The Effects of Internet Usage on Health Outcomes in Africa: A Short-Run and Long-Run Analysis.

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January 1, 2026

Abstract

This paper examines the effects of internet usage and mobile subscriptions on health outcomes in 43 African countries from 2000 to 2022, while employing both panel ARDL and panel VAR models. The findings suggest that both internet usage and mobile subscriptions have long-term impacts on health outcomes in Africa. The impulse response functions suggest that the internet and mobile subscriptions have some instantaneous effects on life expectancy, highlighting the essential role of digital infrastructure in public health initiatives and, hence, the need to advocate for increased investments in digital access to improve health outcomes globally.

1 Introduction

Information and Communication Technology (ICT) has become an essential tool in the social, economic, and health landscapes for both individuals and countries globally (Kim et al., 2017; Diaz et al., 2002). Its significance is particularly pronounced in developing countries, where it serves as a vital conduit to essential services such as healthcare. As the digital environment continues to expand, there is considerable optimism regarding future societal advancements, particularly in regions like Africa. The vast potential of online content to enhance health and wellness remains largely untapped and unevenly distributed. In Africa, despite the improvements in connectivity within urban areas, large rural populations still face considerable challenges in accessing health information, resulting in inefficiencies. The disparity in internet access across various parts of Africa

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highlights a broader digital divide that adversely impacts health outcomes. A key component for enhancing public health literacy involves ensuring consistent and timely access to health information, which empowers individuals to make timely and informed decisions that are critical for dealing with health issues.

Addressing health issues like infant mortality, HIV, maternal death, and malaria, among others, has been the concern of major global organisations, like the United Nations and the World Health Organization. For instance, the United Nations initially established the "Millennium Development Goals", which ran for 15 years (2000 to 2015), with the goals of reducing child mortality, improving maternal health, and fighting HIV and other diseases (UN, 2015). However, given the rampant and persistent nature of the aforementioned health challenges, the UN continues to battle them through its "Sustainable Development Goals" [1] for the next 15 years post "Millennium Development Goals". Thus, while there have been some successes achieved in combating such public health issues as are portrayed in Figure 1, it remains essential to explore effective ways to combat these global public health challenges, especially in Africa, where some devastating effects are experienced because of high illiteracy and poverty rates. As shown in Figure 2, the usage of the internet on the African continent has been increasing significantly, especially after 2010, coupled with significant growth in mobile subscriptions.

This research, therefore, aims to assess whether this improvement in internet usage and mobile subscriptions is having some effects on health outcomes on the African continent. To answer the research questions, this study employs a panel ARDL model for long-run analysis, which is well-suited for handling variables with mixed orders of integration, while allowing us to understand the equilibrium relationships alongside dynamic adjustments throughout our investigation. The panel ARDL framework enables us to isolate the percentage of changes in health outcomes attributable to variations in internet usage and mobile subscriptions over different time spans. The study also employs a panel vector autoregressive (panel VAR) model to analyse the interdependencies and short-term dynamic interactions among life expectancy, internet usage, mobile subscriptions, GDP per capita growth and population growth across different countries.

This paper makes two key contributions to the growing literature on ICT and eHealth on health outcomes. First of all, while other previous studies like Zhiang et al. (2022), Kouton et al. (2020),

[1]SDG: Goal 3

and Njoh et al. (2019) focused on the impact of Information and Communication Technology penetration on population mortality, this study tends to disaggregate population mortality into female mortality, male mortality, and infant mortality, and also assesses its effects on the lifetime risk of maternal death. This study asserts that women and men in general react differently to information about health. Secondly, previous studies have demonstrated that increased internet usage correlates with increased health literacy and improved self-management practices regarding health issues (Zhiang et al., 2022; Tavares, 2018; Kim et al., 2017; Diaz et al., 2002). Collectively, these studies suggest that greater internet accessibility leads to better health outcomes through enhanced knowledge and awareness. However, this literature focuses on the contemporaneous effects of ICT on health outcomes. Therefore, this study seeks to add to the existing body of literature by undertaking a comprehensive analysis of the short-run and long-run effects of digital inclusion and technological penetration on health outcomes within Africa.

Our findings support arguments that advocate for enhanced internet access and effective mobile connectivity, as they are beneficial for improving the overall health outcomes for the people living in Africa. While promoting nuanced understanding at the policy level, we also encourage appropriate resource allocation and strategic measures necessary for leveraging the potential benefits of digital connectivity across Africa. The structure of the remainder of this paper consists of three sections: Section 2 provides an extensive literature review; Section 3 details the data sources employed along with the methodological approaches used; Section 4 presents the results from the estimations; and finally, Section 5 concludes the paper.

2 Review of Literature

Zhiang et al. (2022) studied the effect of ICT diffusion on public health outcomes in China. They also investigated the mechanism through which this relationship occurs at both macro and micro levels. Their findings suggest that ICT adoption reduces population mortality and emphasize that ICT improves health outcomes through enhancing health literacy and boosting public healthcare costs. Again, the study by Njoh et al. (2019) suggests that the provision of basic utility services, including access to telecommunication networks, plays a major role in reducing infant mortality in Africa. The growth in internet usage and mobile applications in healthcare delivery has been

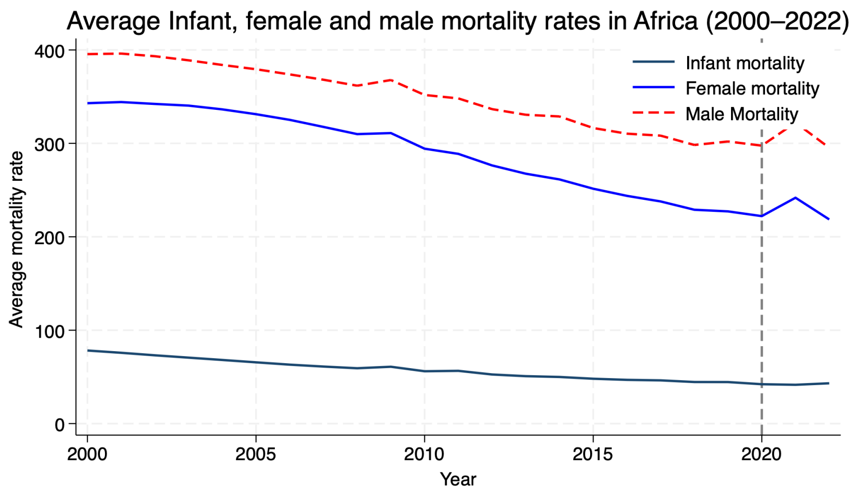


Figure 1: Average infant, female, and male mortality rates in Africa from 2000 to 2022

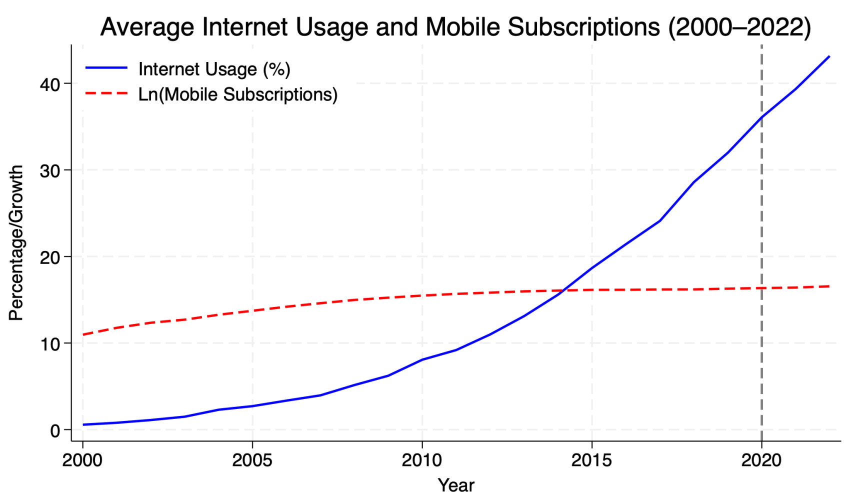


Figure 2: Average internet usage and mobile subscriptions in Africa from 2000 to 2022

unprecedented in recent times, especially after the COVID-19 global health pandemic. Indeed, there has been an emergence of the use of advanced medical technology in healthcare provision, which can be associated with the increasing adoption of ICT.

Furthermore, the internet has become a major source for health- and medicine-related information, making it possible for people to use it as a tool for daily health management (Kim et al., 2017; Diaz et al., 2002). Again, ICT provides the medium that makes it possible for individuals, especially old people, to communicate with relatives and health professionals about clinical decision-making, disease management, and health education in general (Hardey, 2010; Haddon, 2004; Ling, 2004; Wilson and Lankton, 2004; Ball and Lillis, 2001).

Another research closer to this paper is the study by Kouton et al. (2020), in which they studied how ICT diffusion, together with economic freedom, affects the under-five (5) mortality rate in Africa. While ICT diffusion was found to reduce under-five (5) mortality, their findings suggest a positive but weakly marginal impact of the interaction between ICT and economic freedom on the dependent variable, which they argue could be because the level of economic freedom in African countries is not sufficient to affect health outcomes through ICT diffusion.

Tavares (2018) assessed how a country's adoption of ICT in general and electronic health technologies (eHealth) for primary care impacts self-reported health issues in Europe. Interestingly, he found no significant effects of eHealth and ICT on self-reported health outcomes, which was consistent with the study by Black et al. (2011). However, he attributed it to several factors, such as possible lagging effects of these factors and the absence of some fixed effects in the analysis. Nonetheless, the study found that as a country becomes more advanced in ICT adoption, the higher the share of people who self-report chronic health challenges in the European Union, pointing to the role of ICT in increasing health information sharing among individuals and health workers.

Bordé et al. (2009) found that the use of ICT in health delivery tends to increase the risk of maternal death and infant mortality. For instance, they found that the introduction of the "Telephone for Health" birth notification system led to the reduction of births that take place in hospitals. Other studies, like those of Forsman and Nordmyr (2017) and Griffiths and Christensen (2007), have established that the adoption of ICT affects the physical and mental health of people.

3 Data & Methodology

3.1 Data

The study utilises a longitudinal dataset sourced from the World Development Indicators (WDI), encompassing 43 African countries[2] that span the period from 2000 to 2022 in Appendix A.1 for a list of countries considered for the study. The study examines various health outcomes as the dependent variable, with a particular focus on female mortality rate, male mortality rate, infant mortality, and risk of maternal death. These health indicators were chosen based on their significant importance for both public health and developmental advancements across different areas.

Table 1: Variable definition and source

Variable	**Definition**	**Source**
Fmort	Adult female mortality rate (per 1,000 female adults)	World Bank Data
Mmort	Adult male mortality rate (per 1,000 male adults)	World Bank Data
Imort	Infant mortality rate (per 1,000 live births)	World Bank Data
Riskmd	Lifetime risk of maternal death (%)	World Bank Data
Lexp	Life expectancy at birth (years)	World Bank Data
Internet	Individuals using the internet (% of population)	World Bank Data
Mobile	Mobile Cellular Subscriptions	World Bank Data
GDPpcgr	GDP per growth (%)	World Bank Data
Popgr	Population growth (%)	World Bank Data
Electricity	(%) Access to electricity (% population)	World Bank Data
Urbanization	(%) Urban population growth (%)	World Bank Data

[2]See Table 11 in the appendix for the list of countries

3.2 Summary Statistics

The values presented in Table 2 for infant, female, and male mortality rates signal a critical public health problem. The descriptive statistics suggest that out of 1000 male adults, about 346 will die before turning 60 years old. In the case of female adults, about 285 out of 1000 will die before the age of 60 years. Also, 56 out of 1000 live births do not live till age 1. All these values are higher than their global averages. Moreover, the table depicts an average life expectancy of approximately 59 years, which is lower than the global average, stressing the existing public health challenges. With a standard deviation of 7.33 years and a range extending from approximately 42 to 77 years, this data shows considerable variations in health outcomes. Such discrepancies may be attributed to inequalities in healthcare access, nutritional standards, and various environmental factors present among the selected countries.

Table 2: Summary statistics

Variable	**N**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Fmort	989	285.291	121.023	59.929	841.557
Mmort	989	345.886	125.016	82.734	995.058
Imort	989	56.495	24.073	11.5	234.9
Riskmd	989	2.389	1.908	0.0544	9.065
Lexp	989	58.889	7.335	41.957	77.129
Internet	980	14.139	18.337	0.006	89.9
Ln(Mobile)	974	14.919	2.119	7.151	19.218
GDPpcgr	989	1.634	4.288	-36.778	27.831
Popgr	989	2.428	0.899	-0.920	5.906
Electricity	987	41.909	28.519	1.3	100
Urbanization	989	3.846	1.753	-0.416	10.666

As a matter of fact, the average internet penetration rate of 14.14% is relatively low. This suggests that a significant proportion of the population lacks internet access, highlighting a notable digital divide in the region. The dataset reveals highly uneven access, as evidenced by a standard deviation of 18.33%, with values fluctuating from an almost negligible 0.00% to nearly universal connectivity at 89.90%. This variation underscores the fact that while certain regions enjoy extensive digital connectivity, others remain considerably underserved. The average growth in mobile subscriptions is 14.92%. This suggests a moderate level of mobile phone penetration in the region. However, the substantial standard deviation of 2.12% and a range from 7.15% to 19.22% indicate considerable variability in the growth of mobile connectivity across different areas. The average GDP per capita growth across the sample is 1.63%, suggesting a moderate level of economic prosperity overall. However, a standard deviation of 5.21% depicts significant volatility, with annual growth fluctuating from a recession of -36.78% to a boom of 27.83%. This shows the level of economic growth instability in the region.

3.3 Model Specification

The study adopts the panel-ARDL model since the variables considered for the study are a mixture of I(0) and I(1). The framework is supported by the studies of Pesaran et al. (1999), Demetriades & Hook Law (2006), and da Silva et al. (2018).

Suppose $t = 1,2,..., T$ and $i = 1,2,...,N$, the estimated model (1) is in the form of an ARDL(p,q,...,q) model:

$$H_{it} = \sum_{j=1}^{p} \alpha_{ij} H_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} X_{i,t-j} + \mu_i + \varepsilon_{it} \cdots\cdots (1)$$

where H is the dependent variable, which includes health outcomes such as female mortality rate, male mortality rate, infant mortality, and risk of maternal death. X_{it} is a k x 1 vector of regressors, including internet usage and mobile subscriptions, which can either be I(0) or I(1) or cointegrated. α_{ij} are the coefficients of the lagged dependent variables, which are scalars. δ'_{ij} are a k x 1 coefficient vectors. p and q are the optimal lag orders. μ_i is the fixed effects. ε_{it} is the error term.

After reparameterising equation 1, the model becomes:

$$\Delta H_{it} = \phi_i(H_{it-1} - \beta_i' X_{it}) + \sum_{j=1}^{p-1} \alpha_{ij} \Delta H_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}' \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \cdots\cdots (2)$$

where β_i is the vector of interest, which measures the long-run impact of the explanatory variables on the health outcomes, and ϕ_i measures the impact of the error-correcting mechanism. The other remaining parameters are the short-run coefficients. ε_{it} is the disturbance term, which is assumed to be independently distributed across time and countries, with zero mean and constant variance within each country.

According to the studies of Pesaran and Smith (1995) and Pesaran et al. (1995), the model (1) permits the parameters to vary between countries, which can be estimated by using the Mean Group (MG) estimator, which estimates the parameters for each country and then uses the average for the whole panel. They also established that the Pooled Mean Group (PMG) is a more efficient estimator in situations where the long-run coefficients are homogeneous across groups, and the short-run coefficients are heterogeneous among countries. To apply these two methods, the variables have to be a mixture of I(1) and I(0), and they have to be cointegrated for the model to present an error correction term. The Hausman test is then used to decipher which of these models is suitable for the analysis.

The study only had 22 years, which is a relatively short period, not long enough to extend the number of lags beyond the first lag. Hence, the study adopts an ARDL(1,1,...,1) model, where the analysis is done using a lag of one for both dependent and independent variables. This assertion is supported by the studies of Pesaran et al. (1999) and Demetriades & Hook Law (2006), who recommend a common lag structure in the event of data limitation.

3.4 Stationarity and Cointegration

3.4.1 Unit Root Tests

To establish stationarity of the variables, the study conducts several unit root tests considering the sample size and the asymptotic properties of the test. The tests include the Im-Pesaran-Shin (IPS) test, the Levin-Lin-Chu (LLC) test, the Breitung test, and the Fisher-ADF, which assume the presence of unit roots as the null hypothesis, and the Hadri Lagrange multiplier (LM) test, which assumes stationarity for the null hypothesis. The results for stationarity at levels and the first differences are shown in Table 3 and Table 4, respectively. Considering the variables in levels, most of the tests posit that the dependent variables, including female mortality (Fmort), male mortality (Mmort), lifetime risk of maternal death (Riskmd), and life expectancy (Lexp), are not stationary. Also, the main explanatory variables, internet usage and log of mobile subscriptions, are not stationary at levels. However, infant mortality (Imort), GDP per capita growth rate (GDPpcgr), and population growth rate (Popgr) are stationary at levels (I(0)). Nonetheless, results from the same tests for the first differences show that the first difference of all the dependent variables and the regressors are stationary, making them I(1). This means that the variables considered in the study are a mixture of I(1) and I(0), which meets the requirements to be able to estimate a panel ARDL.

Table 3: Stationarity Tests of the Variables at Levels

Variable	IPS		LLC		Breitung		Fisher-ADF		Hadri	
	Constant	Trend	Constant	Trend	Constant	Trend	Constant	Trend	Constant	Trend
Fmort	3.087 [0.999]	2.424 [0.992]	**-4.588 [0.000]**	-0.391 [0.348]	8.571 [1.000]	5.924 [1.000]	92.668 [0.292]	106.675 [0.065]	24.652 [0.000]	-8.770 [0.000]
Mmort	0.262 [0.604]	-0.658 [0.255]	**-6.901 [0.000]**	**-4.618 [0.000]**	7.190 [1.000]	5.202 [1.000]	**138.111 [0.000]**	**171.784 [0.000]**	67.288 [0.000]	16.614 [0.000]
Imort	**-9.202 [0.000]**	**-121.317 [0.000]**	**-15.277 [0.000]**	**-25.545 [0.000]**	**-3.818 [0.000]**	2.858 [0.998]	**460.036 [0.000]**	**524.435 [0.000]**	64.748 [0.000]	14.648 [0.000]
Riskmd	3.124 [0.999]	0.334 [0.631]	**-2.679 [0.004]**	**-3.346 [0.000]**	5.133 [1.000]	2.283 [0.989]	94.450 [0.250]	**110.102 [0.041]**	76.634 [0.000]	44.034 [0.000]
Lexp	**-2.258 [0.012]**	7.403 [1.000]	**-8.948 [0.000]**	3.528 [1.000]	3.561 [1.000]	5.678 [1.000]	**142.823 [0.000]**	42.439 [1.000]	84.824 [0.000]	43.710 [0.000]
Internet	18.403 [1.000]	9.290 [1.000]	(-)	(-)	(-)	(-)	2.364 [1.000]	39.713 [1.000]	(-)	(-)
Ln(Mobile)	-15.254 [1.000]	1.136 [1.000]	(-)	(-)	(-)	(-)	**564.45 [0.000]**	**180.316 [0.000]**	(-)	(-)
GDPpcgr	**-9.569 [0.000]**	**-10.173 [0.000]**	**-8.420 [0.000]**	**-8.785 [0.000]**	**-6.402 [0.000]**	**-5.405 [0.000]**	**299.788 [0.000]**	**329.163 [0.000]**	8.605 [0.000]	2.097 [0.000]
Popgr	**-5.034 [0.000]**	**-4.803 [0.000]**	**-6.180 [0.000]**	**-8.708 [0.000]**	**-3.907 [0.000]**	**-0.540 [0.000]**	**259.589 [0.000]**	**248.317 [0.000]**	36.019 [0.000]	30.535 [0.000]
Electricity	7.674 [1.000]	**-3.255 [0.000]**	(-)	(-)	(-)	(-)	53.918 [0.997]	**171.436 [0.000]**	(-)	(-)
Urban	**-2.263 [0.012]**	**-3.768 [0.000]**	**-4.429 [0.000]**	**-7.106 [0.000]**	-1.637 [0.051]	0.936 [0.825]	**182.249 [0.000]**	**228.808 [0.000]**	51.961 [0.000]	44.868 [0.000]

Notes: p-values are reported in square brackets. Bold values indicate rejection of the null hypothesis of a unit root at the 5% significance level. (-) denotes no results due to insufficient number of observations.

Table 4: Stationarity Tests of the First Difference of the Variables

Variable	IPS		LLC		Breitung		Fisher-ADF		Hadri	
	Constant	Trend	Constant	Trend	Constant	Trend	Constant	Trend	Constant	Trend
$\Delta Fmort$	**-8.770** **[0.000]**	**-7.429** **[0.000]**	3.080 [0.999]	9.653 [1.000]	**-6.550** **[0.000]**	6.546 [1.000]	**355.772** **[0.000]**	**373.516** **[0.000]**	**-1.264** **[0.897]**	**-2.250** **[0.988]**
$\Delta Mmort$	**-13.034** **[0.000]**	**-12.748** **[0.000]**	-1.557 [0.060]	4.034 [1.000]	**-6.853** **[0.000]**	6.804 [1.000]	**501.671** **[0.000]**	**523.120** **[0.000]**	**-3.685** **[1.000]**	**-5.667** **[1.000]**
$\Delta Riskmd$	**-7.464** **[0.000]**	**-5.469** **[0.000]**	**-5.888** **[0.000]**	**-5.030** **[0.000]**	**-6.068** **[0.000]**	0.947 [0.828]	**263.044** **[0.000]**	**220.000** **[0.000]**	2.142 [0.016]	2.327 [0.010]
$\Delta Lexp$	**-6.075** **[0.000]**	**-7.237** **[0.000]**	**-4.022** **[0.000]**	-4.333 [1.000]	**-5.914** **[0.000]**	3.105 [0.999]	**22.073** **[0.000]**	**319.706** **[0.000]**	14.415 [0.000]	22.286 [0.000]
$\Delta Internet$	**-2.021** **[0.022]**	**-3.915** **[0.000]**	(-)	(-)	(-)	(-)	**140.570** **[0.000]**	**195.085** **[0.000]**	(-)	(-)
$\Delta Ln(Mobile)$	**-4.031** **[0.000]**	**-6.309** **[0.000]**	(-)	(-)	(-)	(-)	**195.076** **[0.000]**	**282.360** **[0.000]**	(-)	(-)
$\Delta Electricity$	**-21.136** **[0.000]**	**-18.472** **[0.000]**	(-)	(-)	(-)	(-)	**807.683** **[0.000]**	**687.332** **[0.000]**	(-)	(-)

Notes: p-values are reported in square brackets. Bold values indicate rejection of the null hypothesis of a unit root at the 5% significance level. (-) denotes no results due to insufficient number of observations.

3.4.2 Cointegration

Conducting a separate cointegration test is not strictly required for the variables in the panel ARDL model. This study, therefore, infers cointegration from the error correction model in the panel ARDL model, which will be negative and significant if there is a long-run relationship among the variables (Pesaran et al. 1999 & 2001).

4 Results

4.1 Panel ARDL Model

The estimation results for the long-term relationship between internet usage and health outcomes, including female mortality (Columns 1 & 2), male mortality (Columns 3 & 4), infant mortality (Columns 5 & 6), and the lifetime risk of maternal death (Columns 7 & 8), are presented in Table 5. In the analysis, we adopted the Mean Group (MG) model, the Pooled Mean Group (PMG), and the Dynamic Fixed Effect model (DFE) to estimate the panel ARDL model. However, the Hausman test was used to determine the best model for our analysis. The results from the Hausman test point to the Pooled Mean Group (PMG) model as the most suitable model, which means that the long-run estimates are constant for all units, while the short-run estimates are heterogeneous across the units. The error correction terms are negative and statistically significant across all specifications, ranging from 0.067 to 0.170. This means that between 6.7% and 17% of short-run deviations from long-run health equilibrium are corrected each year, confirming the existence of a stable long-run relationship between internet usage and health outcomes. The results show that internet usage reduces female mortality, male mortality, and the lifetime risk of maternal death in Africa. These results are consistent with the findings of Zhang et al. (2022), Njoh et al. (2019), Moahi (2009), Lindsay et al. (2008), and Ruxwana et al. (2010). Surprisingly, internet usage does not have a significant effect on infant mortality. The results from the control variables provide some compelling results, in that, while GDP per capita growth and access to electricity have a significant negative effect on adult mortality (female and male), urbanisation tends to increase among adults and infants, as well as the risk of maternal death.

The results from Table 6, which shows the effect of mobile subscriptions on health outcomes, are no different from those of Table 5 except for the effect on the lifetime risk of maternal death. The coefficient of the error correction mechanism is significant for all cases, which varies from -0.064 to -0.249, meaning that between 6.4% and 25% of short-run deviations from long-run health equilibrium are corrected each year. The results show that mobile subscriptions reduce female mortality, male mortality, and infant mortality in Africa. However, on the contrary, the results suggest that mobile subscriptions increase the lifetime risk of maternal death. From the perspective of the control variables, GDP per capita growth has a negative effect on female mortality, male mortality, and the lifetime risk of maternal death, but no significant effect on infant mortality. The results also suggest that access to electricity decreases adult mortality, infant mortality, and the lifetime risk of maternal death. Similar to the results in Table 5, urbanization increases both adult and infant mortality. Population growth has a negative relationship with female and male mortality, but positively affects the lifetime risk of maternal death.

Table 5: The Long-term Effects of Internet Usage on Health Outcomes

	Dependent Variable: Health Outcomes							
	Female Mortality		Male Mortality		Infant Mortality		Risk of Maternal Death	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Internet	-1.557***	-0.180***	-6.327***	-0.502***	-0.011	0.000	-0.041***	-0.025***
	(0.130)	(0.128)	(0.432)	(0.092)	(0.022)	(0.020)	(0.003)	(0.003)
GDPpcgr	-17.472***	-0.028	-8.110***	-7.103***	-0.163**	-0.017	0.007*	-0.001
	(2.410)	(0.153)	(1.454)	(0.922)	(0.072)	0.051	(0.004)	(0.064)
Popgr	18.050**	-3.199	-11.065*	-18.046**	1.879*	0.698	1.098***	0.225***
	(8.093)	(3.420)	(5.749)	(6.709)	(1.033)	(0.862)	(0.122)	(0.064)
Electricity		-0.224*		-1.906***		-0.162***		-0.022***
		(0.128)		(0.225)		(0.038)		(0.004)
Urbanization		6.148***		21.653***		2.634***		0.142***
		(1.574)		(3.551)		(0.306)		(0.024)
EC.coef	-0.067***	-0.145***	-0.120***	-0.170***	-0.112***	-0.091***	-0.086***	-0.112***
	(0.017)	(0.053)	(0.033)	(0.032)	(0.0383)	(0.030)	(0.020)	(0.028)
Hausman	0.79	0.41	2.35	0.43	0.56	0.25	1.02	1.90
	(0.853)	(0.965)	(0.503)	(0.994)	(0.905)	(0.999)	(0.797)	(0.863)
N	932	930	932	930	932	930	932	930

**Notes: Standard errors are reported in parentheses. ***** $p < 0.01$, ****** $p < 0.05$, ***** $p < 0.1$

Table 6: The Long-term Effects of Mobile Subscriptions on Health Outcomes

	Dependent Variable: Health Outcomes							
	Female Mortality		Male Mortality		Infant Mortality		Risk of Maternal Death	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(Mobile)	-7.701***	-4.854***	-4.920***	-6.228***	-0.974***	-0.971***	0.084***	0.459***
	(0.673)	(0.907)	(0.421)	(0.847)	(0.101)	(0.083)	(0.017)	(0.058)
GDPpcgr	-2.368***	-2.400***	-1.141***	-4.110***	0.040	0.038	-0.021***	-0.010
	(0.447)	(0.353)	(0.276)	(0.569)	(0.044)	(0.040)	(0.005)	(0.012)
Popgr	-21.521***	-35.076***	-30.593***	-3.995	0.937**	-1.444***	0.409***	0.640***
	(3.513)	(3.918)	(2.754)	(4.805)	(0.452)	(0.495)	(0.039)	(0.154)
Electricity		-0.632***		-1.988***		-0.045		-0.084***
		(0.135)		(0.164)		(0.028)		(0.006)
Urbanization		7.653***		17.641***		2.591***		
		(1.094)		(2.865)		(0.310)		
EC.coef	-0.160***	-0.206***	-0.249***	-0.222***	-0.108***	-0.098***	-0.082***	-0.064***
	(0.038)	(0.045)	(0.054)	(0.036)	(0.029)	(0.031)	(0.025)	(0.018)
Hausman	1.45	2.93	5.31	1.90	3.19	0.29	0.67	1.27
	(0.694)	(0.711)	(0.150)	(0.863)	(0.363)	(0.998)	(0.881)	(0.867)
N	927	927	927	927	927	927	927	927

Notes: Standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.2 Panel Vector Autoregressive Model (PVAR)

The study employs a panel vector autoregressive (Panel VAR) model to analyze the interdependencies and short-term dynamic interactions among life expectancy, internet usage, mobile subscriptions, GDP per capita growth, and population growth across different countries. This approach allows us to account for individual heterogeneity and temporal dynamics simultaneously, ensuring our results are robust against potential specification errors and omitted variable bias. Following the study of Abrigo and Love (2016), a k-variate homogeneous panel VAR model of order p is specified as follows:

$$\mathbf{Y}_{it} = \mathbf{Y}_{i,t-1}\mathbf{A}_1 + \cdots + \mathbf{Y}_{i,t-p}\mathbf{A}_p + \mathbf{X}_{it}\mathbf{B} + + \mathbf{u}_i + \mathbf{e}_{it}$$

where:

- Y_{it}: This is a $(1 \times k)$ vector that includes the endogenous variables Internet Usage, GDP Growth, Mobile Subscriptions, and Life Expectancy for country i at time t
- A_1,...,A_p: These are $(k \times k)$ matrices of coefficients corresponding to the lags of the endogenous variables, capturing the dynamic interactions within and across the variables.
- $\mathbf{X}_{it}$: A vector of exogenous covariates
- $\mathbf{B}$: This is $(l \times k)$ matrix of parameters for the exogenous covariates
- $\mathbf{u}_i$: This represents the vector of fixed effects for each country i, capturing unobserved heterogeneity that could influence the dependent variables consistently over time but varies across countries.
- $\mathbf{e}_{it}$: This is a vector of error terms for country i at time t, assumed to be independently and identically distributed with a mean of zero and a constant variance, reflecting the stochastic innovations.

Table 7 presents the estimates to prove the stability of the panel VAR model. In general, the standard condition to assess the stability of the panel VAR model is to compare the eigenvalues and modulus. The panel VAR model is said to be stable if all the modulus values are less than one.

From Table 7, all the eigenvalues are real with zero imaginary components, and their corresponding modulus value is below one (1). The results show that all the roots lie inside the unit circle, as shown in Figure 3. This indicates that the panel VAR model satisfies the stability condition, which means that the model is dynamically stable and hence confirms the validity and reliability of the results from the impulse response functions and variance decomposition.

Table 7: Eigenvalue stability condition

Eigenvalue		
Real	Imaginary	Modulus
0.8710621	0	0.8710621
0.6557924	0	0.6557924
0.5386414	0	0.5386414
0.1772084	0	0.1772084
0.1554798	0	0.1554798

Notes: All the eigenvalues lie inside the unit circle. VAR satisfies the stability condition.

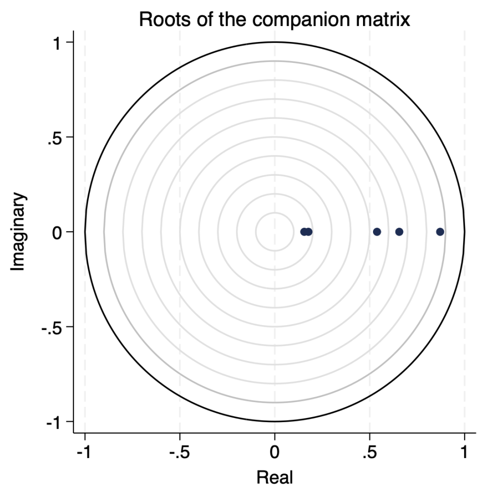


Figure 3: Companion Matrix's Eigenvalues

Table 8: Results from Five-Variable Panel VAR Model

Response to	**Response of**				
	$\Delta Lexp_{t-1}$	$\Delta Ln(Internet)_{t-1}$	$\Delta Ln(Mobile)_{t-1}$	$GDPpcgr_{t-1}$	$Popgr_{t-1}$
$\Delta Lexp$	0.648***	0.096	0.067*	0.022***	-0.119
	(0.111)	(0.094)	(0.036)	(0.008)	(0.239)
$\Delta Ln(Internet)$	0.028*	0.270***	0.167***	0.002	0.153***
	(0.015)	(0.052)	(0.055)	(0.002)	(0.048)
$\Delta Ln(Mobile)$	0.075*	0.202***	0.431***	0.004	0.259***
	(0.025)	(0.025)	(0.067)	(0.004)	(0.081)
$GDPpcgr$	0.484*	0.779	1.120**	0.198***	0.938
	(0.275)	(0.629)	(0.521)	(0.069)	(1.010)
$Popgr$	0.028*	0.270***	0.167***	0.002	0.153***
	(0.015)	(0.052)	(0.055)	(0.002)	(0.048)
No. of Observations	814	814	814	814	814
No. of groups	43	43	43	43	43

Notes: Standard errors are reported in parentheses. ***** $p < 0.01$, **** $p < 0.05$**, *** $p < 0.1$

Table 8 displays the results from the five-variable panel VAR model analysis using GMM estimations. From the findings, GDP per capita growth rate positively affects life expectancy, where a one percentage change in GDP per capita growth increases life expectancy by 0.022% at a 1% significance level. Moreover, a one percentage point increase in mobile subscriptions and population growth will increase internet usage by 0.167% and 0.153% at a 1% significance level, respectively, showing the positive effects the mobile subscriptions and population growth have on internet usage. Interestingly, the results also show that internet usage and population growth have positive effects on mobile subscriptions, while on the other hand, internet usage and mobile subscriptions have positive effects on population growth. Thus, these results indicate the bidirectional relationship among internet usage, mobile subscriptions, and population growth. The results also provide evidence of strong persistence among the variables past values of the variables positively affect their contemporaneous values.

We conducted a multivariate Granger causality estimation to assess how robust the results from Table 8 are. The results from the multivariate Granger causality tests are presented in Table 9. The results from the Granger causality estimations are similar to those presented in Table 8. From the findings, GDP per capita growth Granger-causes life expectancy, indicating that improved economic growth has the tendency to improve the overall longevity of individuals, which might be a result of improved health care provision and access to proper infrastructure like good roads as well as better health financing. The results also reveal that mobile subscriptions and population growth Granger-cause internet usage. Again, the results suggest that life expectancy, internet usage, and population group Granger-cause mobile subscriptions.

Table 9: Multivariate Granger Causality Test

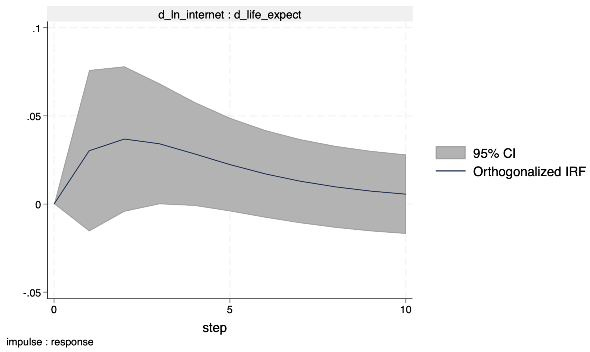
Equation	Excluded	chi2	df	P-Value
$\Delta Lexp$	$\Delta Ln(Internet)$	0.880	1	0.348
	$\Delta Ln(Mobile)$	2.016	1	0.156
	$GDPpcgr$	4.783	1	0.029
	$Popgr$	0.284	1	0.594
	ALL	13.211	4	0.010
$\Delta Ln(Internet)$	$\Delta Lexp$	2.066	1	0.151
	$\Delta Ln(Mobile)$	8.193	1	0.004
	$GDPpcgr$	0.161	1	0.688
	$Popgr$	4.174	1	0.041
	ALL	29.052	4	0.000
$\Delta Ln(Mobile)$	$\Delta Lexp$	15.493	1	0.000
	$\Delta Ln(Internet)$	8.427	1	0.004
	$GDPpcgr$	1.583	1	0.208
	$Popgr$	14.679	1	0.000
	ALL	37.770	4	0.000
$GDPpcgr$	$\Delta Lexp$	1.986	1	0.159
	$\Delta Ln(Internet)$	1.493	1	0.222
	$\Delta Ln(Mobile)$	4.596	1	0.032
	$Popgr$	0.843	1	0.359
	ALL	12.133	4	0.016
$Popgr$	$\Delta Lexp$	12.082	1	0.001
	$\Delta Ln(Internet)$	0.051	1	0.821
	$\Delta Ln(Mobile)$	0.022	1	0.882
	$GDPpcgr$	0.320	1	0.571
	ALL	16.009	4	0.003

Table 10: Forecast Error Variance Decomposition

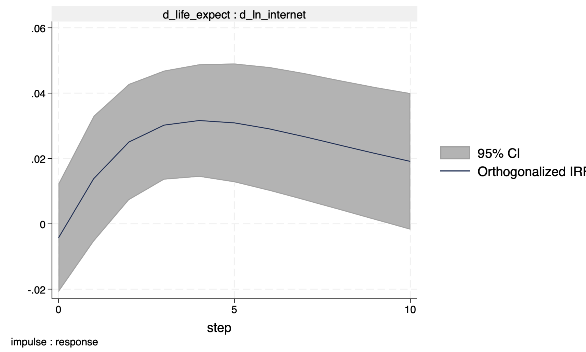
Response Variable	**Periods Ahead**	**Impulse Variable**				
		$\Delta Lexp$	$\Delta Ln(Internet)$	$\Delta Ln(Mobile)$	$GDPpcgr$	$Popgr$
$\Delta Lexp$	5	0.9479848	0.0084502	0.0059762	0.0337956	0.0037932
	10	0.9425088	0 .0103291	0.0078593	0.0354458	0.003857
$\Delta Ln(Internet)$	5	0.0389749	0.8338816 0	0.0519665	0.0038236	0.0713533
	10	0.0797888	0.7476657	0.052809	0.0079822	0.1117542
$\Delta Ln(Mobile)$	5	0.1157921	0.0990091	0.6142719	0.011519	0.1594079
	10	0.1823835	0.0842705	0.4996464	0.0183701	0.2153295
$GDPpcgr$	5	0.0348755	0.0121367	0.0286117	0.9080817	0.0162945
	10	0.0480249	0.0126951	0.0296017	0.8821002	0.027578
$Popgr$	5	0.1066953	0.0017143	0.0218418	0.0099529	0.8597958
	10	0.1741591	0.0043234	0.025521	0.0169207	0.7790757

We conducted a forecast error variance decomposition (FEVD) based on 300 Monte Carlo simulations, which is reported in Table 10. The results show that life expectancy will contribute to about 8% and 18% of variations in internet usage and mobile subscriptions, respectively, when we consider 10 periods ahead. Interestingly, while mobile subscriptions contribute to about 5% of the future variations in internet usage for both 5 and 10 periods ahead, internet usage tends to contribute about 10% and 8% of variations in mobile subscriptions for 5 and 10 periods ahead. As expected, as much as 10 to 17% of the variations in population growth are explained by life expectancy as we move from 5 to 10 periods ahead. The results reveal that about 11% and 22% of variations in internet usage and mobile subscriptions will be caused by population growth, respectively, looking at 10 periods ahead. Also, the results show that considering 10 periods, the contributions of life expectancy, internet usage, mobile subscriptions, and population growth to the variations in GDP per capita growth will be approximately 5%, 1%, 3%, and 3%, respectively.

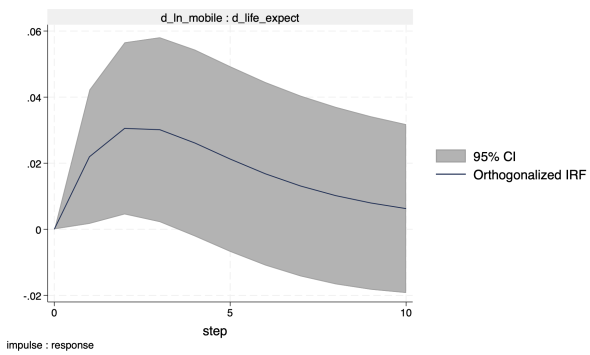
4.2.1 Impulse Response Functions



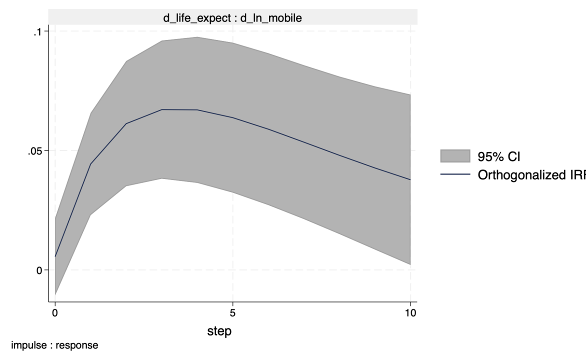
(a)



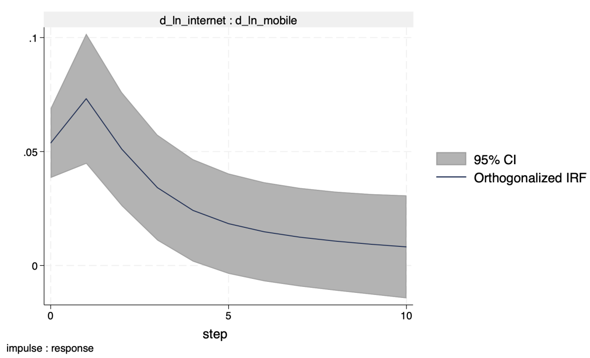
(b)



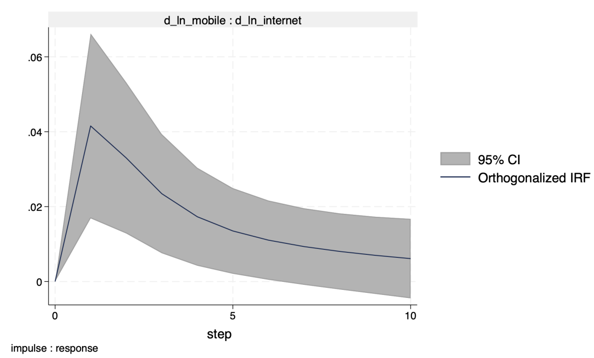
(c)



(d)



(e)



(f)

Figure 4: Impulse Response Functions

The results from the impulse response functions (IRFs) between life expectancy, internet usage, and mobile subscriptions are shown in Figure 4. IRF results reveal that shocks to both mobile penetration and internet usage generate strong and statistically significant positive short-run responses in life expectancy, with the effects peaking within three periods before gradually declining. These findings suggest that ICT development enhances health outcomes through improved health information access, communication, and service connectivity. The effects are stronger for mobile subscriptions than for internet usage, indicating that mobile-based technologies remain the most influential ICT channel in health transmission. Conversely, shocks to life expectancy produce relatively weaker and less persistent responses in ICT diffusion, implying limited reverse causality and supporting an asymmetric relationship running primarily from ICT to health outcomes. Furthermore, shocks to internet usage and mobile penetration mutually reinforce one another, confirming the presence of technological complementarity in ICT diffusion.

5 Conclusion and Policy Recommendations

In investigating the intricate relationships among internet usage and mobile subscriptions on health outcomes, this study utilises a comprehensive panel data framework to analyse 43 African countries over a span of 22 years from 2000 to 2022. By employing panel ARDL and panel VAR, the research unequivocally demonstrates that access to technology, specifically internet usage and mobile subscriptions, significantly contributes to improvements in health outcomes, both in the short run and over the long term. The results reveal the considerable influence of technological infrastructure on health outcomes, which is consistent with the results of other recent studies by Zhiang et al. (2022), Kouton et al. (2020), and Njoh et al. (2019). Improved internet connectivity and mobile access enable the broad dissemination of health information, enhance patient management systems, and increase the accessibility and efficiency of healthcare services. This transformation is especially crucial in developing regions where conventional healthcare frameworks may be inadequate; here, digital solutions present an essential alternative for driving health progress. Also, the findings suggest that GDP per capita growth significantly reduces infant and adult mortality. This indicates that economic growth, together with a robust digital infrastructure, may suffice to ensure optimal health outcomes.

In light of these findings, several policy recommendations emerge. Firstly, governments and international organisations must prioritise investments in digital infrastructure. Expanding internet access and mobile connectivity in underserved rural areas can help close the digital divide while fostering healthcare advancements. Additionally, there should be a dedicated effort to incorporate digital technologies within healthcare systems. Promoting telemedicine, online health education programmes, electronic health records, and mobile health applications can significantly improve service delivery and reach. Furthermore, collaborative initiatives between technology providers and the healthcare sector are essential. These partnerships should concentrate on effectively translating technological innovations into tangible health benefits through joint research efforts, training healthcare professionals in digital competencies, and developing localised health applications that cater to specific community needs. Continuous assessment of how technological implementations affect health outcomes is vital alongside ongoing research into the mechanisms by which technology influences healthcare delivery.

While this study offers comprehensive insights, it recognises certain limitations, such as variations in data quality across different countries over time, that may impact the reliability of its conclusions. Future investigations could focus on studies within particular nations to examine the direct effects of technology integration on health metrics over extended periods. Exploring socioeconomic and cultural factors that shape the effectiveness of technological interventions will provide valuable insights into optimising digital strategies for diverse populations.

In summary, this research emphasises the pivotal role of digital infrastructure in enhancing global public health outcomes. As society increasingly adopts technological innovations, it becomes crucial for policymakers to utilise these insights when formulating comprehensive and sustainable health policies. The future trajectory of public health interventions is closely linked to advancements in digital technologies; thus, embracing this paradigm shift is fundamental for promoting equity in healthcare access and improving population well-being worldwide. This holistic approach not only underscores the significance of digital inclusion within public health strategies but also lays a foundation for future initiatives aimed at integrating technology into efforts against health disparities.

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A Appendix A

A.1 List of Countries

Table 11: List of Countries

Algeria	Ethiopia	Namibia
Angola	Gabon	Niger
Benin	Gambia, The	Nigeria
Botswana	Ghana	Rwanda
Burkina Faso	Guinea	Senegal
Burundi	Guinea-Bissau	Sierra Leone
Cape Verde	Kenya	Somalia
Cameroon	Lesotho	South Africa
Central African Republic	Madagascar	Tanzania
Chad	Malawi	Togo
Congo (DR)	Mali	Tunisia
Congo	Mauritania	Uganda
Côte D'Ivoire	Morocco	Zambia
Egypt	Mozambique	Zimbabwe
Eswatini		

A.2 Correlation among Variables

Table 12: Correlation Matrix

	Fmort	Mmort	Imort	Riskmd	Lexp	Internet	Ln(Mobile)	GDPpcgr	Popgr	Elec	Urban
Fmort	1.0000	-	-	-	-	-	-	-	-	-	-
Mmort	0.9639	1.0000	-	-	-	-	-	-	-	-	-
Imort	0.6191	0.5494	1.0000	-	-	-	-	-	-	-	-
Riskmd	0.3762	0.3001	0.7843	1.0000	-	-	-	-	-	-	-
Lexp	-0.8909	-0.8229	-0.8230	-0.6397	1.0000	-	-	-	-	-	-
Internet	-0.4369	-0.3570	-0.5786	-0.4735	0.5780	1.0000	-	-	-	-	-
Ln(Mobile)	-0.3824	-0.3588	-0.5229	-0.3660	0.4891	0.4628	1.0000	-	-	-	-
GDPpcgr	0.0019	0.0033	0.0580	0.0318	-0.0169	-0.0943	0.0188	1.0000	-	-	-
Popgr	-0.1191	-0.2016	0.2679	0.3942	-0.1888	-0.3583	0.0103	0.0067	1.0000	-	-
Elec	-0.4815	-0.4380	-0.6492	-0.6133	0.6785	0.6550	0.4306	-0.0049	-0.4673	1.0000	-
Urban	0.2075	0.1822	0.1942	0.1805	-0.3055	-0.2913	-0.1049	0.0067	0.4096	-0.3913	1.0000