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IMPACT OF TECHNOLOGY ON IMPROVING HIV AND TUBERCULOSIS HEALTH OUTCOMES AMONG AFRICAN COUNTRIES

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DEDICATION

To my beloved parents– Elder Fred & Late Grace Ibeneme, thank you for the strict upbringing. I now understand it was meant for my good. I am blessed to have you as parents.

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PREFACE

This dissertation explored the system-wide effect of information technology on population health outcomes among sovereign countries of Africa. It was a perfect research topic choice for me because it touches on several issues that relate to my career interests including: health system strengthening, information science, global health, impact evaluation, and global policy and advocacy

I embarked on the PhD program because I sought to increase my knowledge of population health. I sought to acquire professional competence on health policy and management, advance my analytical skills in health systems and policy research, and build networks that I could leverage in addressing problems among global health systems, especially those African nations in dire need of competent leadership in the healthcare sector. I am glad to say that I have accomplished these aims to a satisfactory level and feel ready to launch into the field to apply the knowledge and skills I have acquired at the University of Texas School of Public Health, Houston, Texas, USA.

Thank you everyone who has contributed in several ways to the realization of this dream. This achievement means a lot to me, and I promise to reward your kind gestures by making sure that I put to good use the opportunities that come with this achievement.

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I am eternally grateful to God almighty for the wonderful life that I have lived over the years – The good times and the bad times, the sunny days and the dark moments. He kept me through them all and helped me prevail against all odds. In a very special way I appreciate the divine gift of my lovely wife, Mary, whose support, patience and understanding has been amazing and crucial in this journey. To my loving parents, Elder Fred & Late Grace Ibeneme, and siblings whose support has brought me this far in life; may God continue to bless you all.

Many thanks to my dissertation committee members: Dr. James Langabeer, my dissertation supervisor and chair – who believes in me even more than I believe in myself and was a wonderful guide over the course of my doctoral program; Dr. Lee Revere – my academic advisor who mentored me, and ensured my dissertation was completed without hitches; Dr. Lu-Yu Hwang who was instrumental in motivating my passion for global health and Dr. Suja Rajan who built my confidence in econometric modelling. Your guidance was essential to the completion of this work, and I appreciate you all.

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This study used health analytics approach to evaluate the association between population health outcomes and Information and Communication Technology (ICT) infrastructures at a country level. This study used aggregate data obtained from the World Bank database, and the International Telecommunication Union (ITU) database for 53 African countries for the periods 2000 to 2016, and quantitatively explored the impact of ICT infrastructures' diffusion on population health outcomes.

ICT data was obtained from the ITU database. Similarly, population health attributes were retrieved from the World Bank database. ICT infrastructure variables used in this study include: internet access, mobile phone use, and fixed telephone subscriptions. However, population health outcome variables for this study include: HIV prevalence, access to antiretroviral therapy, Tuberculosis incidence, and mortality rates.

Econometric study methodology involved a Dynamic Panel Model (DPM). Study findings showed that promoting ICT use among the public has opportunities for improving Tuberculosis (TB) and HIV health outcomes. However, the impact of each ICT infrastructures on improving TB and HIV health outcomes differed, which this study inferred to be as a result of different functionalities of the ICT infrastructures, as well as the peculiar features of the health outcomes studied.

This study also did an Exploratory Spatial Data Analysis (ESDA) of TB treatment completion rates among health systems in Africa to help visualize trends and identify patterns, clusters and outliers. It evaluated spatial relationships between mobile phone use and TB treatment completion rates using differential local Moran's I and bivariate Moran's I techniques. Study result identified statistically significant positive autocorrelation values for the periods evaluated, as well as varying cluster patterns in TB treatment completion rates. The cluster patterns increased across the three-time periods among geographically referenced data evaluated in this study. This study also identified a direct relationship between mobile phone use and TB treatment completion rates among relevant African countries studied.

Thereby, necessitating the need to strengthen national policies that promote TB and HIV medication adherence and completion using eHealth strategies among African health systems. Another important policy implication of this study for African governments is that investing in eHealth, including educating the masses on ICT use, could be an alternative policy to improve population health.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

INTRODUCTION/STUDY MOTIVATION

Discussions regarding the impact of Information and Communication Technology (ICT) on health outcomes have continued to gain traction over the past decades. According to the World Bank, ICT is defined as a group of activities that involves the capturing, processing, storing, transmitting and displaying of information by electronic means. Common devices used in ICT include fixed-telephone lines, computers, wireless electronic gadgets (mobile phones), and internet access among others (World Bank, 2003; Leena et al, 2005; Chinn and Fairlie, 2010; Gagnon et al, 2012). This study focused on mobile phone use, fixed-telephone subscription, and internet access.

Driven by the belief that ICT has opportunities for improving health and healthcare qualities of life, international organizations including developmental agencies have encouraged the use of ICT infrastructures in the health sector (World Bank, 2003; Shehata, 2016; Lee et al, 2016). The World Health Organization (WHO) in 2014 proposed the eHealth strategy in an mHealth publication titled- *New Horizons for Health through Mobile Technologies'*, with the goal of improving processes of healthcare, including infectious disease care coordination (WHO, 2011). Further, in October 2017, the WHO African Region signed a partnership agreement with the International Telecommunication Union (ITU), with the aim of building platforms to scale digital health, building a resilient health sector workforce to effectively use ICT infrastructures, and to strengthening stakeholders' partnership for sustainable eHealth adoption and implementation among African health systems (WHO, 2016; WHO, 2017).

For this study, ICT diffusion is defined as the proportion of the continent of Africa population with access to ICT infrastructures specifically mobile phone use, fixed-telephone subscriptions and internet access. Ideally, the number of individuals utilizing ICT infrastructures for receiving health information would have been used as the independent variable in this study. However, such data are not available for Africa. Thus, individuals with a mobile phone, a landline phone and internet access were used as proxy variables, as they represent the potential for impact on health with utilization of ICT to send/receive health information. In addition, some ICT-related variables could also 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 continental-level but not at the country level. In addition, ICT-related variables such as, the number of households with a computer and the number of households with an internet access, could have been included in this study. However, data on these variables were only available at the continental-level, not at the country level (ITU, 2017).

Theoretically, ICT use can enhance communication and dissemination of information during patient care. It boosts health literacy among individuals with access to ICT infrastructures, thereby empowering users to lead a healthy lifestyle (World Bank, 2003; McNamara, 2007; Ratzan, 2011; Xie, 2011; Lee et al, 2016). One unique feature of the health sector which frequently leads to inefficient patient management and poor outcomes is information asymmetry. ICT use in the health sector addresses this issue by improving patient access to health-related information, thereby enhancing care coordination and efficiency of care (Lewis, 2006). Byrne and Gregory (2007) documented how community-based information systems empowered physicians to reduce mortality associated with childhood illnesses among the KwaZulu-Natal natives of South Africa. Information system adoption in this community facilitated processes of care by enhancing distant consultations to pediatric cases, thereby overcoming geographic barriers (Byrne and Gregory, 2007).

ICT infrastructure diffusion has opportunities for improving public health (Raghupathi and Raghupathi, 2013). The internet has become a feasible platform to publicly discuss public affairs, thereby making government more accountable and transparent in governance (Lewis, 2006; Shim and Eom, 2008). More so, the diffusion of ICT infrastructures may have opportunities for improving health care resource allocation and utilization. This translates to improved healthcare cost savings, and may have a positive impact on healthcare quality, performance and outcome (Berwick et al, 2008). However, ICT diffusion could also be linked with worse health outcomes.

Numerous studies have identified negative externalities associated with ICT use and addiction (Adam and Wood, 1999; Ramli, 2001; Leena et al, 2005; Niemz et al, 2005). Kim et al. (2010) did a study on the effects of internet addiction on the lifestyle and dietary behavior of Korean adolescents. They found that internet addiction may change dietary habits and reduce physical activities among addicts, thereby increasing their health risks (Kim et al, 2010). In addition, access to immoral and illegal materials through ICT becomes a threat to health, safety and freedom (Niemz et al, 2005; Ramli, 2011; Lee et al, 2016). It also leads to an increase in health compromising behaviors among users (Leena et al, 2005; Niemz et al, 2005). Internet use may provide an indecent medium for sexual contacts through the social media, with an increased risk of sexually transmitted diseases (Garofalo et al, 2007, Sowell and Phillips, 2010; Lee et al, 2016).

While multiple studies have documented the effect of ICT adoption and health outcomes for specific cases, it is not immediately clear how ICT infrastructure diffusion impacts health outcomes for entire African countries. Therefore, this study aimed to answer the question- Does ICT infrastructure diffusion have a significant impact on population health outcomes among African countries? To answer this question, the study conducted empirical tests using aggregate data obtained from the World Bank and ITU databases on 53 African sovereign countries for the period 2000 to 2016 (see Appendix). This study focused on the African population because of the presence of a large and diverse population of HIV and Tuberculosis patients. Also, notable access to free antiretroviral medications commenced in 2000 among African health systems (WHO, 2003) and data has been consistently captured for the 53 African countries since 2000.

A major challenge when quantitatively estimating how ICT diffusion impacts health is to isolate the ICT-health relationship from other factors, including observed and unobserved factors, without having biased estimates from such relationships. To address this issue and overcome the difficulty involved in empirical testing, this study used the Dynamic Panel Model (DPM) with Generalized Methods of Moments (GMM) in all estimations. Findings from this study should increase the understanding of how ICT infrastructures impact health outcomes among African countries, and therefore act as reference for other researchers, developmental organizations and policy-makers. It also has opportunities to inform African policy makers on healthcare priority setting and resources allocation.

Research Aims and Hypotheses

Aim 1(A&B): Determine if ICT infrastructure use has a significant impact on Tuberculosis incidence and/ or mortality rates.

Consideration of Aim 1 involved evaluating the association between ICT infrastructures' diffusion and TB incidence and mortality rates among African health systems. Health remains one of the core dimensions of the international development agenda. The United Nations (UN) projected the Millennium Development Goals (MDGs) in the year 2000, with the aim of promoting health among individuals, and hoped to achieve these goals by 2015. Three among the eight major goals are related to health including reduce child mortality, improve maternal health, and combat HIV/AIDS, malaria and other diseases including TB (Bloom et al, 2004; WHO, 2005).

Hypothesis: There is notable reductions in TB incidence and mortality rates following ICT infrastructure diffusion among African health systems.

Aim 2: Determine spatial relationships between mobile phone use and Tuberculosis treatment completion rate.

This was a longitudinal retrospective study conducted to analyze geospatial patterns of Tuberculosis treatment completion rates among health systems in Africa. Evaluating the geospatial relationships between mobile phone use and TB treatment completion rates among African health systems becomes imperative for intervention mapping, resource allocation and policy-making.

Hypothesis: There is positive spatial autocorrelation, as well as significant cluster patterns, in TB treatment completion rates following increase use of mobile phones in TB treatment protocols.

Aim 3(A&B): Determine if ICT infrastructure use has a significant impact on HIV prevalence, and/ or antiretroviral therapy coverage rates among the total number of individuals living with HIV in Africa.

Consideration of Aim 3 involved evaluating the association between ICT infrastructures diffusion and HIV prevalence among African health systems. The association between ICT tools and antiretroviral therapy coverage rates among the total number of individuals living with HIV was also investigated. Health sector ICT use among African health systems proffers smart, cost-effective innovations and solutions by harnessing Africa's digital revolution to strengthen national health systems. These include health service delivery, and providing information to communities through Information, Communication and Education (WHO, 2015; WHO, 2017). Thus, ICT infrastructure use among health systems has opportunities to contribute to the actualization of the Sustainable Development Goals (SDGs), especially SDG-3 which focuses on good health and wellbeing. In addition, ICT infrastructure also has the potential to facilitates the Universal Health

Coverage mandate among African health systems by increasing antiretroviral therapy coverage (WHO, 2017).

Hypothesis: There is notable improvements in antiretroviral therapy coverage rates following ICT infrastructure diffusion among African health systems.

LITERATURE REVIEW

African Health Systems: An Overview

Globally, health systems are a complex adaptive system, with opportunities for improvements. The Sub-Saharan African nations are not left out on this issue. Even with current global advancement in medicine and technology, health indices have remained poor among African countries (WHO, 2014). Most countries of the Sub-Saharan Africa have suffered protracted political instability, military dictatorship and institutionalized corruption. The transition from military to civilian regime had been slow and retrogressive in most African nations. This has led to system failure across boards and has impeded infrastructural development. Thus, most African countries have remained perpetually poor and underdeveloped (Tito et al, 2008; WHO, 2014; Bankole and Mimbi, 2016; Shehata, 2016). Even with the current evolution and spread of orthodox medical practice in Africa, the dearth of contemporary medical infrastructures and technologies remain a threat to the practice of orthodox medicine especially among rural communities. This has contributed substantially to the current status quo among African health systems (Pierce, 2006).

However, describing a rural community in Africa would be to describe a settlement comprising huts built out of corn stalks. A place with limited access to water, toilets, electricity, schools and nearby clinics. Indisputably every day in such an environment is a struggle between life and death, particularly for children and women. Thus, poor health outcomes in rural African community could be linked to poverty cycles. According to Wagstaff (2002), poverty and ill-health are intertwined, and reflects causality in both directions. Individuals are caught in a vicious circle, as poverty breeds ill health, and ill health preserves poverty (Cameron, 2007). Consequently, there is need to take healthcare closer to the people. Community care should be expanded especially among underserved populations. This lends credence to the mandate by the WHO, on the need to improve African health systems (WHO, 2014). The WHO in its 2014 report maintained that the African continent is behind in economic, development and health standards due to inherent systems challenges.

An estimated 45 percent out of 330 million individuals in Africa live on less than one United States (US) dollar per day (WHO, 2014). This status quo is worsened by the deplorable state of healthcare infrastructures, paucity of healthcare professionals and recurring political instability to mention a few. These translate to poor health outcomes (WHO, 2014). For example, life expectancy in Africa is 52 years compared to the global median of 66, and physician to patient ratio is 2.3 in Africa compared to the global average of 14.0 (WHO, 2014). Studies have shown that lack of knowledge, information system and health services are among the major drivers of poor health outcomes among African health systems (Wagstaff, 2002; UNICEF, 2009). Thus, ICT infrastructure use has shown to have opportunities in addressing these issues by bridging the gap in information availability and exchange using mobile phones and the internet between caregivers and patients. Consequently, the use of ICT infrastructures including mobile phones, internets and household telephone connections becomes imperative in empowering individuals, while reducing chronic infectious diseases including HIV/AIDS and Tuberculosis amongst others.

For instance, South Africa is one of the nations with the highest Tuberculosis infection rates. Medically, to treat TB effectively, patients must be strictly compliant to medical treatment.

Ideally, this involves taking four tablets of anti-tuberculosis medications five times per week, for six months. Patients could easily forget to take these medications, which will lead to treatment failure. However, in 2002 the South African health systems introduced the use of ICT infrastructures including mobile phones, Short Message Services (SMS) and computer database to facilitate TB treatments. Every half hour, the computerized database automatically lists TB patients who are due to take their TB medications, and an automatic SMS reminder sent to them via their mobile phones. Study shows that among 138 TB patients treated this way, all but one patient successfully completed their treatment schedule (Kahn, 2004).

ICT and Health Systems

The 21st century healthcare sector is driven by an important mission and a committed sense of purpose. This is evident even in advancements of ICT proliferations and penetrations among global health systems. From a global perspective, improved ICT adoption translates to better healthcare services provisions (Qureshi et al, 2015). This has led to the speculation that ICT has opportunities for improving health systems across boards including developing countries using eHealth and mHealth strategies (Kwankam, 2004; Mars and Scott, 2015). eHealth involves the use of ICT infrastructures among healthcare facilities to enhance healthcare services and processes (Kwankam, 2004). ICT can be used for various care purposes including clinical, administrative, educational and research purposes irrespective of geographic locations and settings (Mars and Scott, 2015). mHealth is a subset of eHealth (Marin et al, 2016). It extends the accuracy and efficiency of an established health system through such devices as mobile telephone networks and Personal Digital Assistants (PDA) to enhance functions like reporting procedures among health systems.

Consequently, ICT becomes a feasible tool to transform the health paradigm, as it shifts the provider-patient configuration (Lucas, 2008). Healthcare services can be extended to underserved populations through electronic telecommunication infrastructures including video chats, healthcare telephone hotlines and automated reminders among others. This arrangement eases patient access to health facilities, improve service utilization and optimize clinical outcomes (Lucas, 2008; Shaqrah, 2010; Durrani et al, 2012). Therefore, eHealth has potential to transform national health systems, by incorporating the delivery of health-related information and trainings through electronic means. For instance, information regarding vaccination campaigns can be disseminated through mobile phones. More so, the internet can provide distant learning, facilitate unrestricted health information access and help individuals acquire knowledge and insights that could impact their health positively (Klasnja and Pratt, 2012; Qureshi et al, 2015).

mHealth is provided mainly through mobile provision of healthcare services. This occurs basically through the integration of mobile healthcare delivery system with wireless mobile telecommunications and multimedia technologies (Kwankam, 2004). mHealth has evolved over time and has been used to address issues related to access, quality, cost and cultural norms among others in the healthcare industry (Istepanian and Lacal, 2003; Qiang et al, 2012). As a network, mHealth integrates people and products using digital technologies, for a purposeful outcome. A typical example can be seen in the WHO report of 2014, where health workers in Botswana use mobile phones to educate network members on HIV/AIDS, offer anonymous counselling and link patients to services. Thus, healthcare information systems have the potential of enhancing health systems and need to be evaluated further.

In a related study, Siika et al. (2005) evaluated healthcare utilization scores following the introduction of automated reminders in an infectious disease unit. This study was carried out among HIV patients receiving ambulatory care in Kenya. The study demonstrated that the use of the electronic reminders led to a two-fold increase in patient turn-out for routine CD4 count investigation, and antiretroviral medication refills. This study demonstrated that information systems use in this facility led to improvements in care coordination across facilities involved in the management of HIV/AIDS patients. Their study showed positive associations between ICT use and improvements in medication adherence, compliance to treatment protocols, and the overall healthcare service utilization (Siika et al, 2005). That notwithstanding, Hoffman et al. (2010) evaluated a novel Mobile Direct Observation Treatment (MDOT) protocol for TB treatment that was newly introduced at the Mbagathi District Hospital, Nairobi, Kenya. The MDOT is a home video therapy innovation that involves making videos. Treatment supporters make short videos using mobile phones where TB patients take their medications. Patient submit these video clips to healthcare professionals for confirmation and are encouraged to watch motivational and educating TB health videos. This method replaces the routine in-person Direct Observational Treatment (DOT) where patients must go to DOT centers to take such medications in front of healthcare workers. Study researchers found that MDOT was technically feasible, and empowered both patients and caregivers to communicate effectively, thereby improving medication adherence and completion (Hoffman et al, 2010).

ICT adoption and penetration

The healthcare sector is driven by an important mission and a committed sense of purpose (Berwick et al, 2008). However, errors and wastes in the system interfere with the quality of services provided by healthcare givers; necessitating the need for the adoption of robust information systems and networks in the healthcare sector (Graban, 2012). Effective adoption of ICT in the health industry is strategic in fostering quality into the health system. Health sector ICT adoption is multidimensional and involves all training activities needed to operationalize this technology within the healthcare sector (Nowinski et al, 2007; Gagnon et al, 2012). This involves learning of the information system configuration content specifics, delivery of the ICT learning content in a user-friendly manner, and the consumption of the learning content on users preferred devices (Dixon, 2007; Karsten and Laine, 2007).

Enablement activities including training is critical in achieving adoption, and it is often neglected in most adoption and implementation plans. A plan for in-depth training must be a part of larger implementation plan to achieve mastery. Such plan should be tailored towards patients' needs and expectations and should ensure compliance to a myriad of regulations. All training activities for healthcare workers should be delivered with clear terminology related to job responsibilities and be made readily available on electronic mobile applications (Bang, and Timpka, 2007; Gagnon et al, 2012). In addition, training can be used to address inherent challenges peculiar to the new information system. Such trainings may help identify affected users and roles, map roles to users' needs, and identify touch-points beyond the IT software (Dixon, 2007; Garavand et al, 2016).

The adoption phase entails learning content-engaging expertise and advanced skills to accomplish skill efficiently using new innovations. Organizing system content by mastery level enables users to progress easily when ready (Nowinski et al, 2007). While understanding and proficiency are parts of IT training activities, adoption entails executing series of activities alongside training. These include communication, post-go-live support, and adoption measurement (Kyhlback and Sutter, 2007; Fickenscher and Bakeman, 2011).

Levy et al. (2010) recognize that effective communication is invaluable in disseminating the impacts, effects and benefits of a newly introduced information system. Effective communication encourages questions and feedback needed for health system quality improvements and validates organizational teams' readiness to put skills to work (Levy et al, 2010). The post-go-live support summarizes a set of activities that are critical to prevent workflow stoppage and correct system errors peculiar with the facility. These support mechanisms include roaming support, in-application guidance, and context-sensitive help among others (Karsten and Laine, 2007; Bang and Timpka, 2007). In effect, they provide guidance and help when needed, and attempt to minimize time lag between training need and system content delivery. Thereby improving the functionality, compliance and operational status of the electronic system. Thus, full adoption of ICT-driven healthcare practice is prerequisite to achieving full benefits expected from this technology. It also offers an opportunity to maximize the benefits from its implementation (Karsten and Laine, 2007; Levy et al, 2010).

Overall, ICT drive transformational changes in national developments and the economy and becomes a feasible tool in all population health campaigns against poverty (Shehata, 2016). For instance, ICT was adopted as a tool to drive the Millennium Development Goals (MDGs) and the Sustainable Development Goals (SDGs) among nations of the world. Consequently, many countries have made substantial progress with respect to ICT infrastructural acquisition, installation and adoption to achieve these goals (ITU, 2011; ICSU & ISSC, 2015; ITU, 2015).

The World Bank bulletin of 2017 reported global mobile cellular use at 98 per 100 people; fixed telephone subscriptions at 14 per 100 individuals; fixed broadband subscriptions at 12 per 100 people, and individuals' use of the internet at 44 percent of global population (World Bank, 2017). However, a recent Mobile Economy African study done in 2016 recorded a more than 50% data traffic growth among providers, and an overall increase in mobile internet subscriptions among African countries. This study demonstrated that by the end of 2015, the number of Africans that subscribed to the mobile internet had tripled in the past 5 years to over 300 million and is expected to increase by an additional 250 million new subscribers by 2020. More than half a billion individuals translating to 46% of the Sub-Saharan African population had subscribed to the mobile services by the end of 2015. It is projected that over the next 5 years, an estimated 168 million more individuals across Africa will subscribe to the mobile services, and 725 million new subscribers by 2020 (Mobile Economy Africa, 2016).

Mobile broadband appears to be the dominant technology among African nations owing to network rollouts, data strategies and mobile operator device. By the end of 2015, the mobile broadband accounted for a quarter of all connections and will rise to approximately two-thirds by 2020. At the end of the 2015 fiscal year, the penetration rate for mobile broadband and the internet was 17.4 and 20 percent respectively. Although the newly launched 4G mobile broadband is gaining traction among African nations, however 3G is expected to remain the main broadband technology over the next 5 years (Mobile Economy Africa, 2016). Compared to America and Europe, Africa still lags in ICT adoption and diffusion (Table-1). Currently, one person in every five persons use the internet among Africans (ITU, 2011; ITU, 2015).

Table 1: Selected ICT indicators

Indicator	Africa	America	Europe	Year
Percentage of household with Internet access	10.7	60.0	82.1	2015
Percentage of individuals using the Internet	20.7	66.0	77.6	2015
Mobile broadband subscriptions per 100 inhabitants	17.4	77.6	78.2	2015

World leaders at the G-8 summit of 2001 in Genoa, Italy, considered the need for the use of ICT as fundamental tool to drive economic growth among poor and developing countries. In addition, international agencies including the World Bank, International Monetary Fund (IMF), World Health Organization (WHO) and the Organization for Economic Co-operation and Development (OECD) have reiterated and expressed an optimistic view on ICT infrastructures being a triggering factor for national economic development (Piotti and Macome, 2007; WHO, 2014). Consequently, there has been notable increment on ICT uptake among African systems, with a positive impact on population health (Bankole and Mimbi, 2016; Shehata, 2016). The ICT ecosystem had made a substantial contribution to the African economy especially with regards to job creation, economic growth and public funding. In 2015, mobile revenues accrue by 3.8% on a yearly basis to $53.5 billion primarily driven by data revenues (Mobile Economy Africa, 2016). However, the adoption of any new technology will involve a thorough appraisal of the technology, and a consideration of other factors in the context where its being integrated.

Historically, technology has expanded rapidly over the past 200 years, and many philosophers have studied the relationship between technology, science and mankind. Findings from such studies have corroborated one another, as they maintain that this interaction has the power and ability to drive societal developments (Smith, 1994; Piotti and Macome, 2007). The relevance of technology is encompassing. It is critical for the living things including biological lives, genetic manipulations, the physical environment, and the world around us. Thus, the social and technical attributes of mankind shape and sustain technology vice-versa (MacKenzie and Wajcman, 1999; Coiera, 2007; Piotti and Macome, 2007). Consequently, information systems are social systems with a technical component. The social and technical components are inseparable. ICT infrastructures are not on their own pure equipment (Coiera, 2007). However, it is advocated that a long period of time be allowed during ICT infrastructure adoption and implementation. This allows new users of this technology time to master and operate the innovation to suit local needs.

This also becomes necessary as the relationship between organizational ICT processes and functions are mutually inclusive (Coiera, 2007; Piotti and Macome, 2007).

ICT Infrastructures and Healthcare Quality Improvements

Health sector information systems use improves the quality and process of care for optimal patient outcomes. It facilitates patient engagement in all lines of care. Thus, it provides a platform where caregivers and patients are on the same page about accessing and sharing patient information (Chiasson et al, 2007; Ellingsen and Obstfelder, 2007). ICT promotes patients' engagement by facilitating patient participation, health promotion, and improvements in health information and knowledge (Sands, 2015). Patient engagement includes cultures that collaborates patients' decisions related to healthcare. Such collaborations involve unrestricted communication among stakeholders involved in patient management. This could be exemplified in HIV management and includes mutual respect and shared decision-making between HIV patients and healthcare givers, as well as total transparency in information sharing and communication (Marin et al, 2016).

Mobile phones are exceptional tools in infectious disease management including HIV/AIDS control (Lester and Karanja, 2015). Healthcare workers at the Pumwani clinic, Kenya, demonstrated how a weekly SMS text messages to patients on Antiretroviral Treatments (ART) facilitated care coordination among these patients. The use of mobile phone use in coordinating care has also facilitated health service delivery with the farthest possible reach; and have also improved clinical effectiveness. Through such SMS, health workers inquire on the wellbeing of their patient, then triage their responses according to individual needs. This boosted medication adherence, increased follow-up visit, led to viral load reduction among patients, and improved the overall quality of life of patients evidenced by increased productivity (Lester and Karanja, 2008). Furthermore, Barnighausen et al. (2011) did a systematic review to evaluate interventions that target to increase antiretroviral adherence among sub-Saharan African HIV patients. They reviewed 26 relevant studies done between 2003 and 2010 across Africa. After analyses, they identified treatment supporters, directly observed therapy and use of mobile cellular text messages as top factors that improved adherence to antiretroviral treatment (Barnighausen et al, 2011). Thus, electronic sharing of patient-level data among physicians mitigates redundancy and removes waste in care management. ICT infrastructure help in monitoring patients' adherence and response to medications. Therefore, ICT infrastructure use is rewarding to both patients and physicians and may lead to better disease management and outcomes (Balka et al, 2007; Green et al, 2008).

The fight against HIV/AIDS, TB, and other diseases are important components of the Millennium Development Goals. The Sub-Saharan Africa has an alarming burden of infectious diseases including HIV/AIDS and TB (ICSU & ISSC, 2015). Multiple studies have demonstrated positive associations between ICT and infectious disease management (Micevska, 2005; Chinn and Fairlie, 2010; Lee et al, 2016; Shehata, 2016). Recent study by Chadha et al. (2017) demonstrated how the ComCare mobile application was used to coordinate Tuberculosis referrals among patients in Khunti District, India. The newly introduced mobile technology increased provider accountability to patients and led to an overall improved coordinated TB patient referrals and care among their networks (Chadha et al, 2017), which corroborated findings from the WelTelKenyal study. The WelTelKenyal study was a Randomized Controlled Trial (RCT) among HIV patients in Kenya that explored patients' engagement using mobile phone. This study found that an interactive mobile phone SMS messaging intervention has opportunities for improving medication adherence that translates to viral load suppression among HIV patient. Thus, it was concluded that patient engagement through mobile phones and other ICT infrastructures are crucial to achieving the full benefits of ART among HIV patients (Smillie, 2014).

In addition, it was also discovered that ICT use in the health sector has opportunities for coordinating networking among physicians and other caregivers. This helps to optimize quality and efficiency of care delivery among health systems (IOM, 2001; Nowinski et al, 2007). Verbeke et al. (2013) demonstrated the impact levels between ICT use and health service delivery among hospitals in the Sub-Saharan Africa. The result of this study showed an overall improved patient identification, robust financial management and a structured reporting system following ICT adoption at these facilities. Nonetheless, related study carried out in the United States (US) also found that information systems have positive impacts on health systems process of care. Randomized Controlled Trial (RCT) studies by Hashim et al. (2001) on the effectiveness of telephone reminders in improving rate of hospital follow-up visit was innovative. This study was done in an urban family residency practice clinic in the US. Study showed that the use of such electronic reminders was accompanied by a relative increase in patients' appointment cancellations. It was noted that such cancellations provided opportunities for scheduling other patients on the waiting list. This led to increased revenue returns in the system that was channeled for other Quality Improvement (QI) projects (Hashim et al, 2001). Thus, health sector information system use has opportunities of helping health systems to achieve the Institute for Health Improvements' (IHI) triple aim of care including improving patients experience of care, improving population health and reducing per capita cost of care (Berwick et al, 2008).

Challenges involved in ICT adoption and diffusion

While some innovations in the health sector have been well adopted and diffused successfully among developed countries, there are still cases where innovations of varied complexity have been poorly adopted among developing countries including the Sub-Saharan Africa. The reasons that are frequently cited in literature for such slow adoption and diffusions include the way individuals perceive the issue which the innovation is intended to address, the institution within health systems adopting the innovation, the contextual and complexity of the health system, including the broad context (Eldredge et al, 2016; Atun, 2012). Further challenges associated with ICT adoption and implementation, especially among third world countries include but not limited to the direct cost involved in innovation purchase, implementation and maintenance, too many competing priorities, and minimal physician motivation and engagement. Others include behavioral adaptations to ICT among patients, physicians and the organization (Wetter, 2007; IOM, 2011; Garavand et al, 2016). The result is gross dissatisfaction among users, leading to a decrease in productivity and efficiency among health systems especially at the early phases of implementation (Hroscikoski et al, 2006).

That notwithstanding, national surveys by Friedberg et al. (2013), highlighted some of the factors that limit the effectiveness of use of ICT infrastructures among health systems to include- poor technology usability, patient information entry difficulties, degraded clinical documentations and inability to share patient-information among different facilities to mention a few. They reported that these factors may reduce the quality of care available for patients; which may account for poor outcomes seen among various health systems (Wetter, 2007; Friedberg et al, 2013; Garavand et al, 2016). Nonetheless, studies by Christianson et al. (2014) reported a loss of half a million dollars, not including the cost of the system itself. This precipitated discouragements among health systems in their uptake and advancement of health information technology. Such facilities claim that beside the direct cost of installations, funds are also needed for quality improvements, performance measurements, and for software procurement, installation and updates (Christianson et al, 2014; Garavand et al, 2016). Consequently, there is a decline in ICT adoption and implementation among hospitals based on cost. This is worse among not-for-profit health facilities, compared to their for-profit counterparts (Zhivan and Diana, 2012). It translates to better quality of care and health outcome from the for-profit hospitals, compared to their not-for-profit counterparts (Zhivan and Diana, 2012; Perna, 2013).

Nevertheless, the dearth in the infrastructural development of African nations, especially the incessant supply of power, as well as the paucity of manpower expertise to run this innovation continues to hinder the penetration of ICT among African countries (Awokola et al, 2013). Studies show that lack of ICT skills, poor strategies and skepticism among physicians (Wetter, 2007; Khan et al, 2012); as well as poor infrastructures, lack of technical expertise and increasing prevalence of notorious online hawkers impede ICT adoption among African health systems. Thereby, making quality of care and health outcomes sloppy in the contemporary African healthcare sector (Mugo and Nzuki, 2014; Garavand et al, 2016).

PUBLIC HEALTH SIGNIFICANCE

This dissertation research sought to improve the understanding of how ICT infrastructures impact population health and healthcare delivery among African countries. Generally, little empirical study has been done on this topic among African health systems. This dissertation was a pioneer study to jointly investigate population health outcomes among Africans using three ICT infrastructures – Mobile phone use, Internet access, and Fixed-telephone subscriptions as key independent variables. Previous studies have mostly evaluated this association using either a unit ICT infrastructure or specific African country. Only a few recent studies investigated the association between ICT infrastructures and health outcome variables from a global perspective (Gagnon et al, 2012; Raghupathi and Raghupathi, 2013; Lee et al, 2016; Shehata, 2016). However, at the continent level (Africa), similar studies evaluated this association using specific ICT infrastructures with specific health outcome measures (Kallander et al, 2013; Deidda et al, 2014;

Bankole and Mimbi, 2016). Other researchers also explored this association for specific countries in Africa (Piotti and Macome, 2007; Byrne and Gregory, 2007; Ruxwana et al, 2010; Jimoh et al, 2012; Leon et al, 2012). However, in comparison to these studies, this dissertation explored the association between multiple ICT infrastructures and population health outcomes at the continent level. This study aims to fill this important research gap by evaluating the impact of ICT infrastructure on population health outcomes among Sub-Saharan African countries. If there is any significant association, then the system will strengthen the eHealth practice including care coordination and health service delivery using ICT infrastructures.

Results from this study will help policy-makers and other key players better understand the impact of ICT infrastructures on population health. This will help them identify opportunities for improving national health systems and saving cost. Clear priorities drive health sector reform and ensures that the best value for money is pursued in the most transparent and accountable means (Ham and Coulter, 2001). Thus, the relevance of good leadership in this regard is invaluable. Furthermore, study results will assist healthcare leaders and policy-makers in all processes of healthcare priority setting and resource allocation, so that health gain maximization is optimal given the limited available resources (WHO, 2012). Government and policy-makers can either encourage investments or disinvestments in ICT-driven healthcare practice in the coming years, especially in the face of austerity hitting most African countries. This research may also serve to inform governments across Africa regarding if investments in ICT tools, and the perception of the use of ICT as an alternative to health improvement is worth it or not. Furthermore, this study may contribute to the identification of an ICT-driven medical practice and guidelines which facilitate clinical practice, improve performance and reduce cost; thereby achieving the Institute for Healthcare Improvement's triple aims of care (Berwick et al, 2008). Achieving the triple aim of care among African health systems could translate to improved patients' outcomes (Cramp and Carson, 2001). However, to actualize this concept, the health sector needs a system approach with robust information system and expertise in place– A combination of ICT-driven healthcare practice with trained professionals who can utilize information systems to deliver healthcare services effectively and efficiently (Atun, 2012). The introduction of such information systems has proven potentials to facilitate and improve quality healthcare, and at a reduced cost (Piotti and Macome, 2007; Berwick et al, 2008).

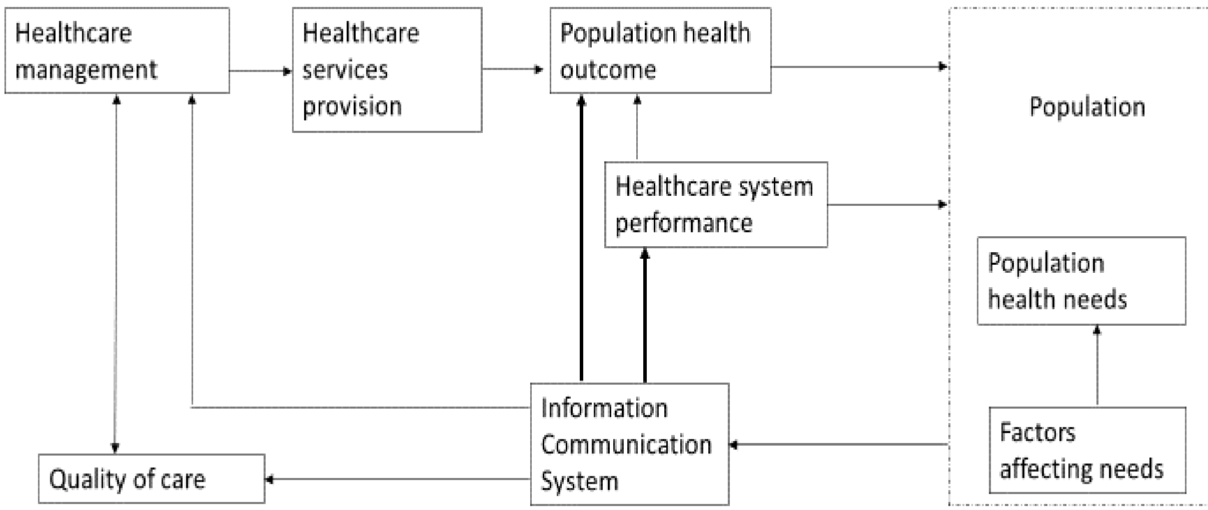
THEORETICAL AND EMPIRICAL BACKGROUND

This first section gives a brief description of the cybernetic conceptual framework, which served as the conceptual foundation for this study. Subsequently, the diffusion of innovation theory will be used to explain the transition from a primitive society to a modern society in terms of technology and infrastructural development and penetration, and how they affect health. This will be followed by an explanation of theoretical bases for this study's main constructs – population health outcomes and ICT infrastructure diffusion. Finally, the two aims of the study and their corresponding hypotheses will be summarized appropriately.

Cybernetic conceptual modelling framework

The complex and interdisciplinary method of providing health care often requires several changes across many departments. A systemic model-based framework to this study involved the use of a cybernetic paradigm (Figure-1) to show how diverse units interconnect for a quality framework in a regulatory feedback fashion. Skiadas et al. (2002) used the cybernetic theory to model telemedicine hemodialysis systems occurring at four European locations. Their study was designed by using the systems approach and a feedback mechanism to evaluate preliminary clinical trials involving 29 patients and 305 hemodialysis sessions. Overall, study results showed that the telemedicine systems methodology had inherent capabilities to satisfy formative evaluations contributed by various system elements in a regulatory feedback fashion (Skiadas et al, 2002).

Figure 1: The Cybernetic Framework



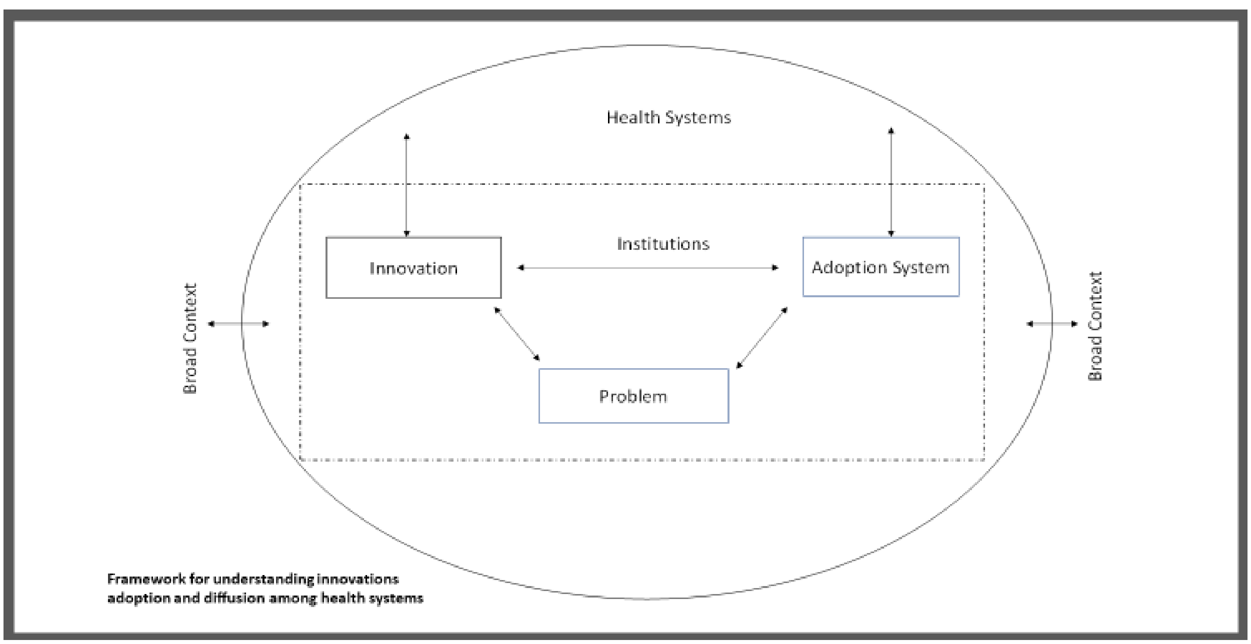
Culled from Cramp and Carson, 2001

The cybernetic model (systems theory) as described by Atun (2012) examines complex adaptive systems with interlinked and dynamic interactions involving contexts, institutions and systems which interact within the contexts of health systems. Interdependent and interconnected elements within systems create network of feedback loops that operate in a cause-and-effect pattern to maintain system equilibrium. Such nonlinear system elements interactions create a dynamic complexity that leads to system response (Atun, 2012; Willis et al, 2012).

Diffusion of Innovation Theory

The Diffusion of Innovation (DOI) theory attempts to explain how innovations are taken up in the contemporary society. It is a model that seek to describe change categories involved in technology advancement and adoption, which are critical for health improvements (Figure-2). Any healthcare related innovation, for instance the use of SMS/email to communicate with patient must be easy to use, understood and communicated. It should easily be adopted with minimal investments of time, risk and commitment before usage (Glanz et al, 2002; Eldredge et al, 2016). Innovations are critical for improving population health outcomes among developed countries (Cutler, 2001), and developing countries for optimal health outcomes (Howitt et al, 2012). According to Atun (2012), health systems innovation includes new ideas, medicines, health technologies, diagnostics, practices objects, practices or organizational activities perceived as novel by any unit of adoption– an individual or institution. Historically, the DOI theory has been widely used in various disciplines. In the academia, schools have used it to investigate the dissemination of AIDS education curricula, and the adoption of safe sex practices. Healthcare professionals have also used it to understand the use and penetration of new tests, programs and technologies (Glanz et al, 2002).

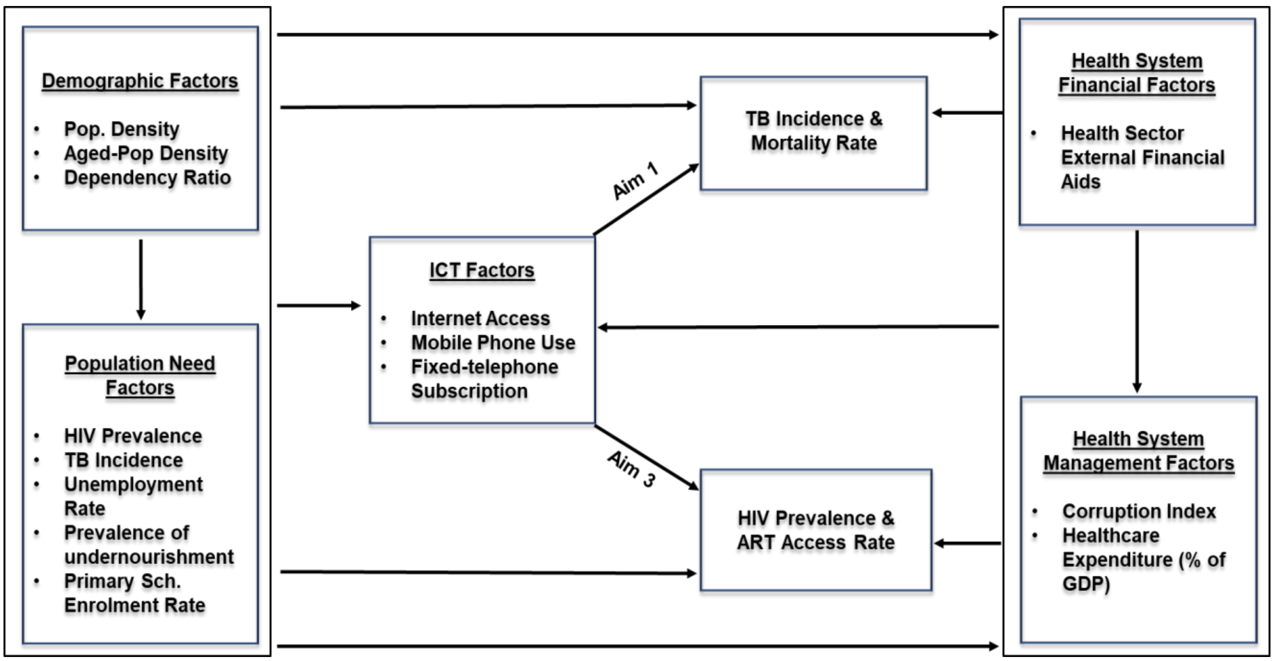
Figure 2: Diffusion of Innovation Framework



Culled from Glanz et al, 2002

Components of this model interact in a bidirectional fashion to create complex adaptive and dynamic health systems. It fosters systems thinking, as it considers key elements of a complex adaptive system that interact to impact innovation adoption and diffusion. Thus, approaches that encourage systems thinking are invaluable while planning health system innovations adoption, to enhance system performance (Atun, 2012; Atun et al, 2010).

Figure 3: Study Model



Consequently, a hybrid of the cybernetic conceptual framework alongside the diffusion of innovation theory was used to structure an assessment of ICT infrastructure diffusion within the larger contextual healthcare environment. These frameworks work to conceptualize the interconnectedness of health system characteristics and ICT infrastructures, which have an inherent ability to improve health outcomes. The Ottawa declaration of 1986 emphasized the need for the re-orientation of healthcare services. This includes basic communication theories and those involving the adoption of new technologies for the enhancement of healthcare effectiveness

(Kickbusch, 2003). Importantly, this model describes a causal connectivity among relevant variables and highlights relevant change directions (Cramp and Carson, 2001; Fahey et al, 2003). The target population was assessed at the base level with respect to perceived health needs, which could be influenced by a myriad of factors including HIV prevalence, TB incidence, prevalence of undernourishment and unemployment rate among others (Figure-3). In addition, population demographic factors including population density, dependency ratio and aged-population density impact population health needs within any specified healthcare system (Lichter and Brown, 2011). The loop on the left arm of this model represents health system management and financial factors including healthcare expenditures, external aid to the health sector, and corruption index among others. This loop is being influenced by community demographic factors and population need factors (Figure-3). This together with other inherent population factors drive change within the population and are pointers for healthcare needs which could be facilitated using ICT infrastructures including mobile phone, internet and fixed telephone (Nowinski et al, 2007; Chiasson et al, 2007). Improvements at this point have opportunities for improving health outcomes including HIV and tuberculosis health outcomes.

METHODS

The objective of this study is to investigate how ICT infrastructures diffusion impact population health outcomes among African health systems. This is important as countries look to justify investing in ICT-driven healthcare practice in Africa. Country-level ICT data was obtained from two different sources: The ITU for the ICT infrastructure variables, and the World Bank database for the population health variables including TB and HIV measures. Relevant studies have used data from these sources for related ICT-health research (Raghupathi and Raghupathi, 2013; Bankole, F., Mimbi, 2016; Lee et al, 2016**).** Specifically, ICT variables for 53 African countries was obtained from the ICT indicator database (http://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx) for the years 2000 – 2016. ITU data has been consistently captured for 53 African countries since 2000 for the telecommunication sector.

The International Telecommunication Union (ITU) is one of the United Nations (UN) groups and has reliable data on ICT infrastructures in the ICT sector. Data are collected annually through an online-questionnaire sampling of government agencies (Ministries and regulatory authorities) in control of ICT. Non-responded questionnaires are imputed by getting data from governments' web sites and annual reports (ITU, 2015). ICT statistics are gathered for approximately 200 economies. The ITU database contains time series annual data for the years 1975 – 2016 for approximately 140 ICT indicator statistics (ITU, 2015). However, ICT variables analyzed in this study were mobile phone use, fixed-telephone subscription, and internet access (Tables 2 – 5).

Similarly, data for health outcomes was obtained from the World Bank Database (**http://data.worldbank.org/**), for the period 2000 to 2016 to match the available ICT data. The World Bank is also one of the UN groups concerned with public health on the international scale, and it provides data on health situations across the globe. Health outcome variables for our study was accessed from the World Development Indicators (WDI) database which is a subset of the World Bank database and includes healthcare outcomes data for the 53 African countries which were the study population for our study. The health outcomes analyzed in this study include the following: antiretroviral therapy coverage rates, TB treatment completion rate, TB mortality rate, TB incidence and HIV prevalence. Relevant covariates needed for this study (Tables 2 – 5) were also obtained from the World Bank Database for the periods 2000 – 2016 and include: primary school enrolment rate, population density, percentage of population over 65 (aged-population), age dependency ratio, health expenditures, external aids to the health sector, and corruption index.

Datasets for ICT and health outcomes were merged using the unique identification of country name (or code). This study used variables with less missing values. Thus, using econometric analyses, this study identified relationships between ICT diffusion and health outcomes. Specifically, analytics was used to describe the relationship between the diffusion of mobile phone, internet, and fixed telephone with health outcome indicators. Ideally, the number of ICT users receiving health informatics via ICT would have been used as the independent variable in this study, however, such data was not available for Africa. Thus, those with a mobile phone, a landline phone and internet access were used as proxy variables as they represented the potential for impact on health with utilization of ICT to send/receive health information. In addition, some ICT-related variables could also have been included in this study including households with a computer at home and households with an internet access at home. However, data on these variables were only available at the continental-level but not at the country level (ITU, 2017).

Conceptually, this study assumed that increases in mobile cellular and internet subscriptions infers a broader access to healthcare services including antiretroviral and TB medications. Furthermore, it was believed that the likelihood of access to healthcare services increases with higher access to ICT infrastructures. Consequently, digital health advocacy among African health systems had opportunities to promote and disseminate healthcare knowledge through Information, Communication and Education (Lee et al, 2016; Shehata, 2016).

Importantly, this study also derived an aggregate variable for ICT using three ICT elements, and computing a common factor score of the three ICT variables using the Principal

Component Analysis (PCA). Mathematically, the PCA takes data matrix of *n*-objects by *p*-variables, which may be correlated, and summarizes them by uncorrelated axes. The result is a linear combination of the original p-variables denoting principal component. Geometrically, the PCA rigidly rotate the p-dimensional axis to new positions called 'principal axis', which has unique features of having the highest variance and a zero covariance (uncorrelation). The first principal component was used to produce fitted values, which served as the derived ICT common score variable denoted as *ictfac* (Abdi and Williams, 2010; Bro and Smilde, 2014). The new variable represents the overall ICT diffusion in the entire African continent.

Study Design

This was a retrospective longitudinal study that involved investigating the impact ICT diffusion had on HIV and TB health outcomes among the entire African countries between the periods 2000 to 2016. Study design involved retrospective time-series data analyses using the Dynamic Panel Model (DPM). However, certain variables were only available for some nations and with limited years. This study did not include countries with incomplete data. Thus, data for 53 countries were available and complete, and was used in all econometric analyses. We believed that this sample was a good representative of the African continent and ideal for econometric analyses. A major problem when quantitatively estimating how ICT diffusion impacts health would be how to isolate ICT-health relationships from other observed and unobserved factors, without having biased estimates from such relationships. For instance, the general socio-economic development of any country could affect people's health condition as well as ICT diffusion rates. More developed nations are inclined to have better health conditions as well as higher ICT diffusion rates (ITU, 2011; ITU, 2015). Thus, positive correlation between ICT and health measures obtained from basic econometric analyses may be because of developmental advancements among sampled nations, without any pointers on the impact of ICT diffusion on health (Lee et al, 2016; Shehata et al, 2016).

In addition, some unobserved qualities of nations could also impact both individuals' health conditions and ICT diffusion levels. A typical example of such unobserved characteristics would be the preferences and ideologies of government (leaders) of any nation. Countries with protracted political instability, military dictatorship and institutionalized autocratic political system may prioritize national defense over socio-economic and infrastructural developments (Okogbule, 2007). This would lead to poor health conditions and poor health outcomes, and an overall decrease in ICT penetration (Okogbule, 2007; Lee et al, 2016). Thus, in this regard, positive associations between health and ICT variables from basic econometric analytics is driven by the values, beliefs and views of the political elites, and not suggestive of a causal relationship between health and ICT diffusion. This may introduce simultaneity problems and may bias the estimates obtained from such econometric analyses (Terza et al, 2008; Wooldridge, 2009; Shehata et al, 2016).

Econometric Data Analyses

Overall, to overcome the rigors in estimation, the Dynamic Panel Model (DPM) and the Generalized Method of Moments (GMM) were used in all econometric analyses. The choice of this model stemmed from its ability to absolve inherent endogeneity issues that may arise from unobserved variables. It does this by utilizing the dynamic features of the data to generate good Instrumental Variables (IV). IVs are variables included in models to address endogeneity problems. Their use becomes necessary when an independent variable is correlated with the error term in any model. Thus, the chosen IVs should correlate substantially with the endogenous regressor and should not be correlated with the error term. It must be relevant and exogenous (Greenland, 2000). For this study, the GMM estimator proposed by Holtz-Eakin et al. (1988) and developed by Blundell and Bond (1998) was used in estimating the study model (Equation 1). Conceptually, the GMM estimator absolves endogeneity problems by using the lagged values of the endogenous explanatory variables as IVs. These lagged independent variables are valid IVs as they are uncorrelated with the error term and are only partially correlated with the endogenous explanatory variables (Terza, 2008; Wooldridge, 2009; Shehata, 2016). Consequently, the GMM model has an inherent ability to address endogeneity issues that may arise from simultaneity, omitted variables or measurement error. Overall, the idea behind the GMM method is to put a slope equation in the form of a DPM, and then take the first difference of the model variables and use their lagged values for the levels of the regressors as IVs (Arellano and Bond, 1991). In addition, to address the issue of autocorrelation in the GMM system, the lagged dependent variable is instrumented using its past values (Arellano and Bond, 1991; Roodman, 2009).

Therefore, to estimate model-1 as shown below (Equation 1), identified instruments must be valid. This means that they must be exogenous and relevant. Furthermore, to test the relevance of the instruments their associated F-statistics for the first-stage regression involving all endogenous variables on the instrument must be greater than 10. This ensures that bias in the estimation is smaller than the OLS estimation bias. Next, the over-identification test must be statistically significant. The J-statistic test confirms or refutes the hypothesis that instruments are exogenous. Thus, if we fail to reject the null hypothesis, then the instruments are exogenous (Terza et al, 2008; Shehata, 2016).

Specific health indices of interest for this study were obtained from the World Bank database. This database contains information on economic and social indicators, which allows this study to include them as relevant covariates representative of national development. These covariates were included to help control for the effect of progress of development of any nation, and as well help to isolate and capture the impact of ICT diffusion on health.

$Health_{it} = \beta_0 + \beta_1.Health_{i,t-1} + \beta_2 ICT_{it} + \delta Z_{it} + \mu_i + \varepsilon_{it}$ ………… … …………………………(Equation 1)

Where *t* represents year, and *i* represents the country. *Z* represents sets of covariates, and μ_i represents country fixed effects, and ε_{it} represents the error term with an assumed zero mean. The dependent variable is $Health_{it}$, which includes antiretroviral therapy coverage rates and TB mortality rates. The lagged of the dependent variable $Health_{it-1}$ was also included in this model as an independent variable to account for the possibility of the persistence of these health conditions in these countries. Conceptually, chronic disease conditions including chronic environmental features may lead to rather slow changes in the health conditions and outcomes of any nation. Thus, health indices in time *t* likely depend on the health indices in time *t-1*. Overall model significance was assessed using the maximum-likelihood test while parameter level tests of significance used the z-statistic based on parameter standard error.

Geospatial Data Analyses

The statistical software tools used for study data analyses was STATA version 14. Stata is a general purpose statistical software package that was created in 1985 by StataCorp. Word Office 2013 package was also used to prepare this dissertation document, and Excel Office used to organize study data for tables. In addition, PowerPoint Office 2013 was used in presenting study findings. That notwithstanding, the Geographic Information System (GIS) software including the ArcGIS and GeoDa software were used to identify spatial relationships between TB health outcomes and mobile phone use among African health systems. Specifically, the GeoDa software was used to generate clusters/hotspots using differential local Moran's I analyses techniques (Anselin, 1995). The Moran's I is a geospatial analytic technique that measures spatial autocorrelation. Ideally, what this test does is to explore if a variable change over time in any location is statistically related to its neighbors or not. Thus, the differential Moran's I test identifies hotspots or clusters among African countries in relation to neighboring countries (Kraak, 2004; Anselin, 2013).

Power Estimation

Altogether, there were 53 countries and 16 variables in this study. Thus, the number of observations was 53*16 = 848. To estimate the power of this study the conventional formula below was used (Aday and Cornelius, 2006).

Power = ES * α * $\sqrt{n}/\sigma$

Expected Power $(1 - \beta)$ =?

Effect Size = 0.51 (Lee et al, 2016)

Alpha (α) = 0.05

Sample size (n) = 848

Standard Error (σ) = 0.86 (Lee et al, 2016)

Therefore, Power = 0.51 * 0.05 * $\sqrt{}$ (848/0.86)

Power = 0.80.

Thus, with 848 study observations, alpha (α) of 0.05, and effect size of 0.51, the power of this study was computed to be 80%. We believed that this is an appropriate power to detect any important effect if it exists.

Variable Descriptions: Dependent Variables

To measure health variables, this study referenced the United Nations MDG. The United Nations proposed the MDG in 2000 with the aim of promoting health among individuals and hoped to achieve these goals by 2015. Three amongst the eight major goals are directly related to health and include: reduce child mortality, improve maternal health, and combat HIV/AIDS, malaria and other diseases including Tuberculosis (ICSU and ISSC, 2015). The World Bank database has data representing these variables, which have been used for multiple studies in the past (Raghupathi and Raghupathi, 2013; Lee et al, 2016; Shehata, 2016). This study used variables to represent aspects of health, for which population health outcome indicators were inclusive. Accordingly, this study has three aims, which measured population health outcomes. Each aim has distinct dependent variables, including antiretroviral coverage rates, TB mortality rates and TB treatment completion rates.

Antiretroviral therapy coverage rate: This variable was used as one of the indicators of population's health outcome. Data for this variable was accessed from the World Bank database. Antiretroviral coverage rate represents the percentage of all people living with HIV in Africa who were receiving Antiretroviral Therapy (ART).

TB mortality rate: This variable was also used as an indicator of the population's health outcome in this study. It represents TB death rate (per 100,000 people). The data for this variable was also accessed from the World Bank database.

TB treatment completion rate: This variable served as one of the indicators of the population's health for this study. It represents TB treatment success/completion rate (% of new cases of TB identified). The data for this variable was obtained from the World Bank database.

Variable Descriptions: ICT Independent Variables

ICT infrastructures were the main independent variables for this study and represents ICT diffusion in any nation. Three variables were used by this study to measure ICT including mobile phone use, fixed-telephone subscription, and internet access.

Internet Subscription: This variable represents the percentage of individuals using the internet at the country-level. This variable was obtained from the International Telecommunication Union and was available for 53 African nations except South Sudan.

Mobile-cellular telephone subscriptions: This variable represents the number of mobile-cellular telephone subscriptions per 100 inhabitants. This variable was obtained from the International Telecommunication Union and was available for 53 African nations except South Sudan.

Fixed-telephone subscriptions: This variable denotes the number of fixed-telephone subscriptions per 100 inhabitants. The variable was obtained from the International Telecommunication Union and was available for 53 African nations except South Sudan.

Variable Descriptions: Independent Variables (Covariates)

The parameter labeled Z in the study model (equation 1) represents a set of covariates. Relevant variables that were representative of national development were included as covariates to control for their impact, and to isolate such impact from ICT-related impact on health conditions. Relevant covariates included were: Health expenditure as a percentage of GDP; Country population density; Age-related dependency ratio– Percentage of the population age 65 and above; Prevalence of undernourishment; Incidence of tuberculosis; Prevalence of HIV; Country-level unemployment rate; Net primary school enrollment rate among the population; Percentile rank of corruption control, and Net official development assistance and official aid received from international bodies/agencies.

Table 2: Measurement Matrix: TB Study Aim 1A

Variable	Description	Variable Type	Variable Source
Dependent Variable			
Incidence of TB	Incidence of tuberculosis (per 100,000 people)	Continuous	World Bank Database
Independent Variables			
Internet Access	Percentage of individuals using the Internet	Continuous	ITU Database
Mobile Phone Use	Mobile-cellular telephone subscriptions per 100 inhabitants.	Continuous	ITU Database
Fixed-telephone Subscription	Fixed-telephone subscriptions per 100 inhabitants	Continuous	ITU Database
ICT Common Factor	ICT common factor score representing overall diffusion of ICT	Continuous	Derived using PCA
Covariates			
Population Needs Factors			
Primary Sch. Enrolment Rate	School enrollment, primary (% net)	Continuous	World Bank Database
Unemployment Rate	The density of the labor force that is without work but available for and seeking employment	Continuous	World Bank Database
Demographic Factors			
Prevalence of undernourishment	Prevalence of undernourishment (% of population).	Continuous	World Bank Database
Population Density	Country total Population, total	Continuous	World Bank Database
Aged Population	Population ages 65 and above (% of total)	Continuous	World Bank Database
Age Dependency Ratio	Age dependency ratio (% of working-age population)	Continuous	World Bank Database
Health System Financial Factors			
Health Expenditure (% of GDP)	Health expenditure, total (% of GDP).	Continuous	World Bank Database
External Aids	Net official development assistance and official aid received (current US$).	Continuous	World Bank Database
Corruption Index	Control of Corruption: Percentile Rank	Continuous	World Bank Database

Sources: WHO, 2017; ITU, 2017

Table 3: Measurement Matrix: TB Study Aim 1B

Variable	Description	Variable Type	Variable Source
Dependent Variable			
TB Mortality Rate	TB death rate (per 100,000 people)	Continuous	World Bank Database
Independent Variables			
Internet Access	Percentage of individuals using the Internet	Continuous	ITU Database
Mobile Phone Use	Mobile-cellular telephone subscriptions per 100 inhabitants.	Continuous	ITU Database
Fixed-telephone Subscription	Fixed-telephone subscriptions per 100 inhabitants	Continuous	ITU Database
ICT Common Factor	ICT common factor score representing overall diffusion of ICT	Continuous	Derived using PCA
Covariates			
Population Needs Factors			
Primary Sch. Enrolment Rate	School enrollment, primary (% net)	Continuous	World Bank Database
Unemployment Rate	The density of the labor force that is without work but available for and seeking employment	Continuous	World Bank Database
Demographic Factors			
Prevalence of undernourishment	Prevalence of undernourishment (% of population).	Continuous	World Bank Database
Population Density	Country total Population, total	Continuous	World Bank Database
Aged Population	Population ages 65 and above (% of total)	Continuous	World Bank Database
Age Dependency Ratio	Age dependency ratio (% of working-age population)	Continuous	World Bank Database
Health System Financial Factors			
Health Expenditure (% of GDP)	Health expenditure, total (% of GDP).	Continuous	World Bank Database
External Aids	Net official development assistance and official aid received (current US$).	Continuous	World Bank Database
Corruption Index	Control of Corruption: Percentile Rank	Continuous	World Bank Database

Sources: WHO, 2017; ITU, 2017

Table 4: Measurement Matrix: HIV Study Aim 3A

Variable	Description	Variable Type	Variable Source
Dependent Variable			
Prevalence of HIV	Prevalence of HIV, total (% of population ages 15-49)	Continuous	World Bank Database
Independent Variables			
Internet Access	Percentage of individuals using the Internet	Continuous	ITU Database
Mobile Phone Use	Mobile-cellular telephone subscriptions per 100 inhabitants.	Continuous	ITU Database
Fixed-telephone Subscription	Fixed-telephone subscriptions per 100 inhabitants	Continuous	ITU Database
ICT Common Factor	ICT common factor score representing overall diffusion of ICT	Continuous	Derived using PCA
Covariates			
Population Needs Factors			
Primary Sch. Enrolment Rate	School enrollment, primary (% net)	Continuous	World Bank Database
Unemployment Rate	The density of the labor force that is without work but available for and seeking employment	Continuous	World Bank Database
Prevalence of undernourishment	Prevalence of undernourishment (% of population).	Continuous	World Bank Database
Demographic Factors			
Population Density	Country total Population, total	Continuous	World Bank Database
Aged Population	Population ages 65 and above (% of total)	Continuous	World Bank Database
Age Dependency Ratio	Age dependency ratio (% of working-age population)	Continuous	World Bank Database
Health System Financial Factors			
Health Expenditure (% of GDP)	Health expenditure, total (% of GDP).	Continuous	World Bank Database
External Aids	Net official development assistance and official aid received (current US$).	Continuous	World Bank Database
Corruption Index	Control of Corruption: Percentile Rank	Continuous	World Bank Database

Sources: WHO, 2017; ITU, 2017

Table 5: Measurement Matrix: HIV Study Aim 3B

Variable	Description	Variable Type	Variable Source
Dependent Variable			
Antiretroviral Therapy Coverage Rate	The percentage of all people living with HIV who are receiving antiretroviral therapy.	Continuous	World Bank Database
Independent Variables			
Internet Access	Percentage of individuals using the Internet	Continuous	ITU Database
Mobile Phone Use	Mobile-cellular telephone subscriptions per 100 inhabitants.	Continuous	ITU Database
Fixed-telephone Subscription	Fixed-telephone subscriptions per 100 inhabitants	Continuous	ITU Database
ICT Common Factor	ICT common factor score representing overall diffusion of ICT	Continuous	Derived using PCA
Covariates			
Population Needs Factors			
Primary Sch. Enrolment Rate	School enrollment, primary (% net)	Continuous	World Bank Database
Unemployment Rate	The density of the labor force that is without work but available for and seeking employment	Continuous	World Bank Database
Prevalence of undernourishment	Prevalence of undernourishment (% of population).	Continuous	World Bank Database
Demographic Factors			
Population Density	Country total Population, total	Continuous	World Bank Database
Aged Population	Population ages 65 and above (% of total)	Continuous	World Bank Database
Age Dependency Ratio	Age dependency ratio (% of working-age population)	Continuous	World Bank Database
Health System Financial Factors			
Health Expenditure (% of GDP)	Health expenditure, total (% of GDP).	Continuous	World Bank Database
External Aids	Net official development assistance and official aid received (current US$).	Continuous	World Bank Database
Corruption Index	Control of Corruption: Percentile Rank	Continuous	World Bank Database

Sources: WHO, 2017; ITU, 2017

Ethical Considerations

This study involved analyzing secondary data, which was publicly available online, and omitted personal identifiers and patient-level information. Therefore, this study qualifies as minimum risk, given that it did not violate the rights or impose any risk on human subjects (Gostin, 2008). Expedited review was obtained from the University of Texas School of Public Health Institutional Review Board (IRB). After this approval from the University review board, relevant data was downloaded from the World Bank and ITU databases. Though these were de-identified variables, the downloaded dataset was cleaned and stored on password protected computers. All analyses were completed in January 2018.

RESULTS

The results of the econometric and geospatial analyses are presented in the form of three journal articles.

JOURNAL ARTICLE 1

Impact of Technology on Improving Tuberculosis Health Outcomes among African Countries

Journal: International Journal of Healthcare Information Systems and Informatics

INTRODUCTION

Tuberculosis remains a significant public health issue. One fourth of the world's population is infected with tuberculosis. In 2016, 10.4 million people across the globe became infected with tuberculosis, and 1.7 million tuberculosis-related deaths were recorded (CDC, 2017). The burden of TB is highest in Sub-Sahara Africa and South-East Asia, where it is fueled by HIV co-infection and other conditions associated with poverty and deprivation (WHO, 2017). Thereby, necessitating innovative system-wide approaches for coordinated TB care and control using eHealth strategies.

The World Health Organization (WHO) in 2014 proposed the eHealth strategy in an mHealth publication titled- '*New Horizons for Health through Mobile Technologies'*, with the goal of improving processes of healthcare using information systems including ICT infrastructures (WHO, 2011). Health sector use of ICT tools has been instrumental in advancing population health. Driven by the belief that ICT have opportunities for improving health and healthcare qualities of life, international organizations including developmental agencies have recommended the use of ICT infrastructures in the health sector (Lee et al, 2016; Shehata, 2016; Choun et al, 2017). Thus, ICT infrastructure use in TB management has opportunities to integrate vital statistics registries, disease surveillance data, and program monitoring data with workforce, financial and management data to inform planning, decision-making and resource distribution.

For this study, ICT diffusion is defined as the proportion of the continent of Africa population with access to ICT infrastructures specifically mobile phones, fixed-telephone subscriptions and internet access. Ideally, the number of individuals utilizing ICT infrastructures in receiving health informatics via ICT would have been used as the independent variable in this study. However, such data are not available for Africa. Thus, those with a mobile phone, a landline phone and internet access were used as proxy variables, as they represent the potential for impact on health with utilization of ICT to send/receive health information. In addition, some ICT-related variables could also 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 continental-level but not at the country level (ITU, 2017).

Theoretically, ICT use can enhance communication and dissemination of information during patient care. It boosts health literacy among individuals with access to ICT infrastructures, thereby empowering users to lead a healthy lifestyle (Ratzan, 2011; Choun et al, 2017). In addition, a unique feature of the health sector which often leads to inefficient patient management and poor outcomes is information asymmetry. Thus, ICT use in the health sector addresses this issue by improving patient access to health-related information. For instance, information regarding vaccination and other preventive health services can be disseminated electronically through mobile phones and other related information systems. Study by Kaplan (2006) identified mobile phones with internet access as feasible ICT tools for advancing healthcare preventive services including TB vaccination campaigns. That notwithstanding, Choun et al. (2017) also demonstrated how mobile phones were used in facilitating TB diagnosis, referrals and treatment completion among patients at the Sihanouk Hospital Center of Hope (SHCH) in Cambodia. Their study identified a remarkable decrease in mortality rates among TB patients following implementation of this strategy (Choun et al, 2017).

Consequently, ICT becomes a feasible tool to transform the health paradigm, as it shifts the provider-patient configuration (Chinn and Fairlie, 2010). Health sector ICT adoption proffers integrated health information systems that has capacity to effectively manage different information systems and networks from diverse centers for an improved functional health system. Hoffman et al. (2010) evaluated a novel Mobile Direct Observation Treatment (MDOT) protocol for TB patients that was newly introduced at the Mbagathi District Hospital, Nairobi, Kenya. The MDOT was a home video-therapy innovation that involved making videos. Treatment supporters make short videos using mobile phones where TB patients take their medications. Patient submit these video clips to healthcare professionals for confirmation and are encouraged to watch motivational and educating TB-related health videos. This method replaced the routine in-person Direct Observational Treatment (DOT) where patients must go to DOT centers to take such medications before healthcare workers. The MDOT strategy was found to be technically feasible. It empowered both patients and caregivers to communicate effectively, thereby improving medication adherence and completion rates (Hoffman et al, 2010). This was akin to study by Ngwatu et al. (2018), who did a systematic study to evaluate the relevance of various digital TB treatment strategies including Short Message Services (SMS), Medication Monitors, and Video-Observed Therapy (VOT) over the conventional in-person DOT strategy. Their study showed that while Medication Monitors increased the probability of cure, SMS had no added significant advantage on treatment completion over DOT. However, VOT had a comparable treatment completion rate compared with DOT strategies (Ngwatu et a, 2018).

Despite the inherent benefits associated with ICT use, various system-level factors have limited its effectiveness in improving outcomes among African health systems. Multiple studies identified lack of knowledge, dearth in information system adoption and poor service delivery as major drivers of poor health outcomes among African health systems (Wagstaff, 2012; WHO, 2014; WHO, 2015). Compared to international standards, ICT penetration among African nations is poor and more efforts required. Mobile broadband penetration level was 17.4 percent in 2015. One in five individuals use the internet among Africans, translating to a 20 percent penetration levels (ITU, 2017). This status quo is further worsened by deplorable healthcare infrastructures, paucity of healthcare workers and recurring political instability among African countries. Therefore, poor health outcomes among African communities could be linked to poverty cycles. Poverty and ill-health are intertwined and reflects causality in both directions. Individuals who are poor are caught in a vicious circle, as poverty breeds ill health, and ill health preserves poverty (Wagstaff, 2002). An estimated 45 percent of the 330 million individuals in the Sub-Saharan Africa live on less than one United States (US) dollar per day (WHO, 2014). These translate to poor health outcomes. For example, latest statistics identified the following– life expectancy in Africa was 54 years compared to the global mean of 66. Physician to patient ratio was 2.3 in Africa compared to the global mean of 14.0; and the burden of new cases of TB was 281 cases per 100, 000 individuals, compared to the global mean of 133 cases per 100,000 population (WHO, 2015).

Conceptually, ICT infrastructures have abilities to address these issues by bridging the gap in information availability and exchange using information systems. For instance, South Africa is one of the nations with the highest burden of global new cases of TB infections (WHO, 2017). Medically, to effectively treat TB, patients must be compliant to medical treatment. This involves taking four pills of anti-tuberculosis medications five times per week, for a period of six months (WHO, 2010). Patients could easily forget to take these medications, which could lead to treatment failure. However, in 2002 the South African government introduced an eHealth system in TB management. This involved the use of ICT infrastructures including mobile cellular applications (SMS) and computer database to facilitate TB treatments. Every half hour, the computerized database automatically lists patients who are due for TB medications, and an automatic SMS reminder sent to their mobile phones. This approach was novel, and improved treatment adherence and completion rates. This study indicated that among the 138 TB patients managed this way, all but one patient successfully completed their treatment (Kahn, 2004).

While multiple researches have documented the effect of ICT adoption and health outcomes for specific cases, it is not immediately clear how ICT infrastructures' diffusion influence population health outcomes for entire African countries. Consequently, this study provides insights to the question: does ICT infrastructure use have any impact on TB incidence and mortality rates among African health systems? To answer these questions, this study conducted empirical tests using aggregate data obtained from the World Bank and ITU databases on 53 African sovereign countries for the period 2000 to 2016 as listed in the appendix (Exhibit A). We chose the Sub-Saharan African population because of data availability, including the presence of a large and diverse TB populations.

Thus, our objective is to quantify the impact of ICT infrastructures on tuberculosis health measures among the African populations. Specifically, we explored how TB incidence and mortality rates were impacted by mobile phone use, fixed-telephone subscriptions, and Internet access. Most prior studies focused on evaluating this association using either a unit ICT infrastructure or specific African country (Kahn, 2004; Kallander et al, 2013; Raghupathi and Raghupathi, 2013). One study reported that mobile phone use and internet access had significant impact on tuberculosis case detection rates. In a recent study, Lee et al. (2016) from a global perspective explored the effect of ICT infrastructures diffusion on TB prevalence and mortality rates. However, the need to explore this in the Sub-Saharan African context cannot be over-emphasized. If there is any significant association, then the system will strengthen eHealth practice in service delivery among African health systems (Raghupathi and Raghupathi, 2013).

Consequently, using analytics, this study identified relationships between ICT diffusion and TB health outcomes. Findings from this study hopefully will increase the understanding of how ICT infrastructures impact health outcomes among African countries, and therefore act as reference for other researchers, developmental organizations and policy-makers. This study provides a timely insight into the identification of an ICT-driven medical practice and guidelines to ease clinical practice, improve service delivery, and reduce healthcare cost. Study results have opportunities to inform policy-makers on healthcare priority setting and resources allocation. Thus, government and policy-makers can either encourage investments or disinvestments in ICT-driven healthcare practice in the coming years, especially in the face of current austerity in most African countries.

Materials and Methods

Data used for this study was obtained from the World Bank and ITU databases for the periods 2000 through 2016. Ideally, collated information is de-identified and aggregated per country and published at the end of each year. Thus, this study qualifies for an Institutional Review Board (IRB) exempt, as it did not violate the rights or impose any risk on human subjects. However, certain variables were only available for some nations and with limited years. Thus, data for 53 countries were available and complete was used in all econometric analyses, which was completed in May 2018. We believed that this sample was a good representative of the African continent, and ideal for econometric analyses.

A major issue when quantitatively estimating how ICT diffusion impacts health would be how to isolate the ICT-health relationship from other observed and unobserved factors, without having biased estimates from such relationships. For instance, the general socio-economic development of any country could affect people's health condition as well as ICT diffusion. More developed countries tend to have better health condition as well as higher ICT diffusion standards (ITU, 2017). Thus, positive correlation between ICT and health variables obtained from basic econometric analyses may be because of developmental progress among sampled nations, without any pointers on the effect of ICT diffusion on health (Lee et al, 2016; Shehata et al, 2016).

Overall, to overcome the rigors in estimation, the Dynamic Panel Model (DPM) and the Generalized Method of Moments (GMM) were used in all econometric analyses. The choice of this model stemmed from its ability to absolve inherent endogeneity issues caused by unobserved variables. It does this by utilizing the dynamic qualities of the data to produce good Instrumental Variables (IV). Thus, the GMM estimator proposed by Holtz-Eakin et al. (1988) and developed by Blundell and Bond (1998) was used in estimating our study model (Equation 1). Conceptually, the GMM estimator absolve endogeneity problems using the lagged values of the endogenous explanatory variables as IVs. The lagged independent variables are valid IVs as they are uncorrelated with the error term and are partially correlated with the endogenous explanatory variables (Terza et al, 2008; Shehata, 2016). The idea behind the GMM method is to put a slope equation in the form of a DPM, and then taking the first difference of the model variables and using their lagged values for the levels of the regressors as IVs (Arellano and Bond, 1991). In addition, to address the issue of autocorrelation in the GMM system, the lagged dependent variable is instrumented using its past values (Arellano and Bond, 1991; Rodman 2009).

Specific health indices of interest for this study were obtained from the World Bank database. This database contains numerous information on economic and social indicators, which allowed this study to include them as covariates representative of national development. Relevant covariates were included to help control for the effect of progress of development of any nation, as well as to isolate and capture the impact ICT diffusion has on health measures. Consequently, this study relied on several analytic methods including:

$$Health_{it} = \beta_0 + \beta_1.Health_{i,\,t-1} + \beta_2.ICT_{it} + \delta Z_{it} + \mu_i + \varepsilon_{it} \text{ ………………………………….(Equation 1)}$$

Where t represents year, and i represents the country. Z represents sets of covariates, and μ_i represents country fixed effects, and ε_{it} represents the error term with an assumed zero mean. The dependent variable is $Health_{it}$, which includes TB incidence and TB mortality rates. The lagged of the dependent variable $Health_{it-1}$ was included in this model as an independent variable to account for the possibility of the persistence of these health outcomes in these countries. Theoretically, chronic disease conditions including chronic environmental features may lead to rather slow changes in the health conditions and outcomes of any nation (Lee et al, 2016). Thus, health indices in time 't' most likely might depend on the health indices in time 't-1'. 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.

Importantly, this study also derived an aggregate variable for ICT using three ICT elements, and computing a common factor score of the three ICT variables using the Principal Component Analysis (PCA). Mathematically, the PCA takes data matrix of *n*-objects by *p*-variables, which may be correlated, and summarizes them by uncorrelated axes. The result is a linear combination of the original p-variables denoting principal component (Abdi and Williams, 2010). The new variable (*ictfac*) represents the overall ICT diffusion in the entire African continent and was included in the study model as one of the primary predictors.

Conceptually, this study assumed that increases in mobile cellular and internet subscriptions implies a broader access to healthcare services. Furthermore, we assumed that the likelihood of access to healthcare services increases with higher access to ICT infrastructures, which have opportunities to reduce TB incidence and mortality rates.

Results

This study used unbalanced panel data for 53 African countries over the period 2000 - 2016 accessed from the World Bank and ITU databases and analyzed in January 2018. Descriptive study summary statistics are shown in Table 1 below. On the average, the incidence of TB per 100,000 of population was 289.73, and the mean TB mortality rate was 35 deaths per 100,000 individuals. The mean percentage of individuals using the internet was 8.4 percent. The mean mobile phone subscription was 41.4 per 100 population, while mean fixed telephone subscription was 3.6 per 100 inhabitants. This study also performed the Hansen test, to test for over-identification of the Dynamic Panel Model estimates. The Hansen test chi-squared statistics (Tables 2&3) were non-significant, indicating no over-identification in the models.

Table 1: Variable Descriptive Statistics

Variables	Definitions	Mean	Standard Deviation	Min	Max
ICT variables					
Internet	Percentage of individuals using the Internet	8.380	11.749	0.006	58.270
Mobile phone	Mobile-cellular telephone subscriptions per 100 inhabitants.	41.440	41.068	0	176.686
Fixed telephone	Fixed-telephone subscriptions per 100 inhabitants	3.615	5..923	0	31.067
ictfac	ICT common factor score representing overall diffusion of ICT	0	1.468	-1.365	6.106
Control variables					
TB_inc	Incidence of tuberculosis (per 100,000 people)	289.731	262.835	7.5	1354
MortalityTB	TB death rate (per 100,000 people)	35.015	27.439	0	157
healthexp	Health expenditure, total (% of GDP).	5.578	2.152	0.260	14.390
educ	School enrollment, primary (% net)	75.102	18.186	0.060	99.634
undernourish	Prevalence of undernourishment (% of population)	22.031	13.450	5	60.600
ext_aids	Net official development assistance and official aid received (current US$)	19.566	1.399	13.162	23.160

Table 2: Estimation results of TB incidence

Variables	Model 1 N=312	Model 2 N=318	Model 3 N=316	Model 4 N=314
	DPM β(p-value)	DPM β(p-value)	DPM β(p-value)	DPM β(p-value)
TB_Inc (t-1)	0.849 (0.000)***	0.852 (0.000)***	0.836 (0.000)***	0.874 (0.000)***
ICT common factor score	-11.084 (0.000)***			
Internet		-0.830 (0.004)***		
Mobile phone			-0.374 (0.000)***	
Fixed telephone				0.246 (0.892)
Healthcare expenditure	-9.013 (0.000)***	-9.877 (0.000)***	-8.123 (0.000)***	-10.116 (0.000)***
Education	-0.393 (0.230)	-0.479 (0.129)	-0.337 (0.278)	-0.736 (0.024)**
External aids (log)	-11.777 (0.000) ***	-13.123 (0.000)***	-9.916 (0.000)***	-14.533 (0.000)***
Under nourishment	-2.445 (0.000)***	-2.300 (0.000)***	-2.544 (0.000)***	-2.113 (0.000)***
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: FD = First Difference; DPM = Dynamic Panel Model. Significance level: *p<0.1; **p<0.05; ***p<0.01

Table 2 above represents the effect of overall ICT diffusion on TB incidence. The coefficient of the lagged TB incidence was positive, statistically significant and close to one, indicating the persistence of tuberculosis among African countries over time. The coefficients on the aggregate ICT score and other ICT variables were all negative and significant but for fixed telephone (Model 4).

Table 3: Estimation result of TB mortality rate.

Variables	Model 5 N=312	Model 6 N=318	Model 7 N=316	Model 8 N=314
	DPM β(p-value)	DPM β(p-value)	DPM β(p-value)	DPM β(p-value)
Mort_TB (t-1)	0.537 (0.000)***	0.639 (0.000)***	0.639 (0.000)***	0.548 (0.000)***
ICT common factor score	-0.178 (0.723)			
Internet		-0.034 (0.587)		
Mobile phone			-0.005 (0.721)	
Fixed telephone				0.614 (0.091)*
Healthcare expenditure	-0.196 (0.525)	-0.048 (0.886)***	0.010 (0.976)	-0.218 (0.477)
Education	-0.170 (0.013)**	-0.209 (0.005)***	-0.187 (0.012)**	-0.194 (0.005)***
External aids (log)	-1.301 (0.025)**	-1.433 (0.022)**	-1.352 (0.034)**	-1.331 (0.023)**
Under nourishment	0.192 (0.123)	0.213 (0.112)	0.182 (0.181)	0.219 (0.079)*
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: FD = First Difference; DPM = Dynamic Panel Model. Significance level: *p<0.1; **p<0.05; ***p<0.01

Table 3 represents the effect of overall ICT diffusion on TB mortality rate. The coefficient of the lagged TB mortality rates was positive, statistically significant and close to one, indicating the persistence of TB-related deaths over time among African countries. The coefficients on the aggregate ICT score and other ICT variables were all negative but for fixed telephone (Model 8).

Discussion

The coefficients of the lagged TB incidence and TB mortality rates were both positive, statistically significant and close to one, indicating the persistence of tuberculosis and TB-related deaths over time among related African nations. The coefficients on the aggregate ICT score and other ICT variables were all negative and significant but for fixed telephone (Model 4). A plausible explanation could be that individuals with access to other ICT tools other than cellular phones and the internet might not use them for TB health-related activities. Thus, analytical results (Table 2) showed that overall ICT diffusion, the use of mobile phones and internet access had significant impact on decreasing the incidence of Tuberculosis among Africans. This finding supports previous study that health sector ICT use reduces TB incidence (Lee et al, 2016); and could probably be linked to the use of ICT infrastructures in disseminating information regarding TB preventive services and programs. As identified by Kaplan (2006), information regarding TB vaccination campaigns disseminated through mobile phones, facilitated increased vaccine uptake, while reducing the incidence of tuberculosis in the society (Kaplan, 2006). Thus, policy should be reviewed with the view of strengthening strategies that promote ICT infrastructure use in promoting TB vaccination campaigns among African health systems.

More so, as shown in Table 3, the coefficients on aggregate ICT variable (ictfac), internet access and mobile phone use, were negative except for fixed telephone (Model 8). These coefficients were statistically insignificant throughout the models. This finding corroborates studies by Shehata (2016), which showed that ICT indicator variables lose their significance as control variables are being added to any model during econometric analysis, especially the DPM. That notwithstanding, findings from this study lend credence to findings documented in the bulletin of the World Health Organization and provide rationale for ICT use in healthcare delivery to reduce TB morbidity and mortality rates. These are linked to the role ICT tools play in coordinating TB management including referral mechanisms, treatment initiations and case monitoring to ensure treatment adherence and completion (Kaplan, 2006). It corroborates study by Choun et al. (2017) who demonstrated how mobile phones with internet access were used in facilitating TB diagnosis, referrals and treatment monitoring among patients at the Sihanouk Hospital Center of Hope (SHCH) in Cambodia that resulted in reductions in mortality rates among registered TB patients.

In addition, findings from this study also support the study by Kahn (2004), which identifies mobile phones as important tool in TB management. To effectively treat TB, patients must be strictly compliant to TB medications protocol – four pills of anti-tuberculosis medications, five times per week for a period of six months (WHO, 2010). Thus, possession of a mobile phone with an internet access has opportunities to improve TB management and reduce morbidity. SMS technology and other treatment-reminder protocols can be harnessed by TB patients, thereby facilitating treatment adherence and completion, and reducing mortality (Kahn, 2004; Lee et al, 2016). Consequently, it is recommended that African governments at all levels review policies in view of consolidating an ICT-driven medical practice and guidelines to ease clinical practice, improve performance and reduce TB-related morbidities and mortalities.

That notwithstanding, results from analytics for the control variables indicated that country health standard was associated with economic and socio-demographic factors. Education, health expenditures and the net external official aid to the health sector had positive associations with study health outcomes. There associations led to a reduction in TB incidence and mortality rates. These findings corroborate findings from study by Gupta et al. (2002) which identified positive associations between population health measures and economic factors. However, undernourishment had significant negative effects on study health outcomes (Table 2). This could be linked to the fact that undernutrition negatively impacts immunity especially among immunocompromised individuals like TB patients. Undernutrition breeds malnutrition and exacerbates TB morbidity and mortality (Cegielski and McMurray, 2004). Nonetheless, of note is the fact that the coefficient on health expenditure was positive (Model 7). A plausible explanation to this is the misallocation of resources and mismanagement of funds meted for the health sector leading to waste of resources and poor health outcomes (Gupta et al, 2002). Thereby, justifying the need for an efficient health sector resource allocation and management.

However, it must be noted that this study had some inherent limitations. For instance, this study found that mobile phone and internet use had significant impact on TB health outcomes. Therefore, we infer this result because of the superior communication functionalities associated with mobile phone and internet use in easing communication and absolving misconceptions related with TB. In addition, the study methodology involved the use of secondary data which may not have been collected under standard procedures. The validity of this data could affect the robustness of our study findings and may affect the transferability of study findings to other population groups. Consequently, future studies, particularly granular small-scale studies, will be required to further explore and validate this study's interpretations.

In recent times phones with internet access are increasingly available, making it difficult to differentiate between mobile phone users and internet users. Thus, in view of this, a new variable should be defined, and its impact on health outcome attributes evaluated in future studies. Besides, this study evaluated data from 2000 until 2016, in this era of big data. Future studies could involve the use of analytics to search through larger volume of rich data across a wider time span to conduct a detailed longitudinal retrospective study, to identify more trends, patterns and associations.

Conclusion and Policy Implications

Overall, study findings showed that promoting ICT use among the public has opportunities for improving tuberculosis incidence and mortality rates. However, the impact of individual ICT infrastructures on improving TB health outcomes are different. This study inferred these differences to be a result of the different functionalities embedded within different ICT infrastructures, and the peculiar features of the health outcomes studied.

Important policy implications of the study findings for the African government and the global community is that ICT use improves health outcomes. In addition to allocating resources to specific health projects or interventions to improve population health, investing in ICT infrastructures, as well as educating the population on the use of ICT tools could be an alternative policy to improve population health. Thus, with efficient guidance, enlightenment and access to ICT infrastructures, individuals could be empowered to become active and independent agents to explore, and benefit from information technology complementing government efforts to improve public health.

Appendix

Exhibit A

Countries used in this analysis as listed by the World Health Organization. Available at: http://www.who.int/countries/en/ accessed May 20, 2017.

African region: Algeria, Burundi, Burkina Faso, Benin, Angola, Cameroon, Botswana, Cape Verde, Central African Republic, Comoros, Chad, Congo, Democratic Republic of Congo, Cote d'Ivoire, Djibouti, Equatorial Guinea, Egypt, Eritrea, Ethiopia, Gabon, Ghana, Guinea-Bissau, Lesotho, Gambia, Guinea, Kenya, Liberia, Libya, Malawi, Mauritania, Mali, Madagascar, Mauritius, Mozambique, Morocco, Nigeria, Namibia, Niger, Sao Tome and Principe, Seychelles, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Swaziland, Togo, Uganda, Tunisia, Tanzania, Zambia, Zimbabwe.

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JOURNAL ARTICLE 2

Mobile Phone Use and Tuberculosis Health Outcomes among African Health Systems: A Geospatial Analytic Approach

Journal: International Journal of Infectious Diseases

BACKGROUND

Mobile phones are increasingly becoming available and accessible globally. An approximated 6.8 billion mobile phones were in use in 2013 compared to 1 billion in 2002 across the globe, corresponding to a 96% penetration rates. This translates to about 128% and 89% penetration rates among developed and developing countries respectively (ICT, 2013). The estimated mobile phones penetration rates among Sub-Saharan Africa was 63% in 2013 and was projected to rise greater than 70% by 2015 (Deloitte, 2012). Many people who could not access traditional fixed-telephones for telecommunication now use mobile phones on daily basis. Compared to the wired information technology, the wireless technology is less expensive and are readily available for individuals in many developing countries. Thus, the wireless technology has opportunities to facilitate communication exchange in remote and impoverished communities (Clifford and Clifton, 2012), and could be harnessed to improve population health.

Information Technology (IT) drive transformational changes in national developments and the economy and becomes a feasible tool in all population health improvement campaigns

(Shehata, 2016). World leaders and notable United Nation agencies had reiterated the need for the use of IT to drive economic growth, empower rural communities and improve population health among developing countries. In addition, reputable agencies including the World Bank, the Organization for Economic Co-operation and Development (OECD) and the International Telecommunication Union (ITU) among others have also expressed optimism on the use of information system strategies to promote population health (WHO, 2014; ITU, 2015).

According to World Bank, common devices used in Information and Communication Technology (ICT) include fixed-telephone lines, computers, wireless cellular phones, and the internet to mention a few (World Bank, 2003; Leena et al, 2005; Chinn and Fairlie, 2010; Gagnon et al, 2012). However, this study focused on mobile phone use, and its impact on TB health outcomes. Mobile phones facilitate information exchange and transfer without spatial barriers at high efficiency and low cost (Shade, 2004; Shehata, 2016). With the advent of smart phones with internets, people can easily access health information and services. Individuals especially those in rural communities have access to mobile phones than computers and are inclined to use them to access health information beside making and receiving calls (Shade et al, 2012).

Numerous studies have shown that increases in smartphones access have a direct relationship with the scope of health information and service provisions and exchange between patients and providers (Micevska, 2005; Chinn and Fairlie, 2010; Lee et al, 2016). Smart phones with internet access facilitates easy browsing of health reliable websites for medical and health-related information. Thus, users can search for information regarding any ailment including available treatment options, medications-related side effects, and treatment specialists. Doctors can also search health-related information in view of learning, research and development. National surveys conducted among 250 women in India, Uganda, Egypt and Guinea Bissau in 2012, showed that an approximate 84% of the women sampled desired to receive healthcare-related information. However, 39% of these women wished to receive such information through their mobile phones than any other ICT tool (AUSAID & USAID, 2012).

Consequently, ICT becomes a feasible tool to transform the health paradigm, as it shifts the provider-patient configuration (Lucas, 2008). Health sector ICT adoption proffers integrated health information systems that has capacity to effectively manage different information systems and networks from diverse centers for an improved functional health system. ICT applications enhance the operational efficiency among medical institutions, research institutions and healthcare centers. For instance, Micevska (2005) discovered that in Peru, Bangladesh, and Laos, basic information systems (telephone services) proffers an opportunity for the real-time transmission of patient-related information. Thus, health personnel and supervisors can track and monitor patients' symptoms through fixed telephones or cellular phones, collate and input data into a central database accessible to other health personnel. Consequently, by updating patients' medical information on this portal in a timely fashion, personnel at medical institutions can track and monitor infection of communicable diseases in hard-to-reach areas, and effectively allocate medical supplies and drugs. This approach enabled healthcare personnel to make better treatment decisions for optimal outcomes (Micevska, 2005).

Mobile phone brought new opportunities to the Sub-Saharan Africa. It links people to people, information and services. In Nigeria, people can call friends over 500 kilometers away with ease. In Niger, artisans can call their contacts in Cameroon to explore job opportunities without making the $100 journey; and in Kenya, tuberculosis patients can receive text messages on daily basis, reminding them to take their anti-tuberculosis medications as scheduled. Therefore, with most of African population in the rural areas, mobile phone use becomes invaluable in facilitating health information and services availability and exchange (ITU, 2003; Shehata, 2016). Doctors irrespective of geographical locations can diagnose and recommend management promptly through conversations over the phone. In Mozambique, mobile health treatment intervention was introduced to enhance communications between patients and healthcare supervisors. The goal was to use the mHealth strategy to facilitate treatment retention and completion among patients receiving anti-tuberculosis medications in Mozambique. This model resulted in higher treatment completion rates among study participants. It improved medication refills, reduced missed-appointments, and improved care coordination among relevant health systems evaluated. Overall, this approach became novel and successful, and served as a model for other health centers regarding TB management (Nhavoto et al, 2017).

Theoretically, mobile phone use in TB control has opportunities to integrate surveillance data with case-management data to improve service provisions. In Vietnam, mHealth strategy was used to curb the incidence of multidrug-resistant TB (MDR-TB). Vietnam is a country with significant burden of TB and has about 90 percent treatment success rates of TB across board. However, an estimated 25 percent of those treated recur as MDR-TB. Thus, with support from Global Fund and Vietnamese government, PATH (an international non-governmental organization) intervened by harnessing the power inherent in mobile technology to keep patients and healthcare workers updated on treatment schedules. They introduced the use of a cellular phone-based system in the Ba Ria-Vung Province of Vietnam to improve TB treatment adherence and completion. Mobile messages were sent to patients to keep them on track on when to attend sputum tests, take TB medications, and come for medication refills. Treatment supervisors at the various health facilities also had access to this digital network. They monitor patients' information including sputum results, treatment regimens, medication side effects and missed-appointments among others. This model resulted in drastic reductions in MDR-TB cases in Vietnam and provided the justification for the inclusion of this strategy into the Vietnamese National Tuberculosis Control Program (PATH, 2017).

That notwithstanding, Chadha and colleague demonstrated how the ComCare mobile application was used to coordinate TB referrals among patients in the Khunti District of India. This study evaluated the impact of a newly introduced mHealth strategy in TB management. Study result showed that this mobile technology increased provider accountability to patients and led to an overall improved coordinated TB patient referral, and care among their networks (Chadha et al, 2017). Findings from this study corroborated study by Khan (2004); who demonstrated how mobile phones were used to efficiently coordinate TB management in South Africa.

Conceptually, to effectively treat TB, patients must take four pills of anti-tuberculosis medications five times per week, for a period of 6 months (WHO, 2010). It is very easy for this treatment to fail because patients could easily forget to take their medications. Therefore, in 2002, the South African health system introduced the use of health information systems including cellular phones, SMS technology, and computer databases, to support patients adhere to treatment protocols. Every half hour, facility database will automatically list the patients who are due for their medications, and an automatic reminder Short Messages Services (SMS) sent to their mobile phones. This model enhanced TB treatment adherent and completion rates among patients included in this treatment program.

While multiple studies have documented the impact of mobile phone use on TB health outcomes for varied settings, it is not immediately clear if there are geospatial autocorrelation in TB treatment completions rates among African countries. Consequently, this study provides insights to the cluster patterns in TB treatment completion rates among African countries. It also investigated geospatial relationships between mobile phone use and TB treatment completion rates among African health systems. To answer these questions, this study conducted geospatial analyses using aggregate data obtained from the World Bank database on 53 African sovereign countries for the periods 2000 through 2015. We focused on Sub-Saharan African population because of data availability, presence of a large and diverse TB populations, and the need to justify the use of mobile phones in TB programs.

Previous studies have focused on evaluating TB medication access using geospatial disaggregated datasets of population characteristics (Aker and Mbiti, 2010). Hassarangsee et al. (2015) investigated the spatial detection and management of Tuberculosis using information systems in Si Sa Ket Province, Thailand. Thus, the need to explore TB treatment completion cluster patterns among African health systems cannot be over-emphasized. Consequently, this study aimed to fill this important research gap by investigating geospatial autocorrelation levels, evaluate patterns of treatment completion clusters among patients on TB medications, and ascertain the spatial relationships between mobile phone use and TB treatment completion rates among African health systems. If there is any significant association, then the system will strengthen policies supporting mHealth strategies in view of TB management. Findings from this study hopefully will increase the understanding of spatial TB treatment outcomes among African countries, and therefore act as reference for other researchers,

This study focused on the use ArcGIS and GeoDa to determine geospatial relationships between mobile phone use and TB treatment completion rates using Exploratory Spatial Data Analysis (EDSA). In addition, geospatial analytic approach was used to assess spatial autocorrelation and to generate hotspots for TB treatment completion rates among the Sub-Saharan African countries. Such geospatial population health analyses have opportunities to support monitoring in many aspects of development, healthcare and resource allocation; and could provide frameworks for policy making. This study provides a timely insight on spatial TB treatment analyses, provides rationale for intervention mapping and reduce healthcare cost. Results from this study will help policy-makers and other key players better understand TB treatment completion cluster patterns among African health systems. This has opportunities for improving national health systems by informing policy-makers on healthcare priority setting and resources allocation.

Materials & Methods

Description of Study Area

According to the CIA World Factbook (2016), Africa is a continent surrounded by water bodies. It is bounded to the West by the Atlantic Ocean, to the south by the Southern Ocean, to the East by the Indian Ocean, and to the North by the Mediterranean Sea and the Red sea. It has a land area of 28,489,869 sq. km, a tropical climate, and terrain from rolling coastal plains to low mountains. As at July 2016, the African population was estimates to be 1,119,307,147, and the population is distributed throughout 54 countries. While the highest point in Africa is Mount Kilimanjaro, the lowest point is Lake Assal (CIA, 2016).

Data Sources

The base map of Africa (Figure 1) was obtained from ArcGIS (ArcGIS, 2017). Data for TB treatment completion rates among African countries was obtained from the World Bank database for the periods 2000 through 2015. However, this was only available for some countries and with limited years. Therefore, this study did not include countries with incomplete data. Altogether, data from 53 countries of Africa was used for this study analyses. We believe that this sample was a good representative of the African continent and suitable for geospatial analyses. Population health outcome data for these countries are usually collated, de-identified and aggregated per country and published at the end of each year by World Bank. Thus, this qualifies as a minimum risk given that it did not violate the rights or impose any risk on human subjects. Thereby, making this study qualify for an Institutional Review Board (IRB) exempt (Gostin, 2008).

Comparative Statistical Analyses

The ArcGIS and GeoDa statistical software were used in all spatial analyses which was done in three stages and was completed in February 2018. In GeoDa, a univariate local Moran's I and a global Moran's I were run on TB treatment completion rates separately, followed by a differential local Moran's I analyses to ascertain differential cluster patterns for different periods. Finally, spatial relationships between mobile phone use and TB treatment completion rates was evaluated using bivariate Moran's I technique (Kraak, 2004).

To investigate the pattern of clusters in TB treatment completion rates among African countries, spatial and tabular data were uploaded into ArcGIS 10.5.1. After data cleaning in Excel, geographically referenced data for mobile phone use and TB treatment completion rates for four time-periods (2000, 2005, 2010, 2015) were extracted for each country. The table representing these two variables were added and joined to the African map by country shapefile. The cumulative percentage of mobile phone use and that of TB treatment completion rates was summed for each country and shaded by these values. Study dataset was further analyzed using an Exploratory Spatial Data Analyses (EDSA) approach to reveal and visualize patterns and identify trends among geographically referenced data.

There are several analytical approaches to EDSA. To measure spatial autocorrelation, Moran's I is classically used (Moran, 1950; Kraak, 2004). Conceptually, the Moran's I measure spatial autocorrelation by exploring if a variable change over time in any location is statistically related to its neighboring locale. The global Moran's I statistic gives an overall measure of spatial autocorrelation (Highfield, 2013). Theoretically, spatial autocorrelation represents a measure of the degree of data dependency in space and is akin to the Pearson correlation coefficient (Anselin, 2000; Highfield, 2013). The Local Indicator of Spatial Association (LISA) represents the localized equivalent of the global Moran's I (Anselin, 2003). Thus, for any location on the map, the LISA statistic measures and statistically tests the similarity of the geographically referenced data for that location (e.g., TB treatment completion rates at the source country tract) with the values of its corresponding local neighbors in space (surrounding country tracts). Local Differential Moran's I (LDMI) statistic measures if a variable change in space over time is related to its neighbors. The principle behind the LDMI is that this measure determines spatial autocorrelation on change over time ($y_t - y_{t-1}$). Thus, for this study, Differential cluster patterns were evaluated between the base time 0 (year 2000) and time 1 (year 2005), time 2 (year 2010) and time 3 (year 2015) respectively. The trend in clusters generated were evaluated in view of TB treatment completion rate outcomes among different African countries and empirical inferences drawn.

Bivariate Local Moran's I Statistic

This study also used a geographically based measure of spatial correlation analytic approach (BiLISA). The rationale for using BiLISA was based on the areal nature of TB data. BiLISA has an inherent ability to account for areal data during spatial autocorrelation assessment using contiguity matrix that assess neighboring values. The formula for calculating the Bivariate Local Moran's I statistic is shown below:

$$I_{kl}^{i} = z_k^i \sum_j w_{ij} z_l^j$$

Where *l* and *k* represent mobile phone use and TB treatment completion rates for country tracts *i* and neighboring tract *j*, respectively. Z_l and Z_k represent standardized Z-scores of the *l* and *k* variables respectively. Overall, for each variable, the standardized Z-score values are calculated as the observed rate (e.g., TB treatment completion rate) at location i minus the mean rate of the surrounding neighbors j (e.g., mean TB treatment completion rates for all neighbors) divided by the standard deviation. W_{ij} represents the geospatial matrix which is a binary contiguity matrix. This matrix provides geospatial structures for all locations included while calculating the Local Moran's I statistic. Conventionally, under the queen first order principle, contiguity geospatial neighbors with common boarders and vertex have weights equals to one. Thus, observations that share common boarders have weights equals to one, else the weights are equals to zero (Anselin, 2003; Highfield, 2013).

The bivariate Moran's I statistic which is also known as bivariate LISA (BiLISA) and evaluates the degree of linear association (negative or positive) between y variable (e.g., TB treatment completion rate) at any given location and the average of the x variable (e.g., mobile phone use) at any given geographic location in space (Anselin, 2003). Comparable to LISA measures, the BiLISA statistic generates two spatial distinguishable clusters – Positive and Negative autocorrelation clusters. While positive spatial autocorrelation is placed into two categories including High-High and Low-Low clusters; the negative autocorrelation is placed into two categories of outliers including High-Low and Low-High cluster patterns. While High-High clusters denotes above-average values of the core countries/regions compared to neighboring regions; Low-Low means below average values of the countries/regions compared to neighboring countries or regions. Low-High clusters would mean small changes in the core countries versus high changes in the surrounding neighbors. Conversely, High-Low cluster patterns means high changes in the core countries/regions versus small changes in the neighbors. Thus, while interpreting the outliers, the focus would be on the magnitude of changes among core countries compared to their neighbors (Anselin, 2003). Therefore, inferences for Moran's I statistics is based on permutation tests, sensitivity analyses (Monte Carlo Simulation) and significance levels. Ideally, a geographically referenced distribution is computed for spatial randomness, and compared with observed data over numerous iterations (Anselin, 1995; Highfield, 2013). For this study, a randomization of 999 permutations was used prior to result interpretations, and his study only analyzed observations with neighbors.

The objective of this study was to identify countries in Africa with low TB treatment completion rates and those with reduced use of mobile phones in coordinating TB programs among the geographically referenced data. Using the ESDA approach to identify these countries would be the first step towards addressing issues related to access and penetration of ICT infrastructures. Thus, the ESDA geospatial model could identify countries with the highest need for intervention in the face of limited resources.

Findings

The study uses geospatial data for 53 African countries (Figure 1) over the period 2000 – 2015 accessed from the World Bank database listed in the appendix section (Exhibit A).

Figure 1: Map of Africa highlighting countries.

African shapefile culled from ArcGIS, (2017)

Results for Univariate global Moran's I analyses

Univariate global Moran's I values and associated pseudo p-values are as shown in Table 1. The scatterplot outputs associated with the univariate Moran's I are also provided in the appendix section (Exhibit B).

Table 1: **Univariate global Moran's I result for the years 2000 – 2015.**

	Variables	Moran's I value	Pseudo p-value
Univariate	TB Rate Year 2000	0.0190	0.021
	TB Rate Year 2005	0.0177	0.032
	TB Rate Year 2010	0.0196	0.025
	TB Rate Year 2015	0.0179	0.031

Figure 2: Clusters and significance levels of TB treatment completion rates in year 2000

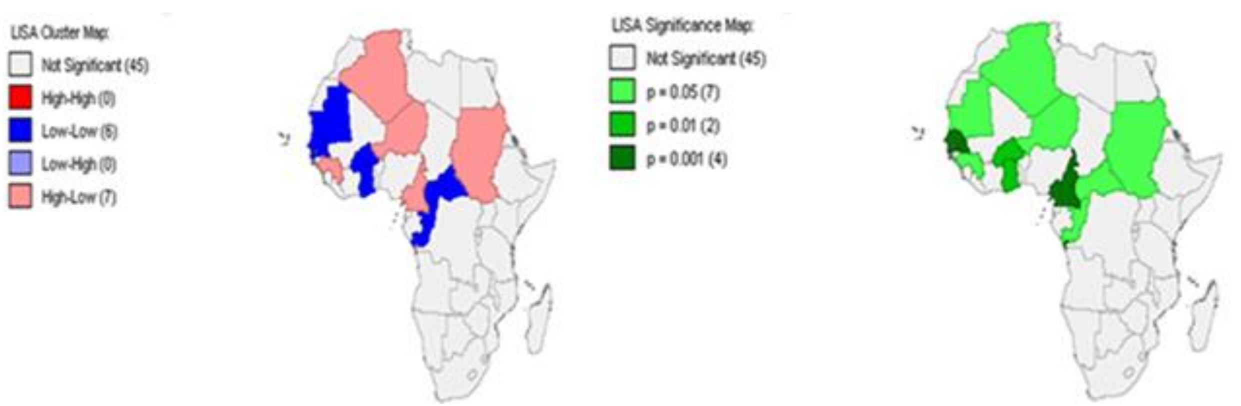


Figure 2 shows the clusters and significance levels of TB treatment completion rates in the year 2000. LISA analytic approach generated thirteen countries with statistically significant spatial autocorrelation cluster patterns at different p-values (0.001, 0.01, 0.05). Two different cluster patterns (High-Low and Low-Low) were generated.

Figure 3: Clusters and significance levels of TB treatment completion rates in year 2005

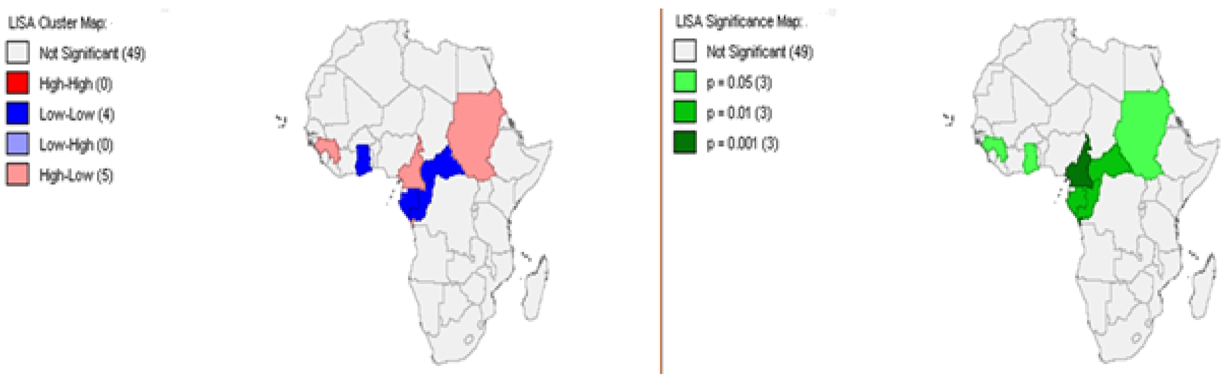
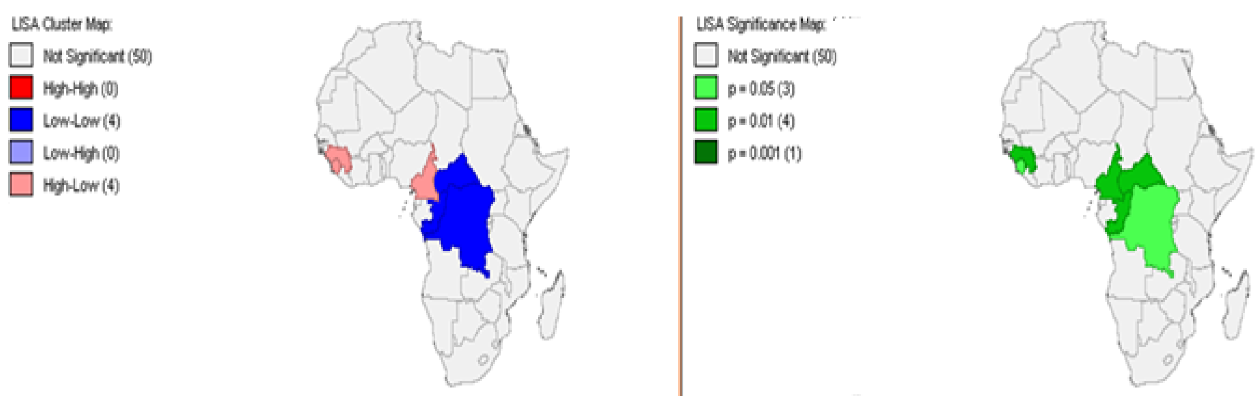


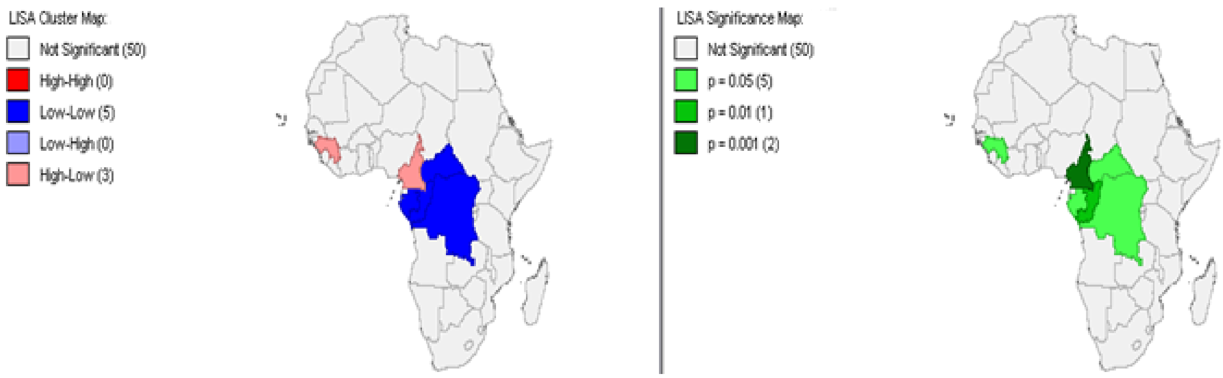
Figure 3 shows the clusters and significance levels of TB treatment completion rates in the year 2005. Nine countries had significant cluster patterns at different p-values (0.001, 0.01, 0.05). Two different cluster patterns (High-Low and Low-Low) were generated using LISA analytic approach (Anselin, 2003).

Figure 4: Clusters and significance levels of TB treatment completion rates in year 2010



The clusters and significance levels of TB treatment completion rates maps for the year 2010 are shown in figure 4. Eight countries had significant clusters at different p-values (0.001, 0.01, 0.05). Low-Low and High-Low cluster patterns were generated After LISA analyses (Anselin, 2003).

Figure 5: Clusters and significance levels of TB treatment completion rates in year 2015



The clusters patterns and significance levels of TB treatment completion rates for the year 2015 are highlighted in figure 5. Overall, eight countries had significant clusters at different p-values (Anselin, 2003).

Results for Differential Local Moran's I analyses

That notwithstanding, results from the differential local Moran's I tests are shown in Table 2. The differential local Moran's estimation was done to ascertain how the pattern of clusters between the base time-0 (year 2000) compares with the other time-periods evaluated in this study including: Time-1 (year 2005), Time-2 (year 2010) and Time-3 (year 2015) respectively. Table 2a gives the result for differential Local Moran's I estimations between time 0 and time 1.

Table 2a: Clusters and significance levels of TB treatment completion rates from differential Local Moran's I estimations between time 0 (2000) and time 1 (2005)

Variable	Countries	Cluster Type	Pseudo p-value
	Algeria	High-Low	<0.05
TB_2000 & 2005	Burkina Faso	Low-Low	<0.05
	Senegal	Low-Low	<0.001

Three countries had significant spatial autocorrelation clusters including Algeria, Burkina Faso and Senegal at different p-values.

Table 2b: Clusters and significance levels of TB treatment completion rates from differential Local Moran's I estimations between time 0 (2000) and time 2 (2010)

Variable	Countries	Cluster Type	Pseudo p-value
	Niger	Low-Low	<0.05
	Senegal	Low-Low	<0.001
	Gambia	Low-Low	<0.001
TB_2000 & 2010	Namibia	Low-High	<0.05
	Lesotho	Low-High	<0.05
	Djibouti	Low-High	<0.05
	Algeria	High-Low	<0.05
	Cameroon	High-Low	<0.05
	South Africa	High-Low	<0.05
	Dem Rep Congo	High-High	<0.05
	Kenya	High-High	<0.05
	Sierra Leone	High-High	<0.05

12 countries had significant spatial autocorrelation clusters at different p-values including Niger, Senegal, Gambia, Namibia, Lesotho, Djibouti, Algeria, Cameroon, South Africa, Democratic Republic of Congo, Kenya, and Sierra Leone. There were four cluster patterns that were significant at varying p-values as shown in the maps in the appendix section (Exhibit C). Three countries had Low-Low cluster patterns; three countries had Low-High cluster patterns;

three countries had High-Low cluster patterns, and an additional three countries had High-High cluster patterns.

Table 2c: Clusters and significance levels of TB treatment completion rates from differential Local Moran's I estimations between time 0 (2000) and time 3 (2015)

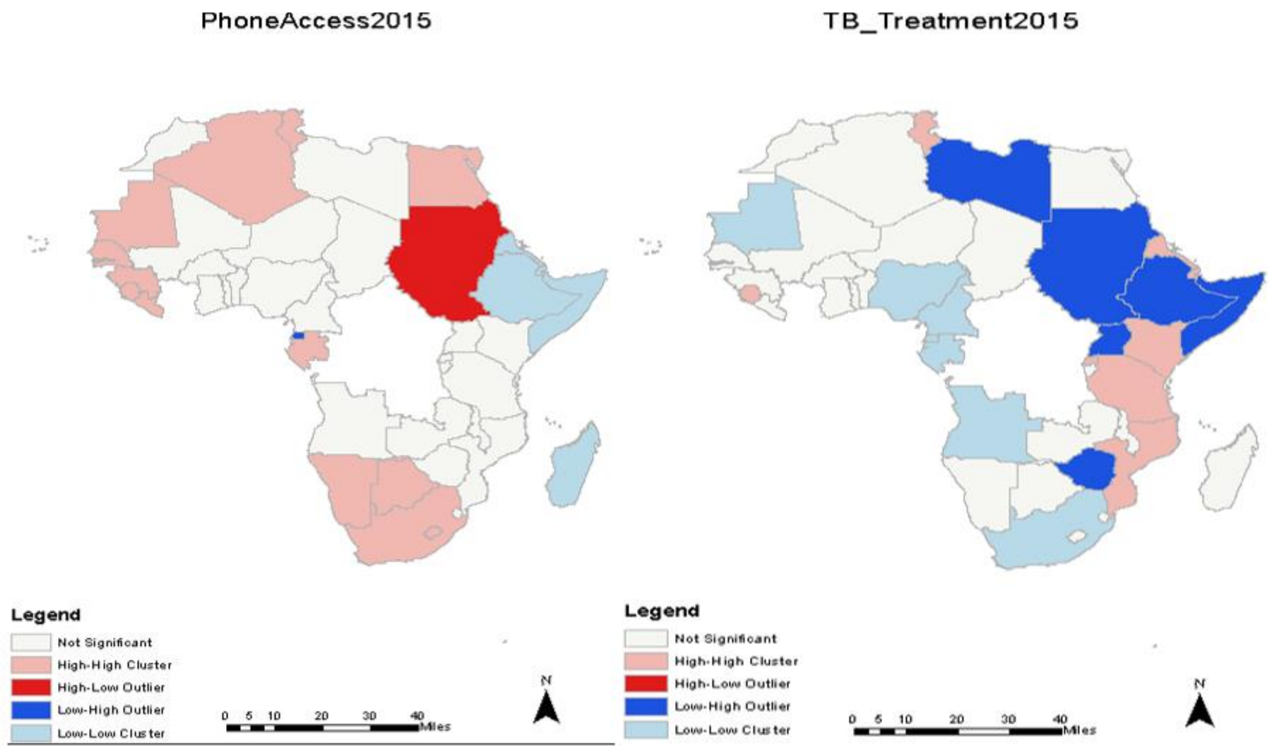
Variable	Countries	Cluster Type	Pseudo p-value
	Niger	Low-Low	<0.01
	Burkina Faso	Low-Low	<0.01
TB_2000 & 2015	Senegal	Low-Low	<0.001
	South Africa	Low-Low	<0.05
	Algeria	High-Low	<0.05
	Cameroon	High-Low	<0.05
	Dem Rep Congo	High-High	<0.05

From the output above, seven countries had significant spatial autocorrelation clusters including Niger, Burkina Faso, Senegal, South Africa, Algeria, Cameroon, and Democratic Republic of Congo. There were three different cluster patterns that were significant at different p-values as shown in the maps in the appendix section (Exhibit C). Four countries had Low-Low cluster patterns; two countries had High-Low cluster patterns, and an additional one country had High-High cluster patterns.

Results for Bivariate Moran's I Analyses

Bivariate Moran's I evaluation between mobile phone use and TB treatment completion rates was done to ascertain spatial correlation levels between these two population health variables among African health systems.

Figure 6: Bivariate Moran's I evaluation result between Mobile Phone and TB treatment Completion Rates



Discussion & Policy Implications

Exploratory spatial data analyses identified statistically significant clusters in TB treatment completion rates among some countries of Africa. Results from the univariate global Moran's I identified positive spatial autocorrelation, represented by significant clusters among relevant African countries (Figures 2 – 5). Ideally, what this test does is to explore if a variable change over time in any location is statistically related to its neighbors or not. Thus, spatial autocorrelation patterns generated across the four periods of study analyses were consistent with Low-Low and High-Low cluster patterns and were significant at different p-values (Figures 2 – 5). Most countries in Africa except those in the Southern region of African had significant clusters (Figures 2 – 5). Majority of the African countries were overrepresented in low-low cluster tracts (14 countries) and high-low cluster tracts (10 countries). Low-Low clusters implies that TB treatment completion rates between 2000 – 2015 were below-average changes in these countries and its neighbors. Similarly, High-Low clusters translate to high changes in the core countries versus low changes in their neighbors (Anselin, 1995; Anselin, 2000). For instance, in 2000, Algeria located in the Northern African region had a “high-low” cluster tract (Figure 2). This implies that the treatment completion rate for TB in Algeria in 2000 is high compared to low rates among her neighboring countries. Similarly, Sudan located in East African had a “low-low” cluster tract – implying that TB treatment completion rates in Sudan in 2005 was below average compared to her spatial neighbors (Figure 3**).** Congo located in the Central African region also had a “low-low” cluster tract in 2010. This means that TB treatment completion rates in Congo in 2010 was below average compared to her spatial neighbors (Figure 4). These findings were consistent with the pattern of TB medication access and adherence among African countries (WHO, 2017), and have opportunities to inform intervention mapping, resource allocation and policy formulation.

Study results also indicated that only a few countries had complete treatment for TB across Africa within the period of this study analyses. Only 13 countries out of 54 had significant TB treatment completion rates in 2000 (Figure 2), nine countries in 2005 (Figure 3), eight countries in 2010 (Figure 4), and eight countries in 2015 (Figure 5). These findings may probably be attributed to the continuous paucity of healthcare professionals, fund mismanagement and health system infrastructural decay that perpetrates African health systems. Thereby, corroborating WHO reports on poor standards among African health systems (Okogbule, 2007; WHO, 2014). It was also noted that a downward trend existed in TB treatment completion rates between 2000 – 2015 (Figures 2 – 5), with fewer countries having TB treatment completion from 2000 through 2015, necessitating immediate review to understand the cause of this negative trend, and possible interventions by relevant stakeholders. Thus, future research could be directed at investigating the cause of this trend, and necessary recommendations made to inform policy.

Furthermore, differential Moran's I cluster maps identified hotspots among African countries, with greater cluster changes occurring across the periods between 2000 and 2015. The base-case analysis identified three countries with significant clusters including Algeria, Burkina Faso and Senegal (Figures 7 – 9). However, as listed in the appendix section (Exhibit C), the cluster patterns in Burkina Faso and Senegal were Low-Low cluster tracts. Low-Low cluster patterns associated with Burkina Faso and Senegal implies that TB treatment completion rates was below average changes in this country compared to her neighbors. Conversely, Algeria was overrepresented with high-low cluster patterns which translates to high changes in TB treatment completion rates in Algeria versus low changes in her neighbors (Figures 7 – 9; Exhibit C).

While the time-period 2 analysis identified 12 countries with positive clusters (Figure 8; Exhibit C); the time-period 3 analysis identified eight countries with significant clusters (Figure 9; Exhibit C). Altogether, two countries including Algeria and Senegal had significant clusters across the three time-periods of study evaluation (Figures 7 – 9; Exhibit C). This finding could plausibly be attributed to the relative political stability and substantial infrastructural developments which have been existent in these two countries since their independence. Studies show that socio-economic stability and development have opportunities to facilitate service delivery and improve health indices (Tito et al, 2008; WHO, 2014).

However, many countries including Democratic Republic of Congo, Niger, South Africa and Cameroon among others also had significant clusters at least in two time-periods (Figures 7 – 9; Exhibit C). These findings could possibly be attributed to improvements in infrastructural and developmental policies in these nations. For example, the WHO regional office for Africa is located at the Republic of Congo. WHO formulates TB treatment guidelines and policies and takes the lead in its implementation. Thus, explaining the persistent high clusters in TB completion rates in Republic of Congo compared to their neighboring countries (Figures 7 – 8; Exhibit C). However, despite significant clusters found in Congo by this study, Linguissi et al. (2017) maintained that the burden of TB remains high. Their study identified Republic of Congo as one of the countries documented by WHO with high burden of TB (Linguissi et al, 2017). Thus, even though the Republic of Congo had significant clusters in TB treatment completion rate compared to neighboring countries, there is need to reinforce strategies and interventions to fight TB to keep its incidence down. This means that identifying significant clusters in TB treatment completion rates in any country does not translate to that country being TB free. We propose future studies to be done in this regard, with the view to evaluate the cause of this high TB burden in Congo Republic despite having significant clusters in TB treatment completion rates.

Furthermore, South Africa is one of the nations with the most coordinated TB programs in Africa (WHO, 2014). Findings from this study corroborates this status quo (Tables 2a-c). South Africa had significant high TB treatment completion rates compared to her neighboring countries (Figures 8 – 9; Exhibit C). This finding could be attributed to the coordinated TB control initiative introduced in 2010 by the South Africa government. This model improved TB treatment adherence and completion rates in South Africa across board (Khan, 2014), and could plausibly explain why significant clusters existed only in 2010 and 2015, and not in 2000 prior to this mHealth strategy implementation (Figures 7 – 9; Exhibit C).

However, despite government efforts to curb the incidence of TB in South Africa, latest study by the WHO (2017) identified South Africa to be one of the seven countries that accounted for 64% of global new cases of TB infections. Other countries include Nigeria, India, China, Indonesia, Pakistan and Philippines (WHO, 2017). Thus, notwithstanding significant TB treatment completion clusters identified by this study, the burden of TB in South Africa remains high. Justifying the need to further explore this disparity by future studies and necessary recommendations made to inform policy.

Exploratory spatial data analyses identified a statistically significant association between mobile phone use and TB treatment completion rates. As mobile phone use increased, TB treatment completion rates increased overall. However, dissecting this association with a local level geographical data revealed different cluster patterns including “high-high, high-low, low-high and low-low” cluster tracts (Figure 6). This study is exploratory in nature. It assesses correlation and not causation and becomes the first step in assessing the relationship between TB health outcomes and potential impacts of information systems, such as mobile phone use in TB programs among African health systems. Thus, bivariate local Moran’s I evaluation identified positive spatial autocorrelation, and significant hotspots (Figure 6). This means that the use of mobile phones in facilitating TB treatment adherence and completion rates among TB patients varied among countries as identified by this study. Relevant countries had varied cluster patterns in view of these two attributes (Figure 6). Altogether, ten countries including Mauritania, Sierra Leone, Equatorial Guinea, Gabon, Tunisia, Sudan, Eritrea, Djibouti, Somalia and South Africa had significant cluster tracts in view of these two attributes compared to their neighboring countries. This could probably be attributed to variations in infrastructural and developmental levels among African countries. Identified countries had advanced mobile phone penetration levels (WHO, 2014; ITU, 2017). Intuitively, high TB treatment completion rates are related to advanced mobile phone adoption levels, which translates to significant clusters compared to neighboring countries. This finding lends credence to studies by Chadha et al. (2017) which found that higher levels of health sector information system use translates to better health outcomes. Their study identified health sector ICT tools as a cost-effective approach towards consolidating TB control and management (Chadha et al, 2017). Thus, policy should be reviewed with the view of strengthening eHealth and mHealth strategies to foster TB medication adherence and completion among African health systems.

As indicated in reviewed literature, TB patients must be strictly compliant to medical treatment to effectively treat TB. This involves taking four pills of anti-tuberculosis medications five times per week, for a period of six months (WHO, 2010). Such adherence could be facilitated by removing barriers to access and utilization. A plausible approach would be utilization of information systems among health systems in all TB programs as documented by Aker and Mbiti, (2010). Consequently, possession of a mobile phone with an internet access can provide platforms through which SMS technology and other treatment-reminder protocols can be harnessed by TB patients, thereby improving efficiency in TB treatment processes. This study serve as baseline resource for future studies on spatial TB treatment cluster patterns as little work has been done in this area so far. Consequently, findings from this study could act as reference for other researchers, developmental organizations and policy-makers. Study findings also has opportunities to inform policy makers on healthcare priority setting, intervention mapping and resources allocation.

However, it must be noted that this study had some limitations. It utilized secondary data in its analyses which may not have been collected under standard procedures. The validity of this data could affect the robustness of our study findings and may affect the transferability of study findings to other population groups. More so, this study did not control for the presence or absence of factors that could influence access and utilization of healthcare services, which could also impact the generalizability of study findings to other settings. In addition, there were some inherent limitations in the datasets used for this study analyses. First, geographical data for cases from the

WHO and ITU were at the country level only. More detailed and granular spatial relationships could have been used and would have revealed if case locations were at a finer resolution or not. Thus, future studies should focus on using granular data for similar geospatial analyses. More so, some variables in the dataset lacked country information, and were not included in this study analyses. Finally, most data were compiled by patient caregivers, who could have been in difficult conditions. These could bias the validity of study results, thereby limiting the generalizability of study findings.

Conclusion

Exploratory spatial data analyses identified positive spatial autocorrelation for the periods evaluated, as well as varying cluster patterns in TB treatment completion rates across the periods of study evaluation. There was also a direct relationship between mobile phone use and TB treatment completion rates among relevant African countries. Thereby, necessitating the need to strengthen national policies that promote TB medication adherence and completion using eHealth strategies among African health systems.

Exhibit A

Countries used in this analysis as listed by the World Health Organization. Available at: http://www.who.int/countries/en/ accessed May 20, 2017.

African region: Algeria, Burundi, Burkina Faso, Benin, Angola, Cameroon, Botswana, Cape Verde, Central African Republic, Comoros, Chad, Congo, Democratic Republic of Congo, Cote d'Ivoire, Djibouti, Equatorial Guinea, Egypt, Eritrea, Ethiopia, Gabon, Ghana, Guinea-Bissau, Lesotho, Gambia, Guinea, Kenya, Liberia, Libya, Malawi, Mauritania, Mali, Madagascar, Mauritius, Mozambique, Morocco, Nigeria, Namibia, Niger, Sao Tome and Principe, Seychelles, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Swaziland, Togo, Uganda, Tunisia, Tanzania, Zambia, Zimbabwe.

Exhibit B

From top to bottom- scatter plots for the univariate global Moran's I test for the four time-periods evaluated in this study.

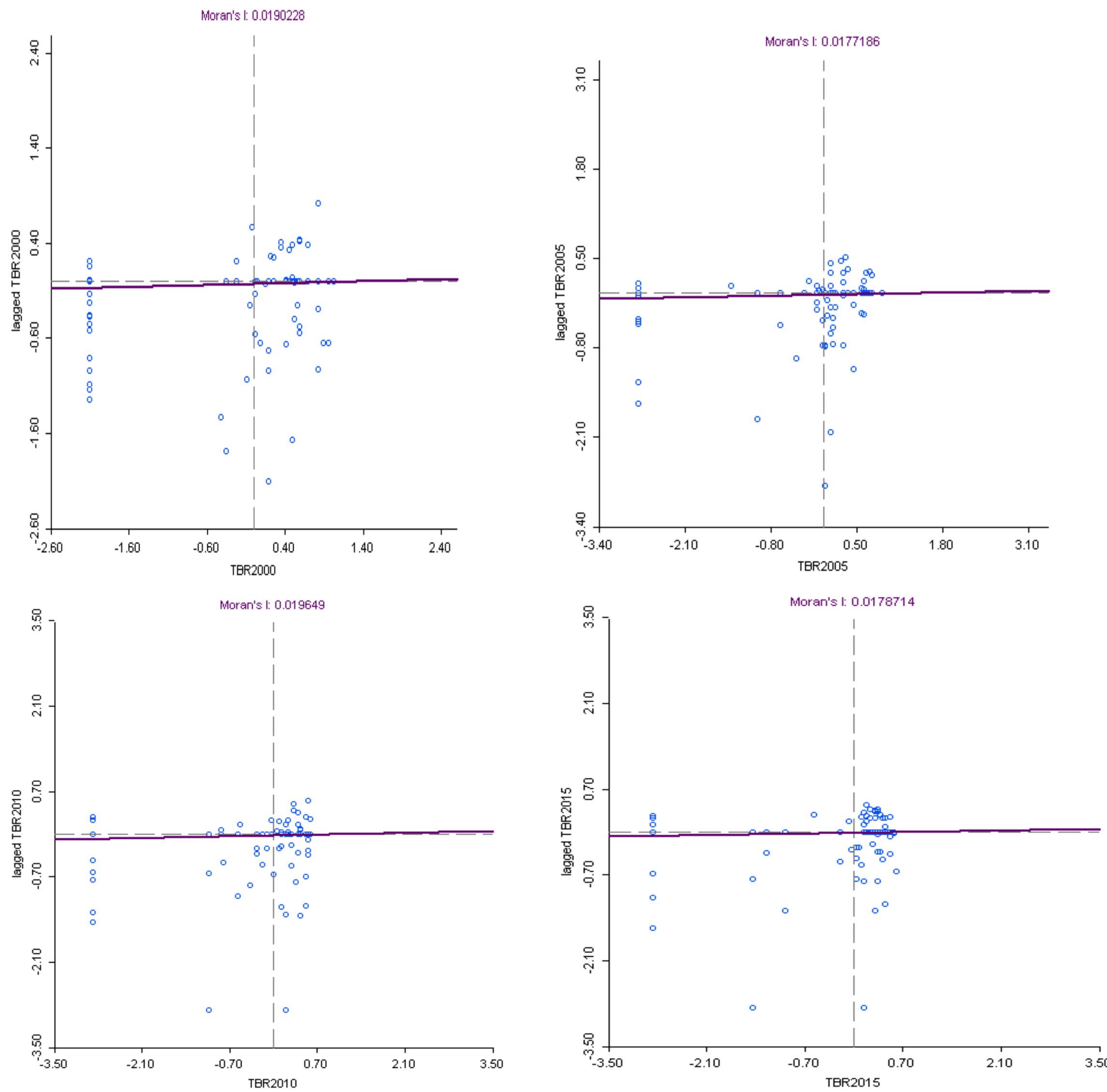


Exhibit C

Figure 7: Clusters and significance levels of TB treatment completion rates from differential Local Moran's I estimations between time 0 (2000) and time 1 (2005)

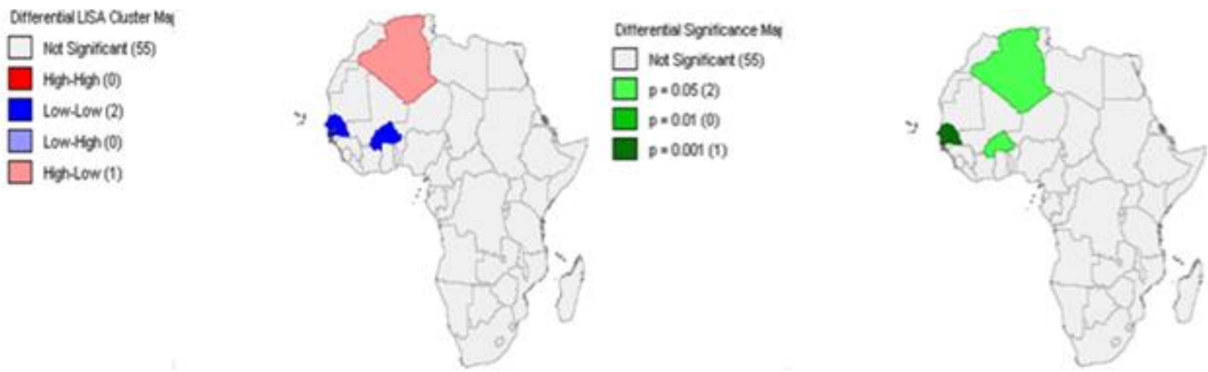


Figure 8: Clusters and significance levels of TB treatment completion rates from differential Local Moran's I estimations between time 0 (2000) and time 2 (2010)

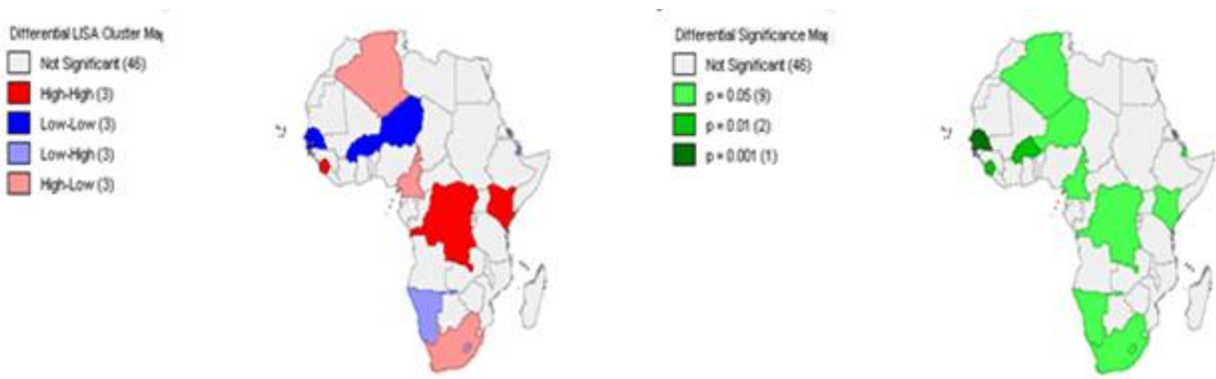
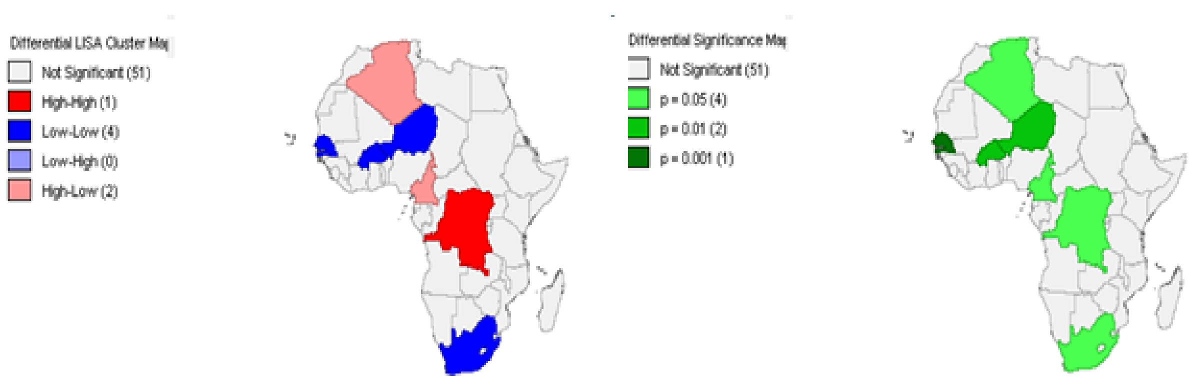


Figure 9: Clusters and significance levels of TB treatment completion rates from differential Local Moran's I estimations between time 0 (2000) and time 3 (2015)



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JOURNAL ARTICLE 3

Journal: Bulletin of the World Health Organization

The impact of Information and Communication Technology Infrastructures on HIV Health Outcomes among African Countries.

Introduction/Background

Discussions regarding eHealth in infectious disease management is well documented, and HIV/AIDS acknowledged as an important public health issue. Globally, new HIV infections dropped from 3.5 million to 2.1 million cases between 2000 and 2013. However, there was a remarkable increase in access to Antiretroviral Therapy (ART) over this period (United Nations, 2015). By June 2014, an estimated 13.6 million People Living with HIV (PLWHIV) had access to ART compared to 2.1 million in 2000. Thereby preventing 7.6 million AIDS-related deaths between 1995 and 2013 (United Nations, 2015). This success had been attributed to innovations among global health systems including advancements in information systems among others (World Bank, 2007).

Despite the success and achievements made so far, studies show that gaps still exist in global ART coverage rates, especially among developing countries. These differences become significant between the rich and the poor. Most impoverished and vulnerable communities are frequently affected – only an approximate 36 percent of the 31.5 million PLWHIV in the developing parts of the world received ART in 2013 (United Nations, 2015). Thereby leaving significant gaps in ART coverage rates and necessitating coordinated HIV care using eHealth strategies.

This study seeks to investigate the effect of Information and Communication Technology (ICT) infrastructures' diffusion on HIV health outcomes among Sub-Saharan African countries. If there is any significant association, then the system will strengthen the eHealth practice including care coordination and service delivery using ICT tools. For this study, ICT diffusion was defined as the proportion of the continent of Africa population with access to ICT infrastructures precisely mobile phones use, internet access and fixed-telephone subscription. Ideally, the number of individuals utilizing ICT tools in receiving health informatics through ICT would have been used as the independent variable in this study. However, such data was not available for Africa on the international scale. Thus, those with a mobile phone, a landline phone and internet access were used as proxy variables, as they represent the potential for impact on health with utilization of ICT to access health information. In addition, some ICT-related variables could also 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 continental-level but not at the country level

Conceptually, ICT use among African health systems proffers smart, cost-effective innovations and solutions by harnessing Africa's digital revolution to strengthen national health systems. These include health information and service delivery to individuals through Information, Communication and Education (ICE). Health sector ICT use has opportunities to contribute to the actualization of the Sustainable Development Goals (SDGs), mainly SDG-3 on good health and wellbeing. In addition, it helps consolidate the Universal Health Coverage mandate among African health systems, including improvements in antiretroviral therapy coverage among others (WHO, 2015).

That notwithstanding, the use of ICT in the health sector also has opportunities for advancing population health strategies (Raghupathi and Raghupathi, 2013). Theoretically, ICT enhances communication and dissemination of information during patient care. It improves patient access to health-related information and services, thereby enhancing patient care coordination, and efficiency of care (Lewis, 2006). Siika et al. (2005) evaluated healthcare service utilization scores among HIV patients receiving ambulatory care in Kenya following the introduction of automated reminders in an infectious disease unit. Their study demonstrated that the use of the electronic reminders led to a two-fold increase in patient turn-out for routine CD4 count investigation, antiretroviral medication refills, and overall service utilization scores (Siika et al, 2005).

Furthermore, health sector ICT use also improves the quality and process of care for optimal patient outcomes (Kallander et al, 2013; Deidda et al, 2014). It facilitates patient engagement in all lines of care by providing platforms where caregivers and patients are on the same page about accessing and sharing patient information (Marin et al, 2016). Common ICT tools including mobile phones and internet access promote patients' engagement during care by facilitating patient participation in health promotion, information and improvement strategies (Sands, 2015). Patient engagement includes cultures that collaborates patients' decisions related to healthcare. Such collaborations involve unrestricted communication among stakeholders involved in patient management. This could be operationalized in HIV management and includes mutual respect and shared decision-making between HIV patients and healthcare givers, as well as total transparency in information sharing and communication (Marin et al, 2016).

Mobile phones are exceptional tools in HIV prevention, control and treatment (Lester and Karanja, 2015). Healthcare workers at the Pumwani clinic, Kenya, demonstrated how a weekly Short Message Services (SMS) text messages to patients on Antiretroviral Therapy (ART) facilitated care coordination among relevant patients. The use of mobile phone use in coordinating care has also facilitated health service delivery with the farthest possible reach; and have also improved clinical effectiveness. Through such SMS, health workers inquire on the wellbeing of their patient, then triage their responses according to individual needs. This boosted medication adherence, increased patient follow-up visit, and led to marked reductions in patients' viral load (Lester and Karanja, 2008).

Nonetheless, electronic sharing of patient-level data among physicians also mitigates redundancy and removes waste in care management. Information systems become useful in monitoring patients' adherence and response to medications (Balka et al, 2007; Green et al, 2008). Barnighausen et al. (2011) did a systematic review to evaluate interventions that target to increase antiretroviral medications adherence among HIV patients in sub-Saharan African countries. They reviewed 26 relevant studies done between 2003 and 2010, and identified treatment supporters, Directly Observed Treatment, and use of mobile phone text message reminders as top factors that improved antiretroviral medication adherence. Other health system factors identified include robust health sector funding and presence of financial support from donor agencies (Barnighausen et al, 2011).

While multiple researches have documented the impact of ICT adoption and health outcome for specific cases, it is not clear how the overall ICT infrastructures' diffusion influence HIV health outcomes for the entire African countries. Numerous studies have described the association between health sector ICT use and health outcomes (Khan, 2004; Raghupathi and Raghupathi, 2013; Bankole and Mimbi, 2016). Few others investigated the association between specific ICT infrastructure and HIV health outcomes among African health systems (Lester and Karanja, 2008; Barnighausen et al, 2011). However, the focus of this study is to evaluate how three ICT tools (mobile phone, internet and fixed telephone) altogether impact HIV health outcomes among the entire African health systems. If there is any association, then the system will consolidate and strengthen eHealth practice. Thus, this study provides insight to the question: does

ICT infrastructure use have any significant impact on the prevalence HIV? As well as on ART coverage rates among African health systems? We constructed a conceptual model to test the hypothesis that there are notable improvements in antiretroviral therapy coverage rates following ICT infrastructures diffusion among African health systems.

To answer these research questions, this study conducted empirical tests using aggregate data obtained from the World Bank and the International Telecommunication Union (ITU) databases on 53 Sub-Saharan African nations for the periods 2000 through 2016 (see exhibit-A). This study focused on Africa, because of data availability, including the presence of a large and diverse HIV population. Thus, using analytics, this study investigated the relationships between ICT diffusion and HIV health outcomes. A major challenge when quantitatively estimating how ICT diffusion impacts health would be how to isolate the ICT-health relationship from other observed and unobserved factors, without having biased estimates from such relationships. However, to address this issue and overcome the difficulty involved in empirical testing, this study used the Dynamic Panel Model (DPM) and First Difference (FD) in all estimations.

Findings from this study hopefully will increase the understanding of how ICT infrastructures impact HIV health outcomes among African countries, and therefore could act as reference for policy-makers, academic researchers, and developmental organizations. Study findings have opportunities to help policy-makers identify opportunities for improving national health systems, by providing frameworks for healthcare priority setting and resource allocation. Thus, African governments can either encourage investments or disinvestments in ICT-driven healthcare practice in the coming years. In addition, findings from this also have opportunities to facilitate the identification of an ICT-driven medical practice and guidelines to ease clinical practice, improve access and reduce healthcare cost.

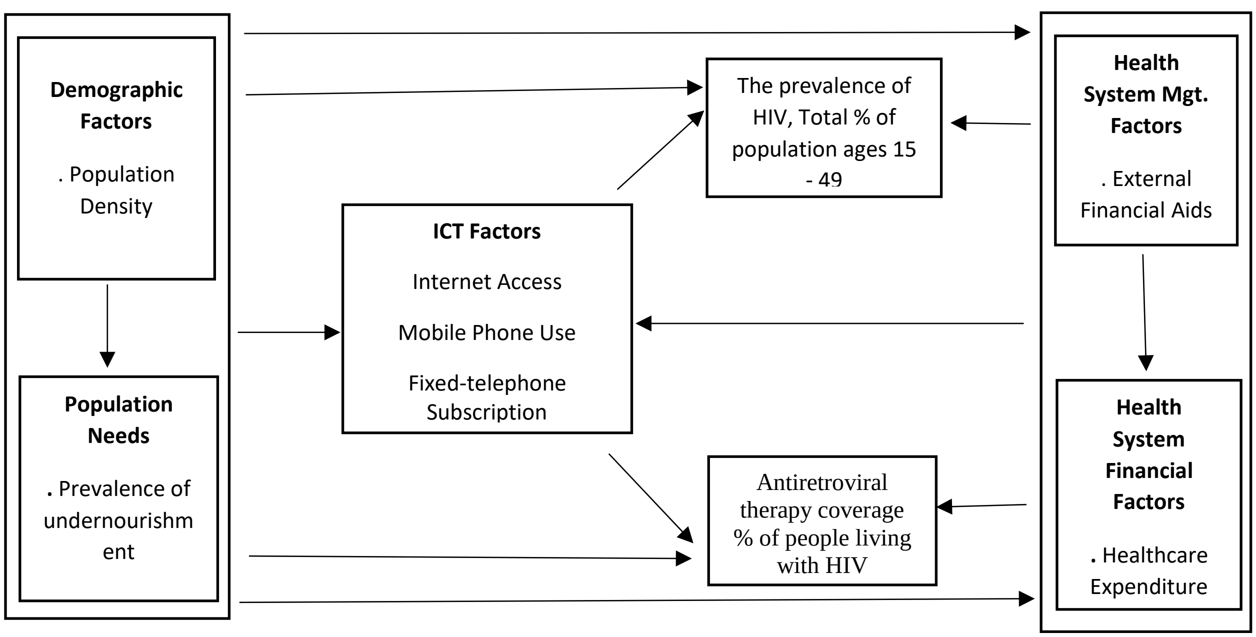
Conceptual Framework

A hybrid of the cybernetic paradigm and Diffusion of Innovation (DOI) theory was used as a systemic model-based framework for this study. The cybernetic model demonstrates how diverse units interconnect for a quality framework in a regulatory feedback mechanism. The cybernetic model (systems theory) examines complex adaptive systems with interlinked and dynamic interactions involving contexts, institutions and systems which interact within the contexts of health systems (Atun, 2012). Interdependent and interconnected elements within systems create network of feedback loops that operate in a cause-and-effect pattern to maintain system equilibrium. Such nonlinear system elements' interactions create a dynamic complexity that leads to system response (Atun, 2012; Willis et al, 2012).

The diffusion of innovation theory gives an insight on how innovations are taken up in the contemporary society. It is a model that describes change categories involved in technology advancement and adoption, which are critical to health. Healthcare-related innovations, for instance the use of SMS or emails to communicate with patient must be easy to use, understood and communicated. They should be easily adopted with minimal investments of time, risk and commitment before usage (Glanz et al, 2002; Eldredge et al, 2016). Innovations are critical for improving population health outcomes among developed countries (Cutler, 2001), and developing countries for optimal health outcomes (Howitt et al, 2012). According to Atun (2012), health systems innovation includes new ideas, medicines, health technologies, diagnostics, practices objects, practices or organizational practices perceived as novel by any unit of adoption – an individual or institution. Historically, the DOI theory has been widely used in various disciplines. In the academia, schools have used it to investigate the dissemination of AIDS education curricula, and the adoption of safe sex practices. Healthcare professionals have also used it to understand the use and penetration of new tests, programs and technologies (Glanz et al, 2002).

Components of this model interact in a bidirectional fashion to create complex adaptive and dynamic health systems. It fosters systems thinking, as it considers key elements of a complex adaptive system that interact to impact innovation adoption and diffusion. Thus, approaches that encourage systems thinking are invaluable when planning health system innovations adoption, to enhance system performance and improve service delivery (Atun, et al. 2010; Atun, 2012).

Figure 1: Study Model



Consequently, a hybrid of the cybernetic conceptual framework alongside the diffusion of innovation theory was used to structure an assessment of ICT infrastructure diffusion within the larger contextual healthcare environment. These frameworks work to conceptualize the interconnectedness of health system characteristics and ICT infrastructures, which have an inherent ability to improve health outcomes. The Ottawa declaration of 1986 emphasized the need for the re-orientation of healthcare services. This includes basic communication theories and those involving the adoption of new technologies for the enhancement of healthcare effectiveness (Kickbusch, 2003). Importantly, this model describes a causal connectivity among relevant variables and highlights relevant change directions (Cramp and Carson, 2001; Fahey et al, 2003).

Target population was assessed at the base level with respect to perceived health needs, which could be influenced by myriad factors exemplified by prevalence of undernourishment (figure 1). In addition, population demographic factors typified by population density impact population health needs within any specified healthcare system (Lichter and Brown, 2011). The loop on the left arm of this model represents health system management and financial factors including healthcare expenditures and external aid to the health sector. This loop is being influenced by community demographic factors and population need factors (Figure 1). This together with other inherent population factors drive change within the population and are pointers for healthcare needs which could be facilitated using ICT infrastructures including mobile phone, internet and fixed telephone (Cramp and Carson, 2001). Improvements at this point have opportunities for improving health outcomes including prevalence of HIV and antiretroviral therapy coverage rates.

Data & Methods

This was a retrospective longitudinal study involving use of secondary data obtained from the World Bank and ITU databases for the periods 2000 through 2016. Ideally, collated information is de-identified and aggregated per country and published at the end of each year. Thus, this study qualifies for an Institutional Review Board (IRB) exempt, as it did not violate the rights or impose any risk on human subjects (Gostin 2008). However, certain variables were only available for some nations and with limited years. Therefore, this study did not include countries with incomplete data. Thus, data for 53 countries were available and complete, and was used in all econometric analyses. We assumed this sample to be a good representative of the African continent and ideal for econometric analyses.

A major issue when quantitatively estimating how ICT diffusion impacts health would be how to isolate the ICT-health relationship from other observed and unobserved factors, 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 advanced countries tend to have better health outcomes as well as higher ICT diffusion (ITU, 2011; ITU, 2017). Therefore, 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 influence of ICT diffusion on health (Lee et al, 2016; Shehata et al, 2016).

However, to overcome the rigors in estimation, the Dynamic Panel Model (DPM) and the Generalized Method of Moments (GMM) were used in all econometric analyses. The choice of this model stemmed from its ability to absolve inherent endogeneity issues caused by unobserved variables. It does this by utilizing the dynamic properties of the data to produce good Instrumental Variables (IV). Consequently, the GMM estimator proposed by Holtz-Eakin et al. (1988) and developed by Blundell and Bond (1998) was used in estimating study model (Equation I). Conceptually, the GMM estimator absolve endogeneity problems by using the lagged values of the endogenous explanatory variables as IVs. These lagged independent variables are valid IVs. They are uncorrelated with the error term and are only partially correlated with the endogenous explanatory variables (Terza, 2008; Shehata, 2016). The idea behind the GMM method is to put a slope equation in the form of a DPM, and then taking the first difference of the model variables and using their lagged values for the levels of the regressors as IVs (Arellano and Bond, 1991). In addition, to address the issue of autocorrelation in the GMM system, the lagged dependent variable is instrumented using its past values (Arellano and Bond, 1991; Roodman, 2009). Consequently, to estimate study model (Equation I), identified instruments must be valid. This means that instruments must be exogenous and relevant. It also ensures that bias in this estimation is smaller than the OLS estimation bias. In addition, the overidentification test must also be statistically significant. Thus, if we fail to reject the null hypothesis, then the instruments are exogenous (Terza et al, 2008).

Specific health indices of interest for this study were obtained from the World Bank database. This database contains numerous information on economic and social indicators, which allowed this study to include them as relevant covariates representative of national development. These cofactors were included to control for the impact of progress of development of any nation, and as well to isolate and capture the impact ICT infrastructures have on health. Consequently, this study relied on several analytic methods including:

$Health_{it} = \beta_0 + \beta_1.Health_{i,t-1} + \beta_2 ICT_{it} + \delta Z_{it} + \mu_i + \varepsilon_{it}$ ……………………………………………(Equation 1)

Where t represents year, and i represents the country. Z represents sets of covariates, and μ_i represents country fixed effects, and ε_{it} represents the error term with an assumed zero mean. The dependent variable is $Health_{it}$, which includes HIV prevalence and antiretroviral therapy coverage rate. The lagged of the dependent variable $Health_{it-1}$ was included in this model as an independent variable to account for the possibility of the persistence of these health outcomes in these countries.

Conceptually, chronic disease conditions including chronic environmental features may lead to rather slow changes in the health conditions and outcomes of any nation (Lee et al, 2016). Thus, health indices in time '*t*' most likely may depend on the health indices in time '*t-1*'. 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.

Importantly, this study also derived an aggregate variable for ICT using three ICT elements, and computing a common factor score of the three ICT variables using the Principal Component Analysis (PCA). Mathematically, the PCA takes data matrix of *n*-objects by *p*-variables, which may be correlated, and summarizes them by uncorrelated axes. The result is a linear combination of the original p-variables denoting principal component (Abdi and Williams, 2010; Bro and Smilde, 2014). The new variable denoted as ictfac represents the overall ICT diffusion in the entire African continent and was included in the study model as one of the primary predictor variables.

Conceptually, this study assumed that an increase in mobile phone use and internet subscriptions among African populations implies a broader access to healthcare services. Furthermore, it was believed that the likelihood of access to healthcare services increases with higher access to ICT infrastructures. Thus, such increases in mobile phones and internets use have opportunities to reduce HIV prevalence, while improving ART coverage rates among African health systems.

Based on reviewed literature, mobile phone use and internet subscriptions are expected to have a positive impact on HIV health outcomes. While it is expected that presence of external aids to the health sector will have a positive impact on HIV health outcomes, population density is expected to have a negative impact on it. However, the impact of health expenditure on HIV health outcome is somewhat ambiguous. Thus, the sign on this variable may not be predicted in advance.

Findings

The study used unbalanced panel data for 53 African nations over the periods 2000 through 2016 accessed from the World Bank and ITU databases and analyzed in March 2018. Table 1 represents study descriptive summary statistics. On the average, the prevalence of HIV per 100,000 of population was 5.44 and mean antiretroviral therapy coverage was approximately 14 patients per 100,000 people living with HIV. The mean percentage of individuals using the internet was 8.4 percent. The mean mobile phone subscription was 41.4 per 100 population, while mean fixed telephone subscription was 3.6 per 100 population. This study also performed the Hansen test to test for over-identification on the Dynamic Panel Model estimates. The Hansen test chi-squared statistics (Tables 2&3) were non-significant, indicating no over-identification in the models.

Table 1: Variable Descriptive Statistics					
Variables	Definition	Mean	Std. Dev	Min	Max
ICT variables					
Internet	Percentage of individuals using the Internet	8.380	11.749	0.006	58.270
Mobile phone	Mobile-cellular telephone subscriptions per 100 inhabitants.	41.440	41.068	0	176.686
Fixedtele	Fixed-telephone subscriptions per 100 inhabitants	3.615	5..923	0	31.067
Ictfac	ICT common factor score representing overall diffusion of ICT	0	1.468	-1.365	6.106
Control Variables					
ART_acc	Antiretroviral therapy coverage (% of people living with HIV)	14.341	16.505	0	77
HIVPrev	Prevalence of HIV, total (% of population ages 15-49)	5.435	6.927	0.1	28.8
healthexp	Health expenditure, total (% of GDP).	5.578	2.152	0.260	14.390
Popldens	Country Population, total	15.821	1.582	11.304	19.041
undernourish	Prevalence of undernourishment (% of population)	22.031	13.450	5	60.600
ext_aids	Net official development assistance and official aid received (current US$)	19.566	1.399	13.162	23.160

Table 2: ICT and HIV Prevalence Estimation Results

Variables	Model 1	Model2	Model 3	Model 4
	DPD (p-value)	DPD (p-value)	DPD (p-value)	DPD (p-value)
HIVPre (t-1)	0.843 (0.000)***	0.844 (0.000)***	0.849 (0.000)***	0.837 (0.000)***
ICT Common factor score	-0.006 (0.567)			
Mobile phone		-0.001 (0.031)**		
Internet			0.001 (0.513)	
Fixed telephone				-0.004 (0.499)
External aids (log)	-0.036 (0.000)***	-0.031 (0.001)***	-0.038 (0.000)***	-0.032 (0.000)***
Health expenditure	-0.039 (0.000)***	-0.036 (0.000)***	-0.038 (0.000)***	-0.040 (0.000)***
Undernourishment	-0.004 (0.010)***	-0.004 (0.008)***	-0.004 (0.017)**	-0.005 (0.003)***
Population density (log)	-0.428 (0.000)***	-0.267 (0.017)**	-0.493 (0.000)***	-0.490 (0.000)***
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
Obs		510	511	507

Note: FD = First Difference; DPM = Dynamic Panel Model. Significance level: *p<0.1; **p<0.05; ***p<0.01

Table 2 shows the effect of overall ICT diffusion on HIV prevalence. The coefficient of the lagged HIV prevalence was positive, statistically significant and close to one, indicating the persistence of HIV among African countries over time (Table 2). The coefficients on the aggregate ICT scores and other ICT variables were all negative but for internet subscription (Model 3).

Table 3: ICT and ART Access Rate Estimation Results

Variables	Model 5	Model 6	Model 7	Model 8
	DPD (p-value)	DPD (p-value)	DPD (p-value)	DPD (p-value)
ART_acc (t-1)	0.901 (0.000)***	0.923 (0.000)***	0.903 (0.000)***	0.924 (0.000)***
ICT common Factor score	0.352 (0.305)			
Mobile phone		0.001 (0.997)		
Internet			0.034 (0.213)	
Fixed telephone				0.093 (0.565)
External aids (log)	0.004 (0.987)	0.053 (0.841)	0.023 (0.929)	0.055 (0.831)
Health Expenditure	-0.051 (0.763)	0.013 (0.937)	-0.035 (0.829)	0.007 (0.966)
Undernourishment	0.012 (0.821)	0.015 (0.772)	0.015 (0.769)	0.021 (0.694)
Population Density (log)	19.183 (0.000)***	19.062 (0.000)***	19.250 (0.000)***	18.979 (0.000)***
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
Obs	527	538	539	535

Note: FD = First Difference; DPM = Dynamic Panel Model. Significance level: *p<0.1; **p<0.05; ***p<0.01

Table 3 shows the effect of overall ICT diffusion on ART therapy access rate. The coefficient of the lagged ART access rate was positive, statistically significant and close to one, indicating the persistence of this health outcome among African countries over time. The coefficients on the aggregate ICT score and other ICT variables were all positive.

Discussion

Study result showed that ICT infrastructure diffusion had a positive impact on HIV outcome among African countries. Analytical results indicated that the coefficients on the aggregate ICT score and other related ICT variables were all negative but for internet subscription (Model 3). Though the coefficient on internet subscription on model 3 was negative, however it was not statistically significant. A plausible explanation to this could be that individuals with access to ICT infrastructures other than mobile phones and fixed landlines might rarely use them in HIV health-related activities. Therefore, analytical results from DPM models (Table 2) demonstrated that overall ICT diffusion including the use of mobile phones and fixed telephones had significant impact on decreasing the prevalence of HIV among PLWHIV in Africa.

This finding supports previous study that demonstrated how health sector ICT use reduced HIV prevalence on a global scale (Lee et al. 2016); and probably could be linked to the use of ICT infrastructures in promoting campaigns against HIV spread. As identified in the WHO bulletin, health sector ICT use among African health systems facilitates health promotion campaigns through Information, Communication and Education (WHO, 2017). Thus, PLWHIV are enlightened on practices that reduce the spread of HIV, and the need for early medical consultation and pharmacotherapy. In view of this, policy should be reviewed with the view of strengthening strategies that promote ICT infrastructure use in HIV enlightenment campaigns among African health systems.

In addition, study analytical result (Table 3) indicated that ICT indices including the aggregate ICT variable score (ictfac), internet access, mobile phone use, and fixed telephone subscriptions had positive impact on ART therapy access rate among PLWHIV in Africa. Though estimation results showed positive associations, however the coefficients on the DPM models were unexpectedly statistically insignificant throughout the models. This finding corroborates a study by Shehata (2016), which showed that ICT indicator variables lose their significance as control variables are added to any model during econometric analytics, especially the DPM. Also, as identified in the literature review section, ICT use promotes ART medication adherence and uptake (Lester and Karanja, 2008). Thus, findings from this study lend credence to findings by Siika et al. (2005) who demonstrated how ICT use improved ART medication access and uptake among HIV patients receiving ambulatory care in Kenya. Through electronic reminders, patients' turnout for ART medication refills was increased. This also corroborates the fact that ICT support patients' treatment, foster anonymous counselling, and links patients to available services (Clifford and Clifton, 2012). By linking patients to services, their likelihood of accessing ART is higher leading to improved outcomes. Thus, in view of this, policy should be reviewed with the view of consolidating an ICT-driven medical practice among HIV programs in Africa to improve access.

That notwithstanding, analytics results for the control variables indicated that county health standards were associated with economic and socio-demographic factors. Health expenditures and net external official aids to the health sector had positive associations with ART access rates (table 3). These findings corroborate study findings by Gupta et al. (2002) which established that economic factors are positively related to population health outcomes. Robust financing and efficient management of healthcare resources positively impact population health measures (Gupta et al. 2002; Gupta et al. 2003). However, of note is the fact that the coefficient on health expenditure and the net external official aids to the health sector were negatively related to the prevalence of HIV in most models (Tables 2&3). A possible explanation to this is the misallocation of resources and mismanagement of funds meted for the health sector leading to waste of resources in the health sector. Most African health sectors have institutionalized corruption and fund misappropriation in their systems that translate to poor outcomes (Tito et al. 2008; Pierce, 2006). Thereby, justifying the need for an efficient resource allocation, transparent fund management and explicit rationing among African health systems. Nonetheless, population density had some negative effects on study health outcomes (Table 2). This probably could be linked to the fact that most African communities are densely populated and are at risk of deprivation and poverty (WHO, 2014). Rural African communities are hard to reach per health service delivery, leading to substantial gaps in ART coverage rates, especially among impoverish and remote African communities (United Nations, 2015).

However, it must be noted that this study had some inherent limitations. For instance, this study found that mobile phone and internet use had significant impact on HIV health outcomes. Thus, we infer this result because of the superior communication functionalities related with mobile phones with internet use in easing communication and absolving misconceptions associated with HIV. Thus, future studies should collect granular data through small-scale case studies to further explore this study's interpretations.

Besides, with the advent of phones with internet applications, it becomes difficult to isolate effects of mobile phones and internet on population health measures. In view of this, future studies should define a new variable that considers these two ICT tools, and its impact on health outcome evaluated. In addition, this study analyzed data between 2000 and 2016. Thus, in this era of big data, future researches should focus on the use of detailed longitudinal retrospective research methods to search through larger volume of rich data to capture robust trends, patterns and associations.

Conclusions

The impact of individual ICT infrastructures on improving HIV health outcomes differed, which this study believed to be as a result of different functionalities of the ICT tools, and the peculiar features of the health outcomes investigated. Empirical results from econometric analyses indicated that ICT factors were positively related with some population health factors. Study analytics showed that the overall diffusion of ICT tools including mobile phones, internet access and fixed-telephone subscriptions were associated with a decrease in the prevalence of HIV. However, there was a significant increase in antiretroviral therapy access mainly in the FD models, following increased diffusion of ICT infrastructures among African health systems.

Thus, study findings provide systematic evidence and justification to inform African government and the global community that beside allocating resources to health projects and interventions targeting to improve public health, investing in ICT-driven healthcare practice, and educating individuals on the use of ICT can be an alternative strategy to improve population health.

Exhibit-A

Countries used in this analysis as listed by the World Health Organization. Available at: http://www.who.int/countries/en/ accessed May 20, 2017.

African region: Algeria, Burundi, Burkina Faso, Benin, Angola, Cameroon, Botswana, Cape Verde, Central African Republic, Comoros, Chad, Congo, Democratic Republic of Congo, Cote d'Ivoire, Djibouti, Equatorial Guinea, Egypt, Eritrea, Ethiopia, Gabon, Ghana, Guinea-Bissau, Lesotho, Gambia, Guinea, Kenya, Liberia, Libya, Malawi, Mauritania, Mali, Madagascar, Mauritius, Mozambique, Morocco, Nigeria, Namibia, Niger, Sao Tome and Principe, Seychelles, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Swaziland, Togo, Uganda, Tunisia, Tanzania, Zambia, Zimbabwe.

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CONCLUSION

This study set out to answer this broad research question: Does ICT infrastructure diffusion have a significant impact on HIV and tuberculosis health outcomes among African health systems. Study findings justify the importance for African government to invest in the eHealth-driven medical practice, in order to improve population health, an issue that gets little or no attention in traditional governance in Africa.

Analytics of secondary data obtained from the World Bank and ITU databases using the DPM demonstrated that ICT infrastructures use had opportunities for improving TB and HIV health outcomes. They support treatment, foster information dissemination, facilitate anonymous counselling, and link patients to available services. However, the impact of individual ICT infrastructures on improving TB and HIV health outcomes differed, which this study inferred to be a result of different functionalities of the ICT infrastructures, and the peculiar features of the health outcomes studied.

This study also investigated geospatial patterns of TB treatment completion rates among health systems in Africa. It evaluated spatial relationships between mobile phone use and TB treatment completion rates using differential local Moran's I and bivariate Moran's I techniques to help visualize cluster patterns and trends. Study result identified statistically significant positive autocorrelation values for the periods evaluated, as well as varying cluster patterns in TB treatment completion rates. The cluster patterns increased across the three-time periods of study evaluations among geographically referenced data. That notwithstanding, this study also identified a direct relationship between mobile phone use and TB treatment completion rates among relevant African countries. Thereby, necessitating the need to strengthen national policies that promote TB medication adherence and completion using mHealth strategies among African health systems.

This study has many strengths, including mixed analytic approaches to make a reasonable attempt at addressing complex policy questions. Study data was robust and came from a reliable source. The World Bank and ITU databases are reputable in collecting accurate data on the international scale. These databases were a good way to get enough sample size that was representative of the African population. In addition, there is a need to routinely evaluate data obtained from these sources per ICT impact on health outcomes, which this study addressed and added to the body of knowledge on this subject. Another strength of this study is the study design. The DPM and GMM models are sound methodologies in determining the effect of the introduction of an intervention and policy at a population level, over a defined period of time, that target population-level health outcomes. More so, time series study designs proffers the strongest, quasi-experimental designs to estimate intervention effects in nonrandomized settings. Besides, the use of geospatial analytic approach brought to light the role of contextual and geographic factors in understanding the impact of ICT infrastructures' use on population health outcomes among African health systems.

However, this study assumed that increases in mobile cellular and internet subscriptions implies broader access to healthcare services. It was believed that the likelihood of access to healthcare services increases with higher access to ICT infrastructures. Ideally, the number of individuals utilizing ICT infrastructures in receiving health informatics via ICT would have been used as study primary predictor variables. However, such data was not available for Africa. Thus, those with a mobile phone, a landline phone, and internet access were used as proxy variables, as they represent the potential for impact on health with utilization of ICT to send/receive health information. In addition, some ICT-related variables could also 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 continental-level but not at the country level. Consequently, follow up assessment should be done to evaluate the impact of these variables on population health outcomes. Besides, with the advent of smartphones with internet applications, it becomes difficult to isolate effects of mobile phones and internet on population health measures.

In view of this, future studies should define a new variable that considers these two ICT tools, and its impact on health outcome evaluated. In addition, this study analyzed data between 2000 and 2016. Thus, in this era of big data, future studies should focus on the use of detailed longitudinal retrospective research methods to search through larger volume of rich data to capture trends, patterns and associations.

APPENDIX

Countries used in this analysis as listed by the World Health Organization. Available at: http://www.who.int/countries/en/ accessed May 20, 2017.

African region: Algeria, Burundi, Burkina Faso, Benin, Angola, Cameroon, Botswana, Cape Verde, Central African Republic, Comoros, Chad, Congo, Democratic Republic of Congo, Cote d'Ivoire, Djibouti, Equatorial Guinea, Egypt, Eritrea, Ethiopia, Gabon, Ghana, Guinea-Bissau, Lesotho, Gambia, Guinea, Kenya, Liberia, Libya, Malawi, Mauritania, Mali, Madagascar, Mauritius, Mozambique, Morocco, Nigeria, Namibia, Niger, Sao Tome and Principe, Seychelles, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, South Sudan, Sudan, Swaziland, Togo, Uganda, Tunisia, Tanzania, Zambia, Zimbabwe.

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