastructure and Skill Set Indicators

7 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. Although the researchers extrapolated to make up for this by taking the average of the differences in preceding and proceeding years, this may have positive or negative effects on the regional averages calculated as the data collected is represented as a percentage of the population of the countries.

8 Conclusion

The research has been able to propose a novel framework for measuring and understanding the educational component of the HDI. This framework has been able to show how data analytics can be employed in education, albeit with respect to ICT4D research, in order to enable policy and decision makers understand and make more informed decisions in utilization of ICT Infrastructure for education. The research has shown how the proposed DPI framework is calculated and utilized using DEA and MI non-parametric methods. 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 viable framework which can be used and expanded upon for future research.

The DPI framework can be used to help decision and policy makers in addressing ICT Infrastructure productivity issues with respect to any of the three composite indices of the HDI. This research focused on the educational component of the HDI, however, the DPI can be implemented using any of the other two composite indices of the HDI, healthcare or GDP as it affects standard of living. In that case, the skill-set indicators will utilize relevant indicators relating to healthcare or GDP as against education as used in this research. An interesting area of future research would be to expand the context of the DPI to other macroeconomic determinant indicators and determine its validity and reliability.

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