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Impact of Information and Communication Technology Diffusion on HIV and Tuberculosis Health Outcomes among African Health Systems

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Abstract: Debate regarding the impact of information and communication technology (ICT) on health outcomes has prompted researchers to conduct analyses across many parts of the globe, yet, still little is known about the ICT impact in the African continent. Using a robust multivariate approach, this study examined system-wide impact of ICT diffusion on multiple health outcomes for HIV and tuberculosis among sovereign countries of Africa. This study utilized longitudinal panel data from the World Bank and International Telecommunication Union databases between 2000 and 2016. We relied on a robust linear dynamic panel model to incorporate lagged time variables to estimate the relationships between ICT infrastructure (mobile phone use, internet access, and fixed-telephone subscriptions) and HIV and tuberculosis outcomes. Econometric analyses found that the coefficients of the aggregate ICT variables were all negative (except for fixed telephones) for tuberculosis health measures and HIV prevalence, and positive for access to antiretroviral therapy. The diffusion of mobile phones and internet was associated with decreased incidence of tuberculosis, HIV prevalence, and tuberculosis mortality rates. However, increased diffusion of these three ICT tools was associated with increased access to antiretroviral therapy. Thus, African governments should identify investment strategies for adopting and implementing ICT to improve population health outcomes.

Keywords: Africa; tuberculosis; HIV; information and communication technology; diffusion

1. Introduction

Discussions regarding the impact of information and communication technology (ICT) on population health have continued to gain traction over the past decades. World Bank defines ICT as a group of activities that involves the capturing, processing, storing, transmitting, and displaying of information by electronic means [1]. Common devices used in ICT include fixed-telephone lines, computers, wireless electronic gadgets (mobile phones), and internet subscriptions [1,2]. This study focused on mobile phone use, fixed-telephone subscriptions, and internet access.

Driven by the belief that ICT has opportunities to improve health and healthcare qualities of life, international organizations, including development agencies, have encouraged the use of ICT infrastructure in the health sector [1–6]. The World Health Organization (WHO) in 2014 proposed

the electronic health strategy in an mHealth publication titled New Horizons for Health through Mobile Technologies, with the goal of improving processes of healthcare using ICT infrastructure. Numerous studies documented positive impacts of ICT use in the health sector. For instance, Siika et al. (2005) documented how a newly installed automated reminder system led to a two-fold increase in patient turn-out for CD4 count investigation and antiretroviral medication refills in Kenya [7]. Khan (2004) documented the case in South Africa and found that innovative Short-Message-Service (SMS) medication reminders increased tuberculosis (TB) treatment adherence and completion rates.

Our study provides a timely insight into the identification of an ICT-driven medical practice and guideline to ease clinical practice, improve service delivery, and reduce healthcare cost. It seeks to investigate the impact of ICT infrastructure diffusion on HIV and TB health outcomes among sub-Saharan African countries. If there is any significant association, then the governmental systems should strengthen eHealth practices. In this study, ICT diffusion was defined as the proportion of the population of the African continent with access to ICT infrastructure, precisely, mobile phone use, internet access, and fixed-telephone subscription. Theoretically, ICT infrastructure has capabilities to strengthen health systems by bridging the gap in information availability and exchange. It resolves health sector information asymmetry that often leads to inefficient patient management and poor outcomes. For example, South Africa has one of the highest burdens of new cases of TB infection globally [6]. Medically, to effectively treat TB, patients must take four tablets of anti-tuberculosis medications five times per week, for six months [8]. It is easy for patients to forget to take these medications, which could lead to treatment failure. The South African government in 2002 introduced an automated system that lists and sends SMS reminders to patients. This model improved adherence and completion rates—among 138 patients enrolled, all but one patient successfully completed their treatment [9].

ICT use enhances communication and dissemination of information during patient care. It boosts health literacy and empowers individuals to live healthy lives. Choun et al. (2017) demonstrated how mobile phone technology facilitated TB diagnosis, treatment completion, and referrals among TB patients at the Sihanouk Hospital Center of Hope, Cambodia. This mHealth strategy led to 12% decreases in mortality rates among sampled patients [10]. In addition, Barnighausen et al. (2011) conducted a systematic review of interventions that targeted increased antiretroviral medication adherence among HIV patients in sub-Saharan Africa. Among 26 studies reviewed, treatment supporters, directly observed therapy, and mobile phone SMS reminders were identified as key factors that improved antiretroviral therapy (ART) adherence. Other health system factors identified included robust health sector financing, school enrollment, and donor support [11]. This corroborated a related study that documented how a weekly SMS optimized HIV care management among patients at the Pumwani clinic, Kenya. This mHealth strategy increased medication adherence and follow-up visits that led to overall reductions in patients' viral load [12].

However, ICT diffusion could also be linked with worse health outcomes. Numerous studies have identified negative externalities associated with ICT use [5,13–15]. For instance, Day (2014) in Sierra Leone and Glik et al. (2014) in Senegal problematize the role of digital technology as a pathway to pornography with likely consequences for sexual health and violence [13,16]. Internet use may provide an indecent medium for sexual contacts, with an increased risk of sexually transmitted diseases (STD). The internet advances online sex-seeking adventures through chat rooms and virtual communities that could initiate sexual contacts with high potential of injuries and infections [5]. The ICT innovative technology also has the potential to widen the social inclusion gap [14,15,17]. Quantitative studies by Haenssgen (2018) and Haenssgen and Ariana (2017) provide evidence that the spread of mobile phones in India and China could increase inequities in access to healthcare. Kim et al. (2010) documented unwholesome physical inactivity and poor dietary habits among Korean adolescents addicted to the internet. Thus, ICT becomes a threat to health, safety and freedom [18].

While multiple studies have documented the impact of ICT adoption on health outcomes for specific cases, it is not immediately clear how the overall diffusion of ICT infrastructure influences

population health outcomes for the entire group of African countries. Our objective was to quantify the impact of ICT infrastructure diffusion on HIV and TB health measures among the African population. We chose the sub-Saharan African population because of data availability, including the presence of diverse HIV and TB populations. Prior studies evaluated this association using either a unit ICT infrastructure or unit African country [9,19]. One study reported that mobile phone use and internet access had significant impact on TB case detection rates [19], and another on HIV prevalence [11]. However, the focus of this study is to evaluate how three types of ICT infrastructure (mobile phone, internet, and fixed telephone) together impact HIV and TB health outcomes among African health systems.

Findings from this study will increase the understanding of how ICT infrastructure impacts health outcomes among African countries, and therefore act as a reference for other researchers, development organizations, and policymakers. This study provides systematic evidence to inform healthcare priority setting, intervention mapping, and resource allocation. Policymakers can either encourage investments or disinvestments in ICT-driven healthcare practice in the coming years, especially in the face of persisting austerity in most African countries. Thus, using a robust multivariate analytic approach, this study examined system-wide impacts of ICT diffusion on multiple health outcomes for HIV and tuberculosis among sovereign countries of Africa. We relied on a robust linear dynamic panel model to incorporate lagged time variables to estimate the relationships between ICT infrastructure and population health measures.

2. Methods

2.1. Data Source

We extracted data from the World Bank and International Telecommunication Union (ITU) databases for the period from 2000 to 2016. These were de-identified information aggregated per country and published at the end of each year, qualifying it for an Institutional Review Board exemption [20]. This study included all countries in Africa except South Sudan, whose data was incomplete for analytics. The World Bank database contains information on economic and social indicators that were included as covariates representative of national development. This helped to control for the impact of progress of development of any nation, as well as to isolate and capture the impact of ICT diffusion on health. A major challenge when quantitatively estimating how ICT diffusion impacts health is isolating the ICT–health relationship from other factors (observed and unobserved), without having biased estimates from such relationships. For instance, the general socio-economic development of any country could impact individuals' health condition as well as ICT diffusion. More developed countries tend to have better health outcomes as well as higher ICT diffusion [5,21]. Consequently, positive correlation between ICT and health variables obtained from basic econometric estimation may be related to developmental progress among sampled nations, without any pointers on the impact of ICT diffusion on health [4,5].

2.2. Econometric Analysis

To overcome the rigors in estimation, a dynamic panel model (DPM) with generalized method of moments (GMM) was used in all econometric analyses. This analytic approach resolves inherent endogeneity issues caused by unobserved variables by using the lagged values of the endogenous explanatory variables as instrumental variables (IVs). To address the issue of autocorrelation in the GMM system, the lagged dependent variable was instrumented using its past values [22–25]. This resolves multicollinearity in the models. Overall model significance was assessed using the maximum likelihood test, and parameter level tests of significance used the z-statistics based on parameter standard error. Consequently, this study relied on several analytic methods including:

$$Health_{it} = \beta_0 + \beta_1.Health_{it-1} + \beta_2.ICT_{it} + \delta Z_{it} + \mu_i + \varepsilon_{it} \tag{1}$$

where t represents year and i represents the country. μ_i represents country fixed effects and ε_{it} represents the error term with an assumed zero mean. The dependent variable is *Health* which includes HIV health measures (HIV prevalence and ART access rates), and TB health measures (TB incidence and TB mortality rates). The lagged dependent variable *Health*$_{it-1}$ was included in the model as an independent variable to account for the possibility of the persistence of these health outcomes in countries [5]. Z represents a set of covariates obtained from the World Bank database including health expenditure, country population density, net primary school enrollment, prevalence of undernourishment, and net official development assistance and official aid received. Inclusion of these covariates in our models reflects the fact that country health measures were associated with economic and socio-demographic factors. However, other control variables (household income, socio-economic inequality, and corruption index scores) that we wanted to include in our regression were omitted due to incomplete data.

This study derived an aggregate ICT variable (ictfac) using three ICT indices and computed a common factor score using principal component analysis (PCA). Mathematically, PCA takes a data matrix of *n*-objects by *p*-variables, which may be correlated, and summarizes them by uncorrelated axes (principal components) that are linear combinations of the original *p*-variables [26]. The new variable (ictfac) represents the overall ICT diffusion for the entire African continent and was included in the study model as one of the primary predictors.

3. Results

The study used unbalanced panel data for 53 African countries. In total, we ran 16 models. Table 1 shows descriptive summary statistics. The average prevalence of HIV per 100,000 population was 5.44, and the mean ART access rate was 14 patients per 100,000 people living with HIV. The incidence of TB per 100,000 population was 289.73, and the mean TB mortality was 35 deaths per 100,000 TB patients. The mean percentage of individuals using the internet was 8.4 percent. In addition, the average mobile phone subscription was 41.4 per 100 population, and the mean fixed telephone subscription was 3.6 per 100 population.

Table 1. Variable definitions and descriptive statistics.

Variables	Definition	Mean	Std. Dev	Min	Max
	ICT Variables				
internet	Percentage of individuals using the Internet	8.38	11.75	0.01	58.27
mobile phone	Mobile-cellular telephone subscriptions per 100 inhabitants	41.44	41.07	0.00	176.69
fixedtele	Fixed-telephone subscriptions per 100 inhabitants	3.62	5.92	0.00	31.07
ictfac	ICT common factor score representing overall diffusion of ICT	0.00	1.47	−1.37	6.11
	Control Variables				
TB_inc	Incidence of tuberculosis (per 100,000 people)	289.73	262.84	7.50	1354.00
MortalityTB	TB death rate (per 100,000 people)	35.02	27.44	0.00	157.00
ART_acc	ART access rate (% of people living with HIV)	14.34	16.51	0.00	77.00
HIVPrev	Prevalence of HIV, total (% of population aged 15–49)	5.44	6.93	0.10	28.80
Healthexp	Health expenditure, total (% of GDP).	5.58	2.15	0.26	14.39
Popldens	Country Population, total	15.82	1.58	11.30	19.04
Educ	School enrollment, primary (% net)	75.10	18.19	0.06	99.63
Undernourish	Prevalence of undernourishment (% of population)	22.03	13.45	5.00	60.60
Ext_aids	Net official development assistance and official aid received (current US$)	19.57	1.40	13.16	23.16

Table 2 shows the impact of ICT diffusion on HIV prevalence. While the coefficients of the aggregate ICT common factor score and fixed telephone were negative and not significant, the coefficient of mobile phone was negative and significant. However, the coefficient of internet subscription was positive but not significant. This study also performed the Hansen test for over-identification on the DPM estimates (Tables 2–5), which were non-significant, indicating no over-identification in the models. To resolve heterogeneity issues in the DPM, we performed a robustness check using multilevel fixed-effects models.

Table 2. Estimation results: information and communication technology (ICT) and HIV prevalence.

Variables	Model 1	Model 2	Model 3	Model 4
	DPM (*p*-Value)	DPM (*p*-Value)	DPM (*p*-Value)	DPM (*p*-Value)
HIVPre ($t - 1$)	0.84 (0.00) ***	0.84 (0.00) ***	0.85 (0.00) ***	0.84 (0.00) ***
ICT Common factor score	−0.01 (0.57)			
Mobile phone		−0.01 (0.03) **		
Internet			0.01 (0.51)	
Fixed telephone				−0.01 (0.50)
External aids (log)	−0.04 (0.00) ***	−0.03 (0.00) ***	−0.04 (0.00) ***	−0.03 (0.00) ***
Health expenditure	−0.04 (0.00) ***	−0.03 (0.00) ***	−0.03 (0.00) ***	−0.04 (0.00) ***
Undernourishment	−0.01 (0.01) ***	−0.01 (0.01) ***	−0.01 (0.02) **	−0.01 (0.00) ***
Population density (log)	−0.43 (0.00) ***	−0.27 (0.02) **	−0.49 (0.00) ***	−0.49 (0.00) ***
AR(2) test	z = 3.03	z = 2.92	z = 3.07	z = 3.01
Hansen test	chi2(90) = 962	chi2(90) = 1006	chi2(90) = 992	chi2(90) = 1013

Note: DPM = dynamic panel model. Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3 shows the impact of ICT diffusion on access to ART. The coefficients of the ICT variables including mobile phone, internet, and fixed telephone were positive but not significant. In addition, the coefficient of the lagged ART access was positive, statistically significant, and close to one.

Table 3. Estimation results: ICT and access to antiretroviral medications.

Variables	Model 5	Model 6	Model 7	Model 8
	DPM (*p*-Value)	DPM (*p*-Value)	DPM (*p*-Value)	DPM (*p*-Value)
ART_acc ($t - 1$)	0.90 (0.00) ***	0.92 (0.00) ***	0.90 (0.00) ***	0.92 (0.00) ***
ICT common Factor score	0.35 (0.31)			
Mobile phone		0.01 (0.997)		
Internet			0.03 (0.21)	
Fixed telephone				0.09 (0.57)
External aids (log)	0.01 (0.987)	0.05 (0.84)	0.02 (0.93)	0.06 (0.83)
Health Expenditure	−0.05 (0.76)	0.01 (0.94)	−0.04 (0.83)	0.01 (0.97)
Undernourishment	0.01 (0.82)	0.02 (0.77)	0.02 (0.77)	0.02 (0.69)
Population Density (log)	19.18 (0.00) ***	19.06 (0.00) ***	19.25 (0.00) ***	18.98 (0.00) ***
AR(2) test	z = 1.02	z = 1.01	Z = 1.05	Z = 0.99
Hansen test	chi2(77) = 128	chi2(77) = 129	chi2(77) = 130	chi2(77) = 128

Note: DPM = dynamic panel model. Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4 shows the impact of ICT diffusion on TB incidence. While the coefficients of mobile phones, internet, and aggregate ICT common factor score were negative and significant, the coefficient of fixed telephone was positive and not significant. However, the coefficient of the lagged ART access was positive, statistically significant, and close to one.

Table 4. Estimation results: ICT and tuberculosis incidence.

Variables	Model 9 N = 312	Model 10 N = 318	Model 11 N = 316	Model 12 N = 314
	DPM β(*p*-Value)	DPM β(*p*-Value)	DPM β(*p*-Value)	DPM β(*p*-Value)
TB_Inc ($t - 1$)	0.85 (0.00) ***	0.85 (0.00) ***	0.84 (0.00) ***	0.87 (0.00) ***
ICT common factor score	−11.08 (0.00) ***			
Internet		−0.83 (0.00) ***		
Mobile phone			−0.37(0.00) ***	
Fixed telephone				0.25 (0.89)
Healthcare expenditure	−9.01 (0.00) ***	−9.88 (0.00) ***	−8.12 (0.00) ***	−10.12 (0.00) ***
Education	−0.39 (0.23)	−0.48 (0.13)	−0.34 (0.28)	−0.74 (0.02) **
External aids (log)	−11.78 (0.00) ***	−13.12 (0.00) ***	−9.92 (0.00) ***	−14.53 (0.00) ***
Undernourishment	−2.45 (0.00) ***	−2.30 (0.00) ***	−2.54 (0.00) ***	−2.11 (0.00) ***
AR(2) test	z = 0.27	z = 0.27	z = 0.28	z = 0.33
Hansen test	chi2(90) = 283	chi2(90) = 289	chi2(90) = 275	chi2(90) = 289

Note: DPM = dynamic panel model. Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 5 shows the impact of ICT diffusion on TB mortality rate. While the coefficients of the internet, mobile phones, and the aggregate ICT common factor score were negative and not significant, the coefficient of fixed telephone was positive and significant. The coefficient of the lagged TB mortality rate was positive, statistically significant, and approximately equal to one.

Table 5. Estimation results: ICT and tuberculosis mortality rate.

Variables	Model 13 N = 312	Model 14 N = 318	Model 15 N = 316	Model 16 N = 314
	DPM β(*p*-Value)	DPM β(*p*-Value)	DPM β(*p*-Value)	DPM β(*p*-Value)
Mort_TB (t − 1)	0.54 (0.00) ***	0.64 (0.00) ***	0.64 (0.00) ***	0.55 (0.00) ***
ICT common factor score	−0.18 (0.72)			
Internet		−0.03 (0.59)		
Mobile phone			−0.01 (0.72)	
Fixed telephone				0.61 (0.09) *
Healthcare expenditure	−0.20 (0.53)	−0.05 (0.89) ***	0.01 (0.98)	−0.22 (0.48)
Education	−0.17 (0.01) **	−0.21 (0.01) ***	−0.19 (0.01) **	−0.19 (0.01) ***
External aids (log)	−1.30 (0.03) **	−1.43 (0.02) **	−1.35 (0.03) **	−1.33 (0.02) **
Under nourishment	0.19 (0.12)	0.21 (0.11)	0.18 (0.18)	0.22 (0.08) *
AR(2) test	z = 0.08	z = 0.09	z = 0.08	Z = 0.09
Hansen test	chi2(90) = 181	chi2(90) = 167	chi2(90) = 166	chi2(90) = 178

Note: DPM = dynamic panel model. Significance level: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

4. Discussion

4.1. HIV Prevalence

Table 2 shows the impact of ICT diffusion on HIV prevalence. This variable appears to trend in the opposite direction with respect to internet subscription. While the coefficients of the aggregate ICT common factor score and fixed telephone were negative and not significant, the coefficient of mobile phone was negative and significant. Though the coefficient on internet subscription was positive, it was not statistically significant (Model 3), suggesting that when other variables are controlled for, increases in ICT diffusion, and particularly internet subscription, are associated with higher HIV prevalence. A plausible explanation could be that positive influences on the diffusion of ICT infrastructure might have been outweighed by negative influences, which corroborates findings of Keller et al. (2002) who demonstrated that internet use worsens sexual health outcomes. Digital technologies could lead to worse health outcomes [17]. Internet subscriptions increase the opportunities for soliciting multiple sexual partners, advance unsafe sex, and facilitate the spread of STDs, including HIV [27].

A related study by Lee et al. (2016) demonstrated that mobile phone use and fixed telephone subscriptions led to an overall reduction in the prevalence of HIV on a global scale [5]. This was linked to the use of this ICT infrastructure in promoting campaigns against HIV/AIDS, and increased access to HIV programs, including antiretroviral medications. As identified by the WHO, ICT provides opportunities to enhance health promotion campaigns through information, education, and communication among African health systems [6,28]. Thus, people living with HIV are enlightened about practices that impede the spread of HIV, and the need for early medical consultation and pharmacotherapy [5].

4.2. Access to Antiretroviral Medications

Study results (Table 3) indicated that increased diffusion of ICT tools, including the ictfac variable, was associated with an increase access to ART. The coefficients of mobile phone, internet, and fixed telephone were positive but not significant, suggesting that these ICT indices had positive impacts on ART access rates. Though estimation results had positive associations, the coefficients of the DPM models were unexpectedly statistically insignificant throughout the models. This corroborates the study by Shehata (2016), which maintained that ICT indicator variables lose their significance as control variables are added to any model during econometric analytics, and particularly the DPM [4].

As identified in the literature review section, ICT infrastructure use promotes ART initiation and adherence [11]. Study findings lend credence to the study by Siika et al. (2005), which demonstrated how ICT infrastructure improved ART access and initiation among HIV patients receiving ambulatory care in Kenya. ICT-enabled reminder systems provide opportunities to increase HIV processes of care, foster anonymous counselling, and link patients to available services [7].

4.3. Tuberculosis Incidence

Table 4 shows the impact of ICT diffusion on the incidence of TB. The coefficient of the lagged TB incidence was positive, statistically significant, and close to one, indicating the persistence of tuberculosis over time in countries. The coefficients of mobile phones, internet, and aggregate ICT common factor score were negative and significant. However, the coefficient of fixed telephone was positive and not significant (Model 12). This finding suggests that mobile phones and the internet had significant impacts on TB incidence, while fixed phones did not. A plausible explanation of these results could be that individuals with access to ICT infrastructure types other than mobile phones and internet access might not use them for TB-related activities. Another possible explanation is that individuals with access to diverse ICT infrastructure may utilize one tool more frequently than others, perhaps due cost, preferences, or other related factors, leading to differential impacts on health [19].

These findings also support the study by Lee et al. (2016), which listed ICT infrastructure as a key element for reducing TB incidence from a global perspective [5]. Their study enumerated ICT infrastructure roles in disseminating information regarding TB preventive services and programs. Information regarding TB vaccination campaigns disseminated through SMS technology enabled an increase in TB vaccine uptake, while reducing TB incidence among developing countries [29].

4.4. Tuberculosis Mortality Rate

Table 5 shows the effect of ICT diffusion on TB mortality rates. The coefficient of fixed telephone was positive and significant. However, the coefficients of the aggregate ICT common factor score, the internet, and mobile phones were negative and statistically insignificant throughout the models (Model 16). This highlights the fact that ICT indicator variables lose their significance as control variables are added to any model during econometric analysis, and particularly the DPM [4]. This lends credence to findings documented by the WHO and provide rationale for ICT use in TB programs. ICT infrastructure plays a critical role for TB management, particularly in coordinating case monitoring, treatment initiations, and referral mechanisms to ensure treatment adherence and completion [29]. This further corroborates findings by Choun et al. (2017), who demonstrated that mobile phones with internet services facilitate TB diagnosis, referrals, and treatment monitoring among TB patients, and led to marked reductions in mortality rates among sampled patients [10]. Consequently, SMS technology and other internet-enabled treatment reminder tools provide opportunities to improve vaccination rates, strengthen service delivery, and track follow-up. Conversely, the usefulness of obsolete fixed telephones is limited among most African communities [6,9].

Results from the analytics for the control variables indicated that country health measures were associated with economic and socio-demographic factors. Education, health expenditures, and the net external official aid to the health sector had positive associations with most of the health measures. These findings corroborate other study findings which identified positive associations between health measures and economic factors [28,30]. However, undernourishment had significant negative effects on study outcome measures (Tables 2 and 4). This plausibly could be linked to the fact that undernutrition negatively impacts immunity, especially among immunocompromised individuals such as HIV and TB patients. Undernutrition breeds malnutrition and exacerbates morbidity among immunocompromised patients [31]. Nonetheless, of note is the fact that the coefficient on health expenditure was positive but not significant (Model 15), suggesting that when other variables are controlled for, increases in healthcare expenditure were associated with an increase in TB mortality rates. This possibly could be

linked to health sector misallocation of resources and mismanagement of funds that pervades most African economies, leading to waste of resources and poor health outcomes [30].

This study assumed that the likelihood of access to healthcare services increases with higher access to ICT infrastructure. Ideally, the number of ICT users utilizing ICT infrastructure in receiving health informatics would have been used as a primary predictor variable. In addition, some ICT-related variables could have been included in this study, including households with a computer and households with an internet access at home. However, data on these variables were only available at the continent level, and not at the country level. Thus, those with a mobile phone, landline phone, and internet access were used as proxy variables, as they represent the potential for an impact on health with utilization of ICT to access health information.

Consequently, follow up assessment should be done to evaluate the impact of these variables on population health outcomes. Moreover, with the advent of smartphones with internet applications, it is difficult to isolate the effects of mobile phones and the internet on population health measures. In view of this, future studies should define a new variable that captures these two types of ICT infrastructure, and their impacts on health outcomes should be evaluated. In addition, this study analyzed data between 2000 and 2016. In this era of big data, future studies should focus on the use of longitudinal retrospective methods to search through a larger volume of rich data to capture robust trends, patterns, and associations.

5. Conclusions

Study findings suggest that ICT diffusion is positively associated with improved health outcomes among African health systems. Thus, promoting ICT use in the African region provides opportunities for improving HIV and TB health outcomes. However, the impacts of individual types of ICT infrastructure on HIV and TB outcomes differ, and are related to the different functionalities of the infrastructure and the peculiar nature of the health measures studied. An important policy implication of this study for African governments is that ICT use provides opportunities to improve health outcomes. Given that most African economies suffer severe health consequences as a result of a lack of health information, education, and communication, in addition to allocating resources to specific health interventions, investing in ICT, as well as educating the public on the use of ICT, could be an additional policy to improve population health.

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