

ICT Adoption, Human Development, and Productivity Change in Sub-Saharan Africa: Evidence from Random Forest and DEA-Malmquist Analysis

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Abstract: Information and Communication Technologies (ICTs) are increasingly recognized as important enablers of human development through improved access to education, healthcare, and information. This study examined the association between ICT adoption, life expectancy, and literacy rates in 49 Sub-Saharan African countries. The study used panel data from 49 Sub-Saharan African countries for the period 2010 to 2022. Random Forest analysis was used to identify patterns and determine the ICT indicators most strongly associated with human development outcomes, while an online survey provided additional insights into ICT adoption. DEA-Malmquist analysis was applied to evaluate productivity growth and technological change over time. The results indicate that ICT adoption is positively associated with life expectancy and literacy rates. Internet penetration emerged as the most influential predictor in both models, accounting for approximately 89% of total feature importance. The DEA-Malmquist analysis revealed average productivity growth of 17.2%, driven mainly by technological change. These findings suggest that expanding access to digital technologies can support improvements in education and health outcomes. The study contributes to ICT4D research by combining Random Forest and DEA-Malmquist methods and provides evidence to inform digital inclusion policies that promote human development in Sub-Saharan Africa.

Keywords: ICT4D; ICT Adoption; Human Development; Life Expectancy; Adult Literacy; Sub-Saharan Africa; Random Forest; DEA-Malmquist Analysis.

1. INTRODUCTION

Information communication Technologies are key to the development of both developed and developing countries in this digital era. The degree of positive responsiveness of inclusive development to ICT varies across fundamental characteristics of human development and ICT dynamics [1]. Ensuring sustainable human development requires equitable access to ICTs across all Sub-Saharan African countries. Increasing information and communication technology (ICT) adoption affects inclusive human development in Sub-Saharan Africa [1]. The research study focuses on the influence ICTs on Human development factors, for example: income levels, literacy rates, legal opinions, life expectancy, resource wealth, political stability.

Policy makers often make assumptions and create plans based on straightforward benefits, but actual research findings suggest that Sub-Saharan African countries vary in terms of ICT adoption. Asongu and Le Roux noted that the adoption and/or penetration rate of ICTs can be influenced by policy to achieve inclusive development outcomes [1]. The policies in African regions need to align with the needs, resources and technological availability of that specific country. It is therefore imperative to have an ICT adoption model in place that aligns with the needs of each specific Sub-Saharan African country. Policy discussions often assume straightforward benefits, but actual evidence varies across different contexts in Sub-Saharan African countries. The research study assesses how ICT penetration relates to life expectancy and adult literacy in Sub-Saharan African countries. The study aims to identify whether ICTs have a positive or negative influence on the education and lifespan of the population in Sub-Saharan African countries.

Kim and Crowston identified several theories used to study ICT adoption and post-adoption behavior, including TRA, TAM, TPB, TAM2, IDT, SCT and UTAUT [2]. Even though the study focuses on country-level indicators, technology adoption theories are helpful in explaining how individuals use ICT services and infrastructure. While these theories do not directly measure national outcomes, they provide useful insights into user behavior that may affect ICT use and development results in different countries.

Oliveira and Martins reported that the most widely adopted technology adoption theories include TAM, TPB, UTAUT, DOI and TOE [3]. The UTAUT framework is discussed

conceptually to interpret ICT adoption dynamics. The UTAUT framework is discussed conceptually to interpret ICT adoption dynamics and provide a theoretical lens for understanding ICT adoption behavior in Sub-Saharan Africa. The empirical analyses are based on country-level ICT penetration indicators and survey responses rather than direct measurement of UTAUT constructs.

Venkatesh et al. proposed the UTAUT model to explain user intentions and technology usage behavior [4]. It is used to examine how key adoption concepts can be used to explain and predict users' intentions to adopt ICTs and their usage behavior. UTAUT is used only as a conceptual lens for interpreting ICT adoption findings and was not empirically tested in this study. It helps in determining how these adoption dynamics influence human development outcomes such as life expectancy and literacy [4]. By employing these constructs, the research study seeks to understand the factors that drive or hinder ICT acceptance within the context of human development in Sub-Saharan African countries.

While UTAUT provides the core framework for this research study, selected frameworks from supporting models such as the Task-Technology Fit (TTF) model are incorporated to better capture contextual factors relevant to ICT use for human development outcomes. This integrative approach enables a more comprehensive analysis of both technology acceptance and its effective utilization in the Sub-Saharan African context. Contemporary machine learning approaches are increasingly applied across healthcare, education, and policy domains because of their ability to uncover hidden patterns and support evidence-based decision-making [4], [5]. The use of machine learning assists the researchers to analyze data to make better informed decisions pertaining to healthcare and literacy outcomes. Machine learning algorithms enables systems to learn patterns from historical data and make predictions without explicit programming, making them suitable for analyzing complex socio-economic datasets** [6], [7], [21] **. Random Forest is a sub-set of machine learning. It is an ensemble learning technique that combines multiple decision trees to improve classification and prediction accuracy while reducing overfitting and sensitivity to noise [6]. Breiman further demonstrated that Random Forest models provide reliable estimates of prediction errors and variable importance, making them suitable for complex predictive analytics applications [8].

1.1. Problem statement

Despite substantial investments in Information Communication Technologies (ICTs) across Sub-Saharan African countries, various regions continue to experience continuous challenges in key human development outcomes such as life expectancy and literacy rates. International institutions, agencies and governments have continuously used ICTs as enablers for advancing access to health care services and educational resources. However, empirical findings on the relationship between ICT adoption and life expectancy remain limited in Sub-Saharan African regions due to their uneven access to ICTs.

The existing literature emphasizes access to ICTs in developing countries while paying limited attention to the key adoption factors that determine the effective use and impact towards literacy and health outcomes. Recent studies provide a global perspective and insight about how ICTs shape the developed world rather than how they impact developing regions in Sub-Saharan African countries. The research findings highlight an existing gap in literature indicating which ICT adoption factors positively or negatively influence life expectancy and literacy rates. The existing gap prevents stakeholders from designing ICT evidence-based policies that address challenges in human development.

There is a need to examine key ICT adoption factors that influence life expectancy and literacy rates in Sub-Saharan African countries. This study aims to address a lack of knowledge by showing how ICT adoption influences human development in Sub-Saharan African countries. This study adds to the existing research about the influence of ICTs and its development by showing which ICT adoption factors help or hinder life expectancy and literacy rates in Sub-Saharan African countries. The research assists in filling the gap in studies that focus specifically on how ICT use affects development outcomes across Sub-Saharan African regions.

1.2 Research Questions

- 1) RQ1: To what extent are internet penetration and mobile subscriptions associated with life expectancy across Sub-Saharan Africa?
- 2) RQ2: To what extent are internet penetration and mobile subscriptions associated with literacy rates across Sub-Saharan Africa?
- 3) RQ3: How did ICT-related productivity change across 49 Sub-Saharan African countries during 2010-2022?

- 4) RQ4: What ICT adoption challenges are perceived by survey respondents in Sub-Saharan Africa?

2. METHODS

2.1. Theoretical Backgrounds

Bayar et al. reported that ICT penetration significantly stimulates sustainable development across African countries specifically mobile usage, broadband connectivity, and internet adoption-significantly stimulates sustainable development, revealing multiple layers of causality between ICT indicators [9]. The study also revealed that the expansion of ICT access-particularly through mobile phone penetration, broadband availability, and increased internet use-substantially promotes sustainable development. The research findings suggest that there is an association between ICT indicators and development outcomes across African regions. Lwoga and Sangeda found that ICT interventions contribute to education, healthcare and economic participation, although long-term impacts remain uneven [10]. The challenges are a more distinct in Sub-Saharan African countries where ICT access varies across the regions. In addition to this, globally, 763 million adults and young people, approximately sixty-six percent of whom are women, still lacking basic literacy skills [11].

A significant proportion of women continue to experience low literacy levels and challenges related to ICT adoption [1]. Across African countries, uneven ICT access has influenced human development factors such as life expectancy and literacy rates. Inadequate infrastructure that leads to limited internet connectivity might deviate digital learning environments, restricting potential for ICTs to consistently strengthen educational outcomes. Digital gaps in digital health systems may also be weakened hindering support for better health services, which could otherwise contribute to increased life expectancy across the region.

In the context of business and productivity, ICTs have proven to be pivotal to the growth of developing countries and more particularly Sub-Saharan African countries. It serves as a foundation to connect developing countries with developed countries at a global scale. It addresses the need for the African continent's need to integrate into worldwide digital ecosystem. However, challenges persist in preventing people from having access

to ICTs, access to ICTs varies greatly across African regions. David demonstrated a statistically significant relationship between ICT diffusion and economic growth in SADC countries [13]. Comprehensive review of ICT4D literature indicates that although ICT initiatives contribute to advancements in education, healthcare, and economic engagement, their long-term benefits remain inconsistent because of persistent infrastructural limitations, socio-technical challenges, and institutional weaknesses [14]. Asongu and Acha-Anyi highlighted that while ICT has a positive effect on Productivity Growth (TFPCH), the incremental gains taper off unless bolstered by sufficiently high levels of mobile penetration (around 100%) and a minimum internet penetration rate of approximately 15% [14]. Key benefits of ICTs towards economic growth and productivity:

- 1) ICT enhances economic performance.
- 2) Improvements in economic conditions further stimulate ICT uptake.
- 3) Improves firm-level productivity.
- 4) Creating a cyclical growth-enhancing mechanism.

2.2. Data Collection

The data collected for the research study entails a sample size of 500 participants from any of the Sub-Saharan African Countries. An online survey was conducted to collect the data from all willing participants. Raw data used was collected from the United Nations data bank for the period of 2010-2022. Data from the United Nations data bank particularly for the 49 sub-Saharan African countries which are: Angola, Burundi, Benin, Burkina Faso, Botswana, Central African Republic, Cote d'Ivoire, Cameroon, Congo, Dem. Rep., Congo, Rep., Comoros, Cabo Verde, Djibouti, Eritrea, Ethiopia, Gabon, Ghana, Guinea, The Gambia, Guinea-Bissau, Equatorial Guinea, Kenya, Liberia, Lesotho, Madagascar, Mali, Mozambique, Mauritania, Mauritius, Malawi, Namibia, Niger, Nigeria, Rwanda, Sudan, Senegal, Sierra Leone, Somalia, South Sudan, Sao Tome and Principe, Eswatini, Seychelles, Chad, Togo, Tanzania, Uganda, South Africa, Zambia and Zimbabwe.

Prior to the analysis, missing data were checked. When some values were missing, they were estimated by using suitable methods for each country and verified for accuracy before the data were normalized. Since only a small amount of data was missing, it was unlikely to have a significant impact on the overall results. The ICT indicators used for this research are Mobile cellular subscribers (per 100 inhabitants) and Internet users (percentage %). The human development indicators are life expectancy at birth (years)

and Literacy rates (percentage %). Table 1 presents the description of Variables, Sources, Units of Measurement, and Analytical Roles in the DEA-Malmquist and Random Forest Models:

Table 1. Description of Variables, Sources, Units of Measurement, and Analytical Roles in the DEA-Malmquist and Random Forest Models

#	Variable	Unit	Source	Role
1	Mobile subscriptions	per 100 inhabitants	United Nations Data	DEA Input / Random Forest Tree Predictor
2	Internet users	% population	United Nations Data	DEA Input / Random Forest Tree Predictor
3	Life expectancy at birth	Years	United Nations Data	DEA Output / Random Forest Tree Outcome
4	Adult literacy rate	% adults	United Nations Data	DEA Output / Random Forest Tree Outcome

2.3. UTAUT Model Analysis

The UTAUT Model provides insights of how ICTs can contribute to improving life expectancy and literacy rates across the regions of African countries [4]. Figure 1 illustrates the UTAUT model [4]:

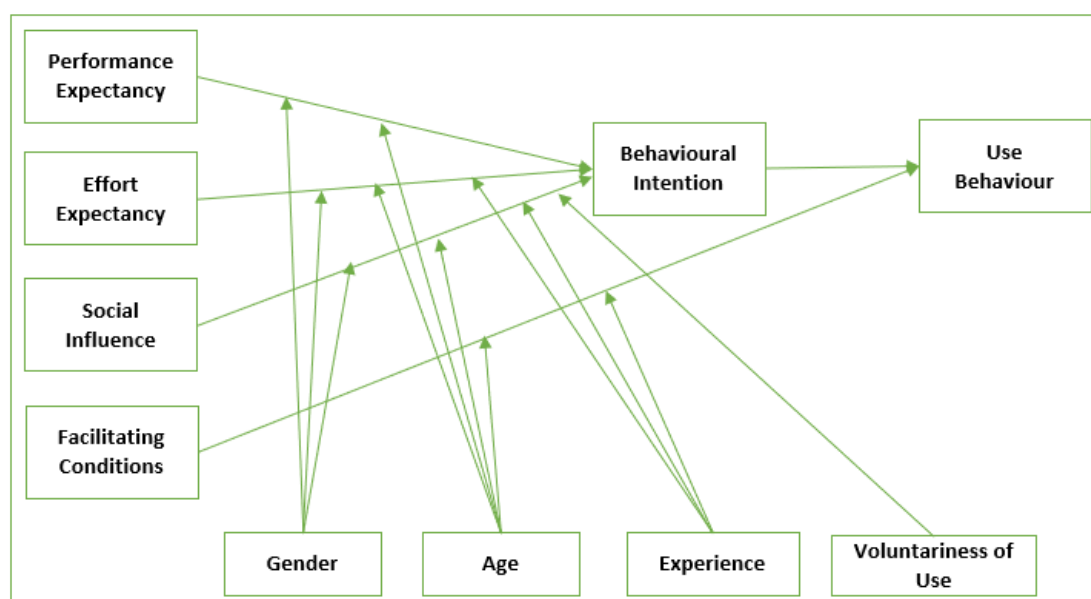


Figure 1. The UTAUT Model [4].

The UTAUT Model [4] model integrates elements from eight technology acceptance theories to provide a unified view of user acceptance. The application and the impact of the UTAUT model in respect to the research study which is on Life Expectancy and Literacy in Sub-Saharan Africa entails the following:

- 1) The UTAUT model explains that communities adopt technology when they have belief in the performance of the technology. In for example, in the health care sector, AI-based diagnostics and health systems can be used for better health services and help increase life expectancy. In education sector, digital platforms can be used to improve literacy and make learning a lot more engaging.
- 2) The people using the technology should find it easy to use and this speaks to effort expectancy. For instance, mobile health apps should make accessing healthcare simple and in the education sector where user-friendly educational tools allow people who cannot attend school to learn online.
- 3) Easy access to information systems encourages people to use the technologies because accessible learning platforms empower people to gain knowledge and advance their education.
- 4) Information Communication Technologies benefit the communities which they serve; there needs to be reliable internet and mobile networks to support the information demand for those communities. There needs to be ICT policies, investments and sustainable plans that will ensure that there is infrastructure to sustain communities at the current moment and the future.
- 5) The culture of technology usage also needs to be driven by community leaders and healthcare professionals to ensure that people see the value of ICTs. When healthcare professionals and community leaders promote ICT and AI, people are more likely to accept and use them.

2.4. Random Forest Analysis

Random Forest is an ensemble learning technique that combines multiple decision trees to improve predictive performance and reduce overfitting [8]. Ensemble approaches generally outperform individual models because they integrate predictions from multiple learners [8]. Machine learning techniques are increasingly used in socio-economic and development research because they can identify complex relationships among variables [5], [8]. The number of trees selected in the Random Forest can influence predictive

performance, although gains become marginal beyond certain thresholds [8], [20]. DEA-Malmquist analysis was conducted using DEAP Version 2.1.

2.5. Data Envelopment Analysis

The study employed an output-oriented DEA-Malmquist analysis with a VRS-based decomposition of efficiency change into pure efficiency change and scale efficiency change. Data Envelopment Analysis (DEA) applies linear programming to develop a non-parametric efficiency frontier, allowing the performance of decision-making units to be assessed relative to the best-performing entities in the dataset [16]. The use of digital technologies and data-driven systems has enabled more reliable and efficient performance assessments, allowing organizations to identify performance gaps, allocate resources strategically, and enhance overall operational productivity [19]. The study employed Data Envelopment Analysis (DEA) to measure the relative efficiency of decision-making units (DMUs), where the 49 Sub-Saharan African countries were treated as DMUs [16]. Python 3.12 and Scikit-learn (Version 1.5) were used to perform the Random Forest analysis.

2.5.1. Data Envelopment Formulas

Equation (1) presents the DEA technical efficiency function. For an output-oriented DEA model, technical efficiency can be expressed as [15], [16]:

$$TE = \frac{\sum_{r=1}^s u_r y_r}{\sum_{i=1}^m v_i x_i} \quad (1)$$

Where:

y_r = output r

x_i = input i

u_r = weight assigned to output r

v_i = weight assigned to input i

Equation (2) presents the Malmquist Productivity Index (MPI). The Malmquist Productivity Index measures productivity change between two periods t and $t + 1$ [15], [17]

$$TFPCH = EFFCH \times TECHCH \quad (2)$$

Where:

TFPCH = Total Factor Productivity Change

EFFCH = Efficiency Change

TECHCH = Technological Change

Interpretation:

TFPCH > 1 indicates productivity growth

EFFCH < 1 indicate productivity decline

TECHCH = 1 indicates no change

Equation (3) presents the Efficiency Change (EFFCH). Efficiency changes measure the movement of a country toward or away from the efficiency frontier [15], [16], [17]:

$$EFFCH = \frac{TE_{t+1}}{TE_t} \quad (3)$$

Where:

TE_t = technical efficiency in period t

TE_{t+1} = technical efficiency in period $t+1$

Equation (4) presents the Technological Change (TECHCH). Technological change measures the shift in the production frontier between periods [15], [16], [17]:

$$TECHCH = \left[\frac{D_t(x_{t+1}, y_{t+1})}{D_{t+1}(x_{t+1}, y_{t+1})} \times \frac{D_t(x_t, y_t)}{D_{t+1}(x_t, y_t)} \right]^{1/2} \quad (4)$$

Where:

D_t and D_{t+1} are distance functions for periods t and $t + 1$.

Equation (5) presents the Pure Efficiency Change (PECH). Pure efficiency change reflects changes in managerial efficiency under Variable Returns to Scale (VRS) [15], [16], [17]:

$$PECH = \frac{PTE_{t+1}}{PTE_t} \quad (5)$$

Where:

PTE_t = pure technical efficiency in period t

PTE_{t+1} = pure technical efficiency in period $t + 1$

Equation (6) presents the Scale Efficiency Change (SECH). Scale efficiency change measures change attributable to operating at a more optimal scale [15], [16], [17]:

$$SECH = \frac{EFFCH}{PECH} \quad (6)$$

or equivalently:

$$EFFCH = PECH \times SECH$$

Where:

SECH > 1 indicates improved scale efficiency

SECH < 1 indicates reduced scale efficiency

Interpretation of DEA-Malmquist Components [10]:

TFPCH > 1 = productivity growth.

TECHCH > 1 = technological change.

EFFCH > 1 = efficiency improvement.

PECH > 1 = managerial efficiency improvement.

SECH > 1 = improved scale efficiency.

2.6. Survey Methodology

A total of 500 participants from Sub-Saharan African countries voluntarily participated in the online survey. The survey was distributed across Sub-Saharan African countries, including the 49 countries represented in the secondary dataset. The respondents were primarily male and female adults between the ages of 18 and 65 years. Participants represented several countries across the Sub-Saharan African region. The survey was distributed electronically through online platforms such as Survey Monkey and social networks using a voluntary convenience sampling approach. Since the data were collected online, people who did not have internet access or who had limited digital skills may not have been fully represented in the survey. Therefore, the results should be interpreted carefully because there may be some bias in the online sample.

Prior to participation, all respondents were provided with a participant information sheet and consent cover letter explaining the purpose of the study, confidentiality provisions, voluntary participation, and the right to withdraw from the study at any stage. Completion of the questionnaire was considered an indication of informed consent. The study complied with applicable research ethics principles regarding informed consent, anonymity, and confidentiality. The demographic characteristics of respondents are summarized in Table 2.

Table 2. Demographic Profile of Survey Respondents (N = 500)

#	Characteristic	Category	Frequency (n)	Percentage (%)
1	Gender	Male	260	52.0
		Female	240	48.0
2	Age Group	18-25 years	110	22.0
		26-35 years	180	36.0
		36-45 years	120	24.0
		46-55 years	60	12.0
		56-65 years	30	6.0
3	Education Level	Secondary School	90	18.0
		Diploma/Certificate	120	24.0
		Bachelor's Degree	180	36.0
		Postgraduate Degree	110	22.0
4	Employment Status	Employed	290	58.0
		Self-Employed	80	16.0

Table 2 presents the demographic profile of the 500 survey respondents from different Sub-Saharan African countries. It highlights the population that participated in the survey for this research study. The sample included both males (52%, $n = 260$) and females (48%, $n = 240$), the table indicates a fair distribution between the males and females. The largest group of respondents are aged between 26-35 years (36%, $n = 180$), followed by those aged 36-45 years (24%, $n = 120$) and 18-25 years (22%, $n = 110$). The smallest group are the elderly aged 56-65 years formed the smallest group (6%, $n = 30$). Regarding education, most respondents held a bachelor's degree (36%, $n = 180$), followed by Diploma/Certificate qualifications (24%, $n = 120$), Postgraduate degrees (22%, $n = 110$), and Secondary School education (18%, $n = 90$). The various demographic characteristics of the respondents provided useful insights on how ICTs are adopted across different population within the Sub-Saharan African regions.

3. RESULTS AND DISCUSSION

3.1. RQ1: Is there a predictive association between life expectancy and ICTs in Sub-Saharan African countries?

To assess the predictive association between ICT indicators and life expectancy, Random Forest results are presented in Figure 2. The above tree diagram indicates Random Forest Tree results in evaluating whether mobile subscription and internet usage has a positive relationship or are contributors to Life expectancy in the African countries. Life expectancy was analyzed as continuous variables. However, the decision-tree diagrams show split points or thresholds based on predictor values. These split points divide the continuous outcomes into different groups for analysis and should not be viewed as fixed categories or classifications.

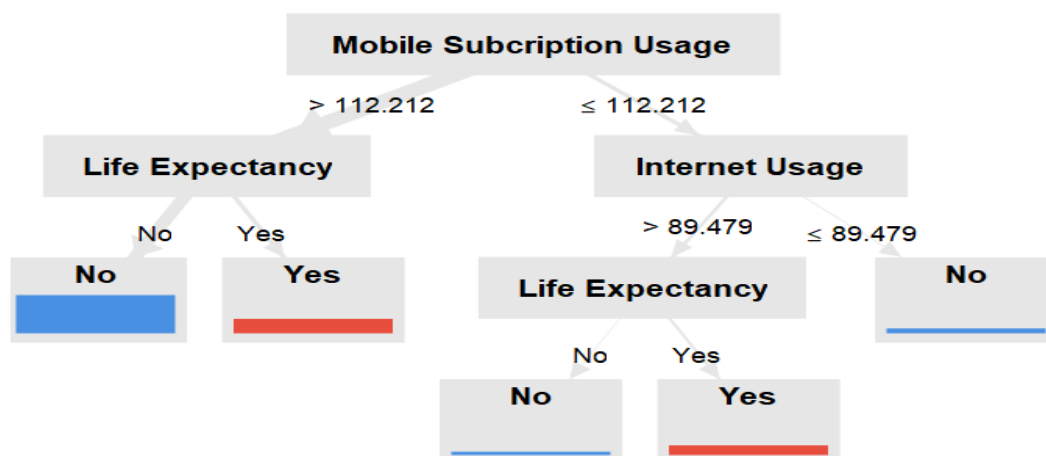


Figure 2. Random Forest Tree for Life Expectancy.

The results indicate the average of the following:

- 1) Mobile subscriptions demonstrated lower predictive importance than internet penetration within the Random Forest models.
- 2) Internet usage accounted for approximately 89% of the total feature importance within the Random Forest model, indicating that it was the dominant predictor of life expectancy relative to mobile subscriptions
- 3) Variable importance analysis showed that internet usage contributed approximately 89% of the model's predictive power, while mobile subscriptions contributed only 11%. This indicates that internet penetration is a substantially stronger predictor of life expectancy than mobile subscription access. These

findings suggest that expanding internet access may yield greater benefits for improving life expectancy through enhanced access to healthcare information, digital health services, and educational resources.

- 4) The original exploratory analysis retained feature importance outputs only. Consequently, the study has been reframed as an exploratory predictive association study rather than a predictive modelling study. This limitation is explicitly acknowledged, and future research will incorporate cross-validation, RMSE, MAE and R^2 reporting.

3.2. RQ2: Is there a predictive association between literacy rates and ICTs in Sub-Saharan African countries?

To examine the predictive association between ICT indicators and literacy outcomes, the Random Forest results are presented in Figure 3.

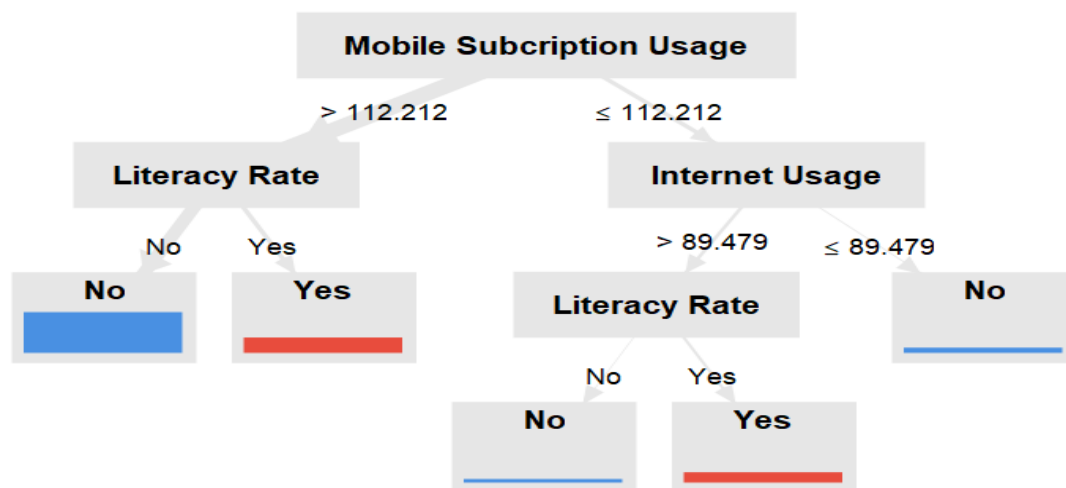


Figure 3. Random Forest Tree for Literacy Rate

Literacy rates were analyzed as continuous variables. However, the decision-tree diagrams show split points or thresholds based on predictor values. These split points divide the continuous outcomes into different groups for analysis and should not be viewed as fixed categories or classifications. The above tree is related to predicting Literacy rate based on mobile subscription and internet usage statistics.

- 1) Internet usage accounted for approximately 89% of the total feature importance within the Random Forest model, suggesting that internet

penetration was the strongest predictor of literacy outcomes among the variables considered.

- 2) The results suggest that internet connectivity was the strongest predictor associated with literacy outcomes.
- 3) Enabling access to digital learning platforms, online educational resources, information sharing, and lifelong learning opportunities across Sub-Saharan African countries.
- 4) The archived software outputs did not retain detailed hyperparameter settings such as the number of trees, maximum tree depth, random seed, and minimum samples split. Consequently, the study focuses on feature importance and predictive associations rather than detailed model optimisation.

3.3. 49 Sub-Saharan African countries based on Life Expectancy, Literacy rate, Internet Usage and Mobile Subscription Usage

Figure 4 presents the Descriptive Statistics Results of the 49 Sub-Saharan African countries based on Life Expectancy, Literacy rate, Internet Usage and Mobile Subscription Usage.

<i>Life Expectancy</i>		<i>Literacy rates</i>	
Mean	186,3469388	Mean	235,5918367
Standard Error	2,1896772	Standard Error	17,51913236
Median	186	Median	231
Mode	183	Mode	130
Standard Deviation	15,3277404	Standard Deviation	122,6339265
Sample Variance	234,9396259	Sample Variance	15039,07993
Kurtosis	1,175074368	Kurtosis	2,731611097
Skewness	0,005691057	Skewness	1,001303212
Range	77	Range	688
Minimum	146	Minimum	0
Maximum	223	Maximum	688
Sum	9131	Sum	11544
Count	49	Count	49
	1		1

<i>Internet Usage</i>		<i>Mobile subscription Usage</i>	
Mean	230,4285714	Mean	259,244898
Standard Error	24,70341076	Standard Error	29,04848063
Median	167	Median	228
Mode	167	Mode	476
Standard Deviation	172,9238754	Standard Deviation	203,3393644
Sample Variance	29902,66667	Sample Variance	41346,89711
Kurtosis	0,43132411	Kurtosis	-0,327968728
Skewness	1,051633232	Skewness	0,753352907
Range	693	Range	759
Minimum	11	Minimum	0
Maximum	704	Maximum	759
Sum	11291	Sum	12703
Count	49	Count	49
	1		1

Figure 4. Descriptive Statistics results

Figure 4 present descriptive Statistics results of the 49 Sub-Saharan African countries based on Life Expectancy, Literacy rate, Internet Usage and Mobile Subscription Usage. Prior to DEA and Random Forest analysis, all variables were normalized using Min-Max scaling according to the formula $X_{norm} = (X - X_{min}) / (X_{max} - X_{min})$, which transformed all variables to a comparable scale before modelling. Table 3 presents descriptive statistics of the scaled variable used in DEA AND Random Forest analyses rather than the original units. The values should be interpreted as normalized scores rather than actual years or percentages.

Table 3. Summary of Descriptive Statistics of Study Variables within 49 Sub-Saharan African countries

#	Variable	Mean	Standard Deviation (SD)	Minimum	Maximum
1	Life Expectancy	186.35	15.33	146	223
2	Literacy Rate	235.59	122.63	0	688
3	Internet Usage	230.43	172.92	11	704
4	Mobile Subscription	259.24	203.34	0	759

Table 3 presents descriptive statistics of the scaled variables used in the DEA-Malmquist and Random Forest analysis. The variables were normalized prior to analysis; the reported values do not represent the original units of measurement such as years or percentages. The statistics in Table 3 are based on data that were processed and standardized for use in statistics, machine learning and DEA analyses. The results should be interpreted as scaled values used for modelling purposes rather than actual life expectancy, literacy, internet usage, or mobile subscription figures. The statistics indicate variation across countries and provide a basis for subsequent machine learning and productivity analyses. The original data were obtained from international databases and adjusted to support the study's analysis. For example: Life expectancy would preferably be numbers between 18 years to 75 years, variables were normalized/scaled prior to DEA and machine learning analysis.

Table 3 shows the descriptive statistics of the variables used in this study for 49 Sub-Saharan African countries. The average life expectancy was 186.35 (SD = 15.33), with values ranging from 146 to 223. Literacy rate varied more across countries, with an average of 235.59 (SD = 122.63) and values ranging from 0 to 688. Internet usage had an average

value of 230.43 (SD = 172.92), with a minimum of 11 and a maximum of 704. Mobile subscriptions showed the highest variation among the ICT variables, with an average of 259.24 (SD = 203.34) and values ranging from 0 to 759. The large standard deviations for literacy rate, internet usage, and mobile subscriptions indicate significant differences among Sub-Saharan African countries in terms of education levels and ICT adoption. Life expectancy showed relatively small differences across countries, while literacy rates, internet use, and mobile subscriptions varied greatly. Mobile subscriptions had the highest level of variation among the ICT variables. These differences suggest that countries in the region are at different stages of development and technology adoption.

3.4. RQ3: How effective are ICTs in enhancing efficiency and productivity in Sub-Saharan African countries?

1) DEA-Malmquist Productivity Analysis

Data Envelopment Analysis (DEA) was employed to evaluate the relative efficiency of Sub-Saharan African countries using multiple ICT and human development indicators [9]. DEA is widely used for efficiency measurement because it accommodates multiple inputs and outputs without requiring assumptions regarding the underlying production function [10]. The Malmquist Productivity Index was subsequently used to assess productivity change over time through efficiency change and technological change components [17]. DEA-based productivity assessments have been applied extensively for benchmarking and comparative performance analysis [18]. DEA Malmquist Summary Index Results for the 49 Sub-Saharan African Countries. Kindly note the following definitions:

- 1) An MSI greater than 1 indicates productivity improvement (positive change).
- 2) An MSI less than 1 indicates productivity decline (negative change).
- 3) An MSI equal to 1 implies there is no change in productivity.

The results for MI Summary of Annual means are illustrated in Table 4. Table 4 highlights that the overall average Productivity Growth (TFPCH) was 17.2% from the time on the year 2010-2022. The mean Efficiency Improvement (EFFCH) = 0.997 suggests that efficiency remained largely stable during the study period, with a slight decline of approximately 0.3%. Technological Change (TECHCH) = 1.176 indicates technological progress of approximately 17.6%. Productivity Growth (TFPCH) = 1.172 indicates a

productivity increase of approximately 17.2%. The percentage results range from the year 2010 until 2022.

Table 4. Results for MI Summary of Annual Means.

Year	efich	techch	pech	sech	tpch
2	0.962	1.636	0.965	0.997	1.574
3	1.000	1.364	1.000	1.000	1.364
4	1.000	1.250	1.000	1.000	1.250
5	1.000	1.190	1.000	1.000	1.190
6	1.027	1.146	1.024	1.003	1.177
7	0.974	1.133	0.976	0.997	1.103
8	1.000	1.111	1.000	1.000	1.111
9	1.000	1.097	1.000	1.000	1.097
10	1.058	1.015	1.055	1.003	1.084
11	0.937	1.153	0.939	0.997	1.080
12	1.000	1.071	1.000	1.000	1.071
13	1.000	1.065	1.000	1.000	1.065
Mean	0.997	1.176	0.997	1.000	1.172

2) Country-Level DEA-Malmquist Results

The DEA-Malmquist analysis showed that all 49 countries experienced productivity growth during the study period, as their Productivity Growth (TFPCH) values were above 1.0. However, the level of growth differed from one country to another. On average, the countries recorded a Productivity Growth (TFPCH) of 1.172, which means productivity increased by about 17.2%. The main reason for this improvement was Technological Change (TECHCH) = 1.176, while Efficiency Improvement (EFFCH) = 0.997 remained almost unchanged across countries. The top 10 countries with Highest Productivity Growth are illustrated in Table 5.

Table 5. Top 10 Countries with Highest Productivity Growth

Rank	Country	TFPCH	Productivity Growth
1	Congo, Dem. Rep.	1.254	25.4%
2	Benin	1.236	23.6%

Rank	Country	TFPCH	Productivity Growth
3	Cameroon	1.236	23.6%
4	Burkina Faso	1.235	23.5%
5	Congo, Rep.	1.235	23.5%
6	Comoros	1.235	23.5%
7	Central African Republic	1.234	23.4%
8	Cote d'Ivoire	1.233	23.3%
9	Djibouti	1.233	23.3%
10	Ghana	1.232	23.2%

The Bottom 10 Countries with Lowest Productivity Growth are illustrated in Table 6.

Table 6. Bottom 10 Countries with Lowest Productivity Growth

Rank	Country	TFPCH	Productivity Growth
1	Seychelles	1.025	2.5%
2	Uganda	1.055	5.5%
3	South Africa	1.061	6.1%
4	Zimbabwe	1.061	6.1%
5	Zambia	1.069	6.9%
6	South Sudan	1.071	7.1%
7	Togo	1.072	7.2%
8	Chad	1.084	8.4%
9	Tanzania	1.084	8.4%
10	Eswatini	1.094	9.4%

The results indicated by DEA-Malmquist showed that productivity growth varied across the 49 Sub-Saharan African countries. The results showed that on average, the Productivity Growth (TFPCH) increased by 17.2% (1.172). The Democratic Republic of Congo recorded the highest Productivity Growth (TFPCH), with an increase of 25.4% (1.254). Benin and Cameroon showed Productivity Growth (TFPCH) = 1.236. On the other hand, Seychelles recorded the lowest Productivity Growth (TFPCH) = 1.025, followed by Uganda Productivity Growth (TFPCH) = 1.055 and both South Africa and Zimbabwe Productivity Growth (TFPCH) = 1.061.

In most countries, Productivity Growth (TFPCH) was mainly driven by better technology rather than Efficiency Improvement (EFFCH). This suggests that technology was associated with Productivity Growth (TFPCH) across the Sub-Saharan African regions.

3.5. RQ4: What are the challenges of ICTs adoption in Sub-Saharan African countries?

The participants of the online survey were asked to respond to open-ended questions. This is the opportunity for the respondents to provide insight and clarity of the views about Information Communication Technologies and its challenges in the African continent. Figure 5 illustrates the challenges Identified in Information Communication Technologies Adoption across 49 Sub-Saharan African countries.

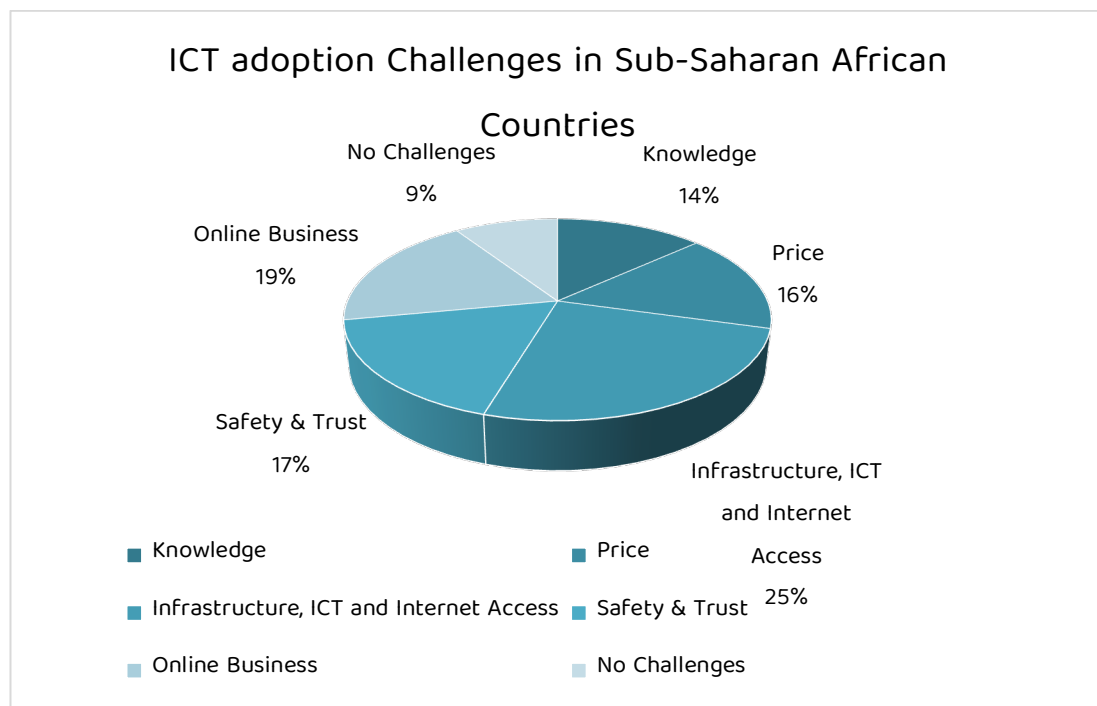


Figure 5. Identified in Information Communication Technologies Adoption

Figure 5 highlights that 25% of the respondents say that Infrastructure, ICTs, and internet access are challenges in their respective countries. This percentage is the highest compared to other challenges that were highlighted, such as Safety and trust, knowledge, price, and online businesses. The methodology entails the coding process. Open-ended survey responses were analyzed using thematic analysis. The responses were reviewed and coded according to recurring themes related to ICT adoption barriers. Similar responses were grouped into six categories: Infrastructure, ICT and Internet Access;

Online Business; Safety and Trust; Price; Knowledge; and No Challenges. The frequency of responses within each category was then calculated and converted into percentages to illustrate the distribution of perceived ICT adoption challenges among respondents.

3.6. Discussion

The research study investigated the role of Information Communication Technologies (ICTs) in providing a foundation for sustainable socio-economic outcomes in Sub-Saharan African countries. This study focuses on life expectancy, literacy rates, productivity and adoption of ICT challenges. The research study findings provide practical evidence that aligns with technology such as Unified Theory of Acceptance and Use of Technology (UTAUT) which emphasize the transformative potential of internet connectivity and technological progress. The research findings are as follows:

1) Question 1: ICTs and Life Expectancy

The Random Forest Tree analysis suggests that internet usage has a positive relationship with life expectancy, accounting for approximately 89% of the predictive weight. Mobile subscriptions contribute less to life expectancy in Sub-Saharan African countries. The results suggest that internet connectivity is a lot more critical to the lives of people living in Sub-Saharan African countries. The results suggest that countries with higher levels of internet penetration tend to exhibit more favourable life expectancy outcomes. However, the findings should be interpreted as associations rather than causal effects. Several confounding factors may influence both ICT penetration and human development outcomes, including GDP per capita, health expenditure, educational investment, urbanization, governance quality, and infrastructure availability. Future studies should incorporate these variables using panel regression or causal inference techniques.

2) Question 2: ICTs and Literacy Rates

The research results suggest that internet connectivity is still the dominant factor to enhancing literacy rates in Sub-Saharan African countries. The results indicate that internet connectivity accounted for approximately 89% of feature importance within the

Random Forest model. These findings highlight that internet connectivity plays a key role in providing a platform for facilitating educational access, e-learning, and knowledge sharing.

3) Question 3: ICTs and Productivity Growth

The Data Envelopment Analysis Malmquist Index was done for 49 Sub-Saharan African countries for this timeframe (2010-2022), and the following trends were noted:

- a) The Productivity Growth (TFPCH): 1.172, indicating a 17.2% improvement in productivity across all 49 Sub-Saharan African countries.
- b) Efficiency Improvement (EFFCH): ~0.997, suggesting near-constant efficiency levels.
- c) Technological Change (TECHCH): 1.176, reflecting a 17.6% improvement, and serving as the primary driver of productivity growth.
- d) Managerial Efficiency Improvement (PECH): ~0.997 and Improved Scale Efficiency (SECH): 1.000 are both stable.

4) Question 4: Challenges in ICT Adoption

An online survey was conducted across 49 Sub-Saharan African countries. The research findings indicated that infrastructure and internet access (25%) as the most significant barriers to ICT adoption, followed by security concerns, knowledge gaps, high costs, and limited online business opportunities. Sub-Saharan African countries' government leaders and policy makers need to start addressing infrastructure deficits and start making sure that there is investment in towards ICTs adoption. Internet usage is the most influential ICT factor for improving life expectancy and literacy rates. What drives Productivity Growth (TFPCH) across Sub-Saharan African countries is the technological advancements rather than efficiency or scale. The primary cause of challenges in ICT adoption is infrastructural limitations. In conclusion, between the year 2010 and 2022, Productivity Growth (TFPCH) is 17.2% across the Sub-Saharan African countries was largely driven by Technological Change (TECHCH) which is 17.6%, supporting that ICT adoption and innovation are the principal engines of socio-economic progress in Sub-Saharan Africa. To conclude the above discussion, Internet penetration may have been a stronger predictor because it gives people direct access to health information, online learning, digital government services, and communication tools. In contrast, mobile phone

subscriptions are already high in many Sub-Saharan African countries. As a result, having more subscriptions may not make much difference in explaining development outcomes, since additional subscriptions provide little new information or impact.

3.7. Recommendations

Information and communication Technologies are not only technological processes, but they shape how human perceptions, social infrastructure and system quality. The successful adoption develops a continuous cycle that improves health and education outcomes in Sub-Saharan African countries thus further ensuring the growth of ICTs.

1) Integrated Technology Adoption Model for ICTs impacting on Literacy and Lifespan in Sub-Saharan African countries

Based on the study findings and theoretical foundations, Figure 6 presents the proposed Integrated Technology Adoption Model. Figure 6 illustrates the key drivers and relationships that influence successful adoption of Information Communication Technologies and influence on life expectancy and literacy rates in Sub-Saharan African countries.

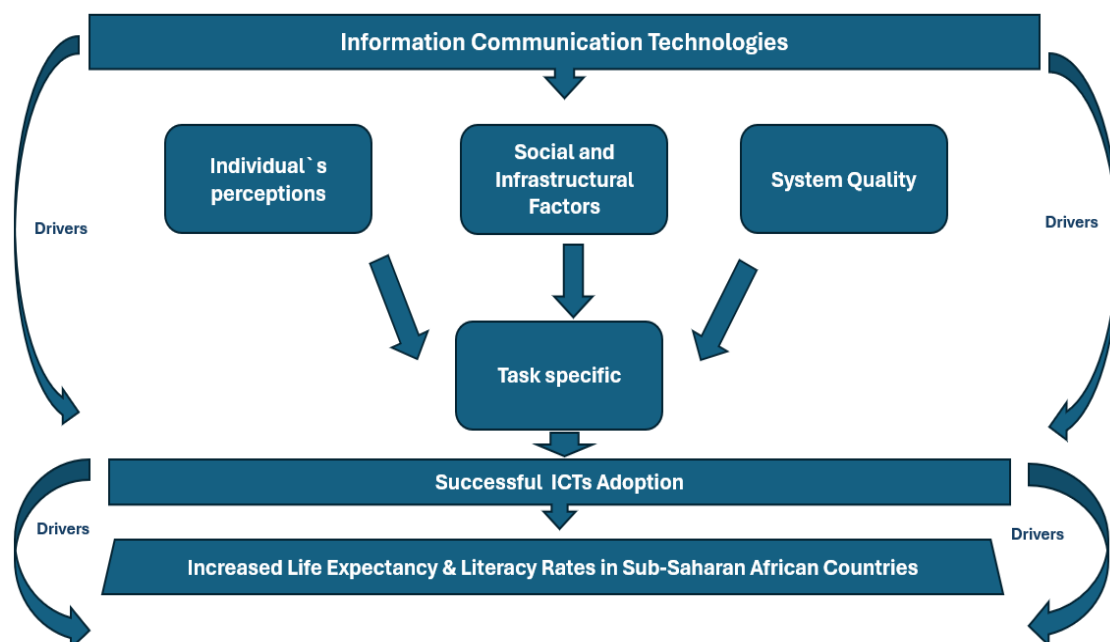


Figure 6. Integrated Technology Adoption Model for ICTs impacting on Literacy and Lifespan in Sub-Saharan African Countries

The key components are as follows:

- a) Information communication Technologies (ICTs)- ICTs comprise of online technologies which may include the following: wireless or broadband Internet access, mobile devices (Phones, laptops, I-pads), and mobile subscriptions.
- b) Influencing factors- This may be individual's perceptions on how they perceive ICT usefulness and ease of use. The societal and infrastructural factors which include the readiness of people to use the new technology, the availability of infrastructure that supports accessibility to online services and applications. The culture norms of society also influence the way people perceive using new technologies and may affect their decision making to use or not use it. The system quality of the technology informs us about the reliability and system performance of the system. The system's usability also informs us whether people can use the technological system or not.
- c) Task-specific configuration- Technology needs to be tested on whether it fulfils the tasks that people are aiming to achieve when they use it. The ability of the system to fulfil key tasks that were manually done by people is key to its adoption by users.
- d) Successful ICT adoption- User needs of the users need to be met for the successful adoption of the system.
- e) Impact- The impact relates to how Information Communication Technologies have impacted society. If ICTs are associated with favourable life expectancy and literacy outcomes in Sub-Saharan African countries, then adoption of ICTs will increase. A positive feedback loop is created further advancing the development of ICTs in Sub-Saharan African countries.
- f) Drivers- The arrows in the diagram illustrate the key drivers that suggest ICT adoption: ICTs technologies driving adoption. The adoption of ICTs that is driving the literacy and health outcomes in Sub-Saharan African countries. The improvements in health and literacy rates further encourage people to use ICTs.

2) A proposed MSI & RF Framework for ICT adoption and Sustainability Policy Making in Sub-Saharan African Countries

This study proposes a dual conceptual framework comprising the Malmquist Summary Index and a Random Forest Tree model to rigorously assess the efficiency and

sustainability of ICT adoption. The benefits of having a dual conceptual framework are as follows:

- It provides a combines efficiency analysis which is done via Malmquist Summary Index with predictive modelling via Random Forest tree which enables comprehensive evaluation of ICT adoption.
- It allows researchers to bridge the gap between productivity measurement and forecasting techniques which are often treated separately in prior research.
- It improves accuracy because Random Forest enhances predictive reliability and Malmquist Index ensures benchmarking of productivity over time.
- It empowers policymakers and organizations to identify both performance trends and future adoption patterns.

Drawing on the DEA-Malmquist and Random Forest findings, Figure 7 presents the proposed MSI-RF Framework for ICT Adoption and Sustainability Policy Making.

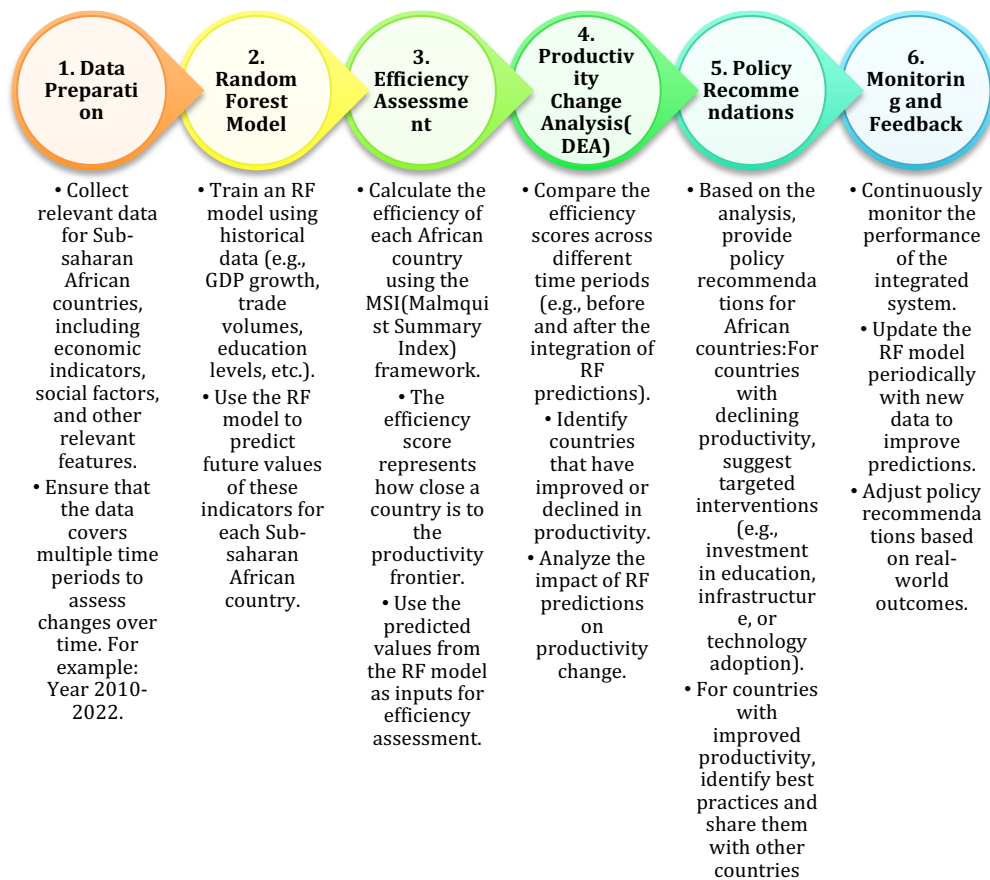


Figure 7. The MSI & RF Framework for ICT Adoption and Sustainability Policy Making in Sub-Saharan African Countries.

The MSI-RF framework should be considered a proposed conceptual policy framework derived from the study findings and existing theory. It has not been empirically validated and requires further testing in future research. This integrated approach combines predictive modelling, efficiency benchmarking, and policy feedback, enabling a holistic, data-driven strategy for improving ICT adoption and its impact on life expectancy and literacy. The MSI & RF Framework for ICT Adoption and Sustainability Policy Making in Sub-Saharan African Countries consists of six steps that entail the following:

Step 1: Data Preparation

The researcher or scientist can collect data from a data bank or source which is multi-year. Multi-year data for example may comprise of data from the year 2016 up until 2021 for Sub-Saharan African countries. One may include economic indicators such as the following: education level, social factors or other contextual features. The data needs to span across multiple periods of time to ensure that trends and changes are noted.

Step 2: Random Forest Tree Model

The Random Forest Tree model needs to be trained by using historical data such as the following for example: educational levels, life expectancy rates, Mobile subscription GDP growth. The Random Forest Tree model can be used to predict future values for these mentioned indicators of each Sub-Saharan African country.

Step 3: Efficiency Assessment

The efficiency score of each Sub-Saharan African country can be calculated by using the MSI framework. The calculated efficiency score will show how close a Sub-Saharan African country is to the productivity benchmark. The Random Forest Tree predicted values will be used as inputs for this efficiency assessment.

Step 4: Productivity Change Analyses (DEA)

A comparison between efficiency rates across different periods will be made. The identification of improved or declined productivity is done across all the Sub-Saharan African countries. Make an analysis of the impact if Random Forest tree scores on productivity change.

Step 5: Policy Recommendations

Targeted Policy recommendations can be made based on the analysis: When the data results suggest that there are countries where productivity is declining then there needs to be interventions for example (education, CT adoption or improvement in infrastructure). By making this comparison, one can identify which countries have improved in productivity and the best practices can be shared amongst them regionally.

Step 6: Monitoring and feedback

Ensure there is continuous monitoring to detect any changes to the productivity of each Sub-Saharan African country. Ensure that the Random Forest Tree model is updated with new data to make better predictions. Ensure that policies are adjusted based on the dynamic world outcomes and the productivity of each Sub-Saharan African country.

This study has several limitations. First, some country-level observations contained missing values that required imputation, which may affect the robustness of the results. Second, the Random Forest analysis identifies predictive patterns but does not establish causal relationships. Third, potentially important confounding variables such as GDP per capita, health expenditure, education expenditure, governance quality, and urbanization were not included in the predictive models. Fourth, the online survey may be subject to sampling bias because respondents without internet access were less likely to participate. Finally, the proposed MSI-RF framework has not yet been empirically validated and should therefore be interpreted as a conceptual contribution.

A further limitation is that detailed Random Forest validation outputs, including training-test split information and predictive performance metrics (e.g., RMSE, MAE, and R^2), were not retained in the archived analysis records. Therefore, the study emphasizes variable importance and pattern identification rather than predictive accuracy assessment. Future studies should incorporate comprehensive model validation procedures and report standard machine learning performance metrics.

Future research should validate the Random Forest models using hold-out testing or cross-validation approaches and report standard performance measures including R^2 , RMSE, MAE, precision, recall, F1-score, and SHAP-based interpretability analyses. In

addition to this, it should incorporate panel regression models, causal inference approaches, SHAP-based model interpretation, and robustness checks to further validate the observed relationships. Future studies should use panel regression models and include economic factors such as GDP per capita, spending on education, spending on healthcare, quality of governance, and urbanization. This will help to further confirm the relationships identified in this study.

4. CONCLUSION

This study examined the association between ICT adoption indicators and selected human development outcomes across 49 Sub-Saharan African countries between 2010 and 2022. Random Forest analysis identified internet penetration as the most important predictive feature for both life expectancy and literacy outcomes, while mobile subscriptions demonstrated comparatively lower predictive importance. In conclusion, research findings suggest that ICT adoption indicators, particularly internet usage, demonstrate predictive associations with life expectancy and literacy outcomes across Sub-Saharan Africa. DEA-Malmquist results further indicate overall productivity growth driven primarily by technological progress. However, these findings should be interpreted as associative rather than causal, as other socio-economic factors may also influence human development outcomes. The DEA-Malmquist analysis revealed average Productivity Growth (TFPCH) growth of approximately 17.2%, largely driven by Technological Change (TECHCH) of approximately 17.6%, while efficiency levels remained relatively stable throughout the study period. Survey findings further identified infrastructure and internet accessibility as the most frequently reported barriers to ICT adoption. The study contributes to ICT4D research by integrating machine learning and productivity analysis techniques in a Sub-Saharan African context. However, the findings remain subject to limitations associated with missing data, potential confounding factors, and survey sampling bias. To further validate the observed ICT-human development relationships, further studies should employ panel regression models that incorporate socio-economic controls

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