Exploring Digital Divide in Mobile Phone Ownership: Evidence from Nigeria

Ivan Forenbacher, Siniša Husnjak, Ivan Cvitić
Department of Information and Communication Traffic
Faculty of Transport and Traffic Sciences
University of Zagreb
Zagreb, CROATIA
ivan.forenbacher@fpz.hr, sinisa.husnjak@fpz.hr, ivan.cvitic@fpz.hr

Abstract—**In 2012, as part of its response to mobile digital divide, the Nigerian government introduced mobile phone subsidies to rural farmers and did not seem to have achieved the expected results. It was argued that no necessary analysis of socio-economic factors affecting mobile phone ownership had been conducted previously. The paper took advantage of this period to examine socio-economic factors affecting the probability of mobile phone ownership in Nigeria. In order to estimate a logit model we used national representative data from *DataFirst* on households and individuals ICT access and usage in 2011-2012. In contrast to what had previously been thought, we found out that poverty may not be correlated with the probability of owning a mobile phone. Type of electricity source, education, and activity has the greatest effect on the probability of owning a mobile phone. The findings may help to improve more coordinated digital divide policy, and serve as a complement to ICT Roadmap 2017 to 2020 in Nigeria and similar countries.**

Keywords- Mobile, Digital Divide, Information Communication Technology (ICT), Nigeria, Africa

I. Introduction And Literature Review

Digital divide today is a well-known phenomenon and reflects the differences in accessing and using Information Communication Technology (ICT). The understanding of digital divide is not comprehensive and is present in both developed and developing countries, including the ones on the African continent [1]. One option to bridge digital divide is through mobile phones. In particular, they can enhance pro-poor development in various important sectors, including health, education, agriculture, and employment and bridge digital divide [2], [3].

Africa has the largest and fastest growing base of mobile phone users [4]. Lots of users, due to cost-effectiveness, leapfrog the traditional technologies like computers and fixed-broadband, and accept wireless technologies [5]. This implies formulation of a coherent and coordinated ICT policy at the national, regional and local level by including a strategic framework.

Performing such analysis for the African continent during the past has had certain difficulties. This is primarily because the quality and credible data from trustworthy sources was rarely available for developing African countries, thus making it harder to perform necessary analysis. Without the right approach and in-depth analysis it may result in inefficient policies and methods for confronting development challenges, including digital divide.

This actually occurred in Nigeria in 2012 as a part of its response to bridge mobile urban/rural digital divide [5]. The government subsidized the mobile phones to rural farmers through Growth Enhancement Support (GES), despite the fact that they didn't prove any *ex-ante* causation between poverty and mobile phone ownership [6]. Moreover, a farmer will not buy mobile phone if he does not see a direct benefit from it, for example, through the use of application for the purchase of seed [6].

One explanation is that policy makers should take a more holistic approach. Instead of focusing just on mobile phone ownership (first-order digital divide), they should also focus on the use of technologies, such as Internet (second-order digital divide) [7]. As a result, much remains to be done to support further growth of mobile markets and services in Nigeria by building integral ICT policy, especially in the advent of the country's ICT Roadmap 2017 to 2020.

At the moment, despite various researches on digital divide in African countries, including Rwanda, Ghana, Uganda, Gabon, Kenya, Somalia, Cameroon, and Ethiopia [8-13], to the best of authors' knowledge, there is lack of research examining digital divide in Nigeria as the largest African economy [14].

Recent findings on mobile digital divide in Nigeria are only based on various consulting reports, stating basic digital divide indicators. Authors in [14] claim that since 2004, the number of mobile subscribers has been growing linearly slow. First significant increase of around 50 million subscribers occurred in the period from 2006 to 2010. It still remains unclear to what extent particular socio-economic factors may have led to such increase.

This suggests the need to gain knowledge about particular socio-economic factors and their magnitude of effect on Nigerian mobile subscriber probability to adopt a mobile phone as the first step. This question is important to investigate because understanding about the reasons behind proliferation of mobile subscribers can lead to efficient future policies.

The present paper uses national representative dataset from [15] on household ICT access and usage from 2011-2012 to estimate logit model which had been previously used by [11] or [18] for measuring digital divide. This, in turn, allowed us to perform initial analysis of the effect of socio-economic factors on the probability of owning a mobile phone in Nigeria at the population level. The results may have important implications for integral digital divide policies in Nigeria and may complement other studies dealing with the use of various technologies and services in other similar countries.

The rest of the paper is organized as follows. In Section 2 the data and methodology used are described. In section 3 the main results are presented. In Section 4 we discuss the results. Finally, in Section 5 we summarize the results and conclude.

II. DATA AND METHODOLOGY

A. Data sources

We had at our disposal dataset from *DataFirst*, South Africa [15]. The data were collected by Research ICT Africa (RIA) as a part of RIA Household and Small Business Access and Usage Survey 2011-2012 [16].

Data collecting mode was face-to-face. Units of the analysis used in the survey were both households and individuals aged 15 or older.

Sampling procedure consisted of random sampling which was performed in five steps for individuals [16]:

- Step 1: The national census sample frame was stratified to urban and rural Enumerated Areas (EA).
- Step 2: EAs were then sampled for each stratum using Probability Proportional to Size (PPS).
- Step 3: For each EA, lists that served as a sample frame for simple random sections were created.
- Step 4: 24 households were sampled using a simple random sample for each selected EA.
- Step 5: One individual was randomly selected based on a simple random sampling from all of household members or visitors staying in the household at the moment survey was performed, and aged 15 years or older.

Sample consisted of total 1552 observations for Nigeria. Therefore, the sample was weighted in order to gross up the data to the population level. The weights were calculated for households and individuals. They were based on the inverse selection probabilities. Applying weights during calculation ensures grossing up the sample of 1552 observations to 90 595 137 individuals which makes the data national representative of the target population aged 15 years or older.

B. Relevant variables to be used in the model

Relevant variables reflecting various socio-economic factors (Table 1) were adopted from previous research, such as [11] and [17] which examined factors affecting probability of mobile phone ownership.

TABLE I. RELEVANT SOCIO-ECONOMIC FACTORS USED TO GENERATE LOGIT MODEL

Concept	Socio-economic factor	Variable	Description
Digital divide	Mobile phone ownership	mpo	Mobile phone owner (1 = yes, 0 = No)
Geographic area	Location	rural	Rural area (1 = yes, 0 = no)
Quality of life	Electrical infrastructure	main electricity grid	Household is connected to main electricity grid (1 = yes, 0 = no)
		generator	Household has generator (1 = yes, 0 = no)
		other	Household uses other electricity sources, e.g. solar (1 = yes, 0 = no)
Personal characteristics	Gender	female	Individual is a female (1 = yes, 0 = no)
	Age	age	Number of years of an individual
Education status	Schooling	primary	Individual has primary degree (1 = yes, 0 = no)
		secondary	Individual has secondary degree (1 = yes, 0 = no)
		tertiary: diploma /certificate	Individual has diploma degree (1 = yes, 0 = no)
		tertiary: bsc/ba	Individual has BSc/Ba degree (1 = yes, 0 = no)
Activity	Activity last 6 months	unpaid house work	Individual is at home, e.g. housewife (1 = yes, 0 = no)
		retired	Individual is retired (1 = yes, 0 = no)
		unemployed	Individual is unemployed (1 = yes, 0 = no)
		disabled and unable to work	Individual is disabled and unable to work (1 = yes, 0 = no)
		employed	Individual is employed (1 = yes, 0 = no)
		self-employed	Individual is self-employed (1 = yes, 0 = no)
Literacy	Reading skills	with difficulty	Reading difficulties (1 = yes, 0 = no)
		not at all	Doesn't know to read (1 = yes, 0 = no)
	Writing skills	with difficulty	Writing difficulties (1 = yes, 0 = no)
		not at all	Doesn't know to write (1 = yes, 0 = no)
	English reading / writing skills	eng_yes	Knows to read and write in English (1 = yes, 0 = no)
Economic status	Earnings	disposable income	Amount of money at disposal each month (1 = yes, 0 = no)

The dependent variable is *mpo* (Mobile Phone Ownership). This is a dichotomous variable indicating whether individual owns a mobile phone ($mpo = 1$) or not ($mpo = 0$).

The explanatory variables were split in two groups – ratio and categorical. The first ratio variable included in the model is *age*. In contrast to other studies [11] and [17], we have not categorized the variable *age*. The second ratio variable is *disposable income* which refers to the amount of money an individual had at free disposal each month.

Categorical variables referred to the type of household location (rural or urban); type of electricity (no electricity, main electricity grid, generator, and other, e.g. solar); gender (male or female); highest level of schooling completed (none, primary, secondary, tertiary with diploma, tertiary with BSc/Ba degree); main activity during last six months (student/pupil, unpaid housework, e.g. housewife, retired, unemployed, disabled and unable to work, employed, and self-employed);

reading and writing skills in the mother tongue and English (easily, with difficulties, and not at all).

Table 1 and table 2 present basic descriptive statistics of the variables used in the model for Nigerian market.

TABLE II. NATIONAL REPRESENTATIVE DESCRIPTIVE STATISTICS FOR CATEGORICAL VARIABLES

Socio-economic factor	Variable	Proportion
Mobile Phone Ownership (MPO), D. V.	no	0.3363
	yes	0.6637
Location	rural	0.498
	urban	0.502
Electrical infrastructure	no	0.2993
	main electricity grid	0.5747
	generator	0.1025
	other	0.0235
Gender	male	0.5315
	female	0.4385
Schooling	none	0.2872
	primary	0.1867
	secondary	0.3777
	tertiary: diploma certif.	0.0972
	tertiary: bsc/ba	0.0512
Activity	student/pupil	0.1548
	unpaid housework	0.2093
	retired	0.0116
	unemployed	0.0603
	disabled - unabled to work	0.0016
	employed	0.1469
	self-employed	0.4156
Reading skills	easily	0.4619
	with difficulties	0.2108
	not at all	0.3273
Writing skills	easily	0.473
	with difficulties	0.2014
	not at all	0.3256
English reading/writing skills	eng_yes	0.5171
	eng_no	0.4829

Number of strata	2	**Number of obs.**	1552
Number of PSUs	63	**Population size**	90 595 137
		Design df	61

TABLE III. NATIONAL REPRESENTATIVE DESCRIPTIVE STATISTICS FOR RATIO VARIABLES

Variable	Mean	Std. error	[95% Conf.	Interval]	Min	Max
age	34.263	0.646	32.970	35.556	15	99
disposable income	6062.294	681.510	4699.53	7425.058	0	200000

Number of strata	2	**Number of obs.**	1552
Number of PSUs	63	**Population size**	90 595 137
		Design df	61

C. The empirical model

The econometric binary logit model to be estimated can be derived from the latent variable model:

$$mpo_i = \begin{cases} 1 & y_i^* = \alpha + \beta x + \varepsilon > 0 \\ 0 & otherwise \end{cases}. \tag{1}$$

where y_i^* is unobserved, latent variable indicating utility of owning a mobile phone. If y_i^* is greater than zero, meaning there is positive usefulness from mobile phone for observation i, we get to observe an individual *i* owning a mobile phone, i.e. $mpo_i = 1$, and $mpo_i = 0$ otherwise. The mpo is, therefore, our limited dependent variable (LDV). The error term ε is unobserved and distributed by the standard logistic distribution.

The α is a constant term and βx refers to a vector of m explanatory variables presented in Table 1 and Table 2 for a single observation i from a sample of total n observations, denoted as x_i with corresponding coefficient β_k. This can be rewritten as $\beta x = \beta_1 x_{ik} + \cdots + \beta_k x_{ik}$ for $k = 1,2,\dots,m$. From this, the primary interest is to determine probability that

$$Prob(mpo_i = 1|x) = Prob(mpo_i = 1|x_1, x_2, \cdots x_k) \tag{2}$$

To avoid limitations of the linear probability model (please see [17] for details), we must consider binary response model

$$Prob(mpo_i = 1|x) = \mathrm{L}(\alpha + \beta x) = L(z) \tag{3}$$

where z is a linear function of our explanatory variables and L is a non-linear function taking values in the range $0 < L(z) < 1$, for all real numbers z. In our case the non-linear function L is from the family of logistic functions defined as follows:

$$Prob(mpo_i = 1|x) = L(z) = \frac{\exp(z)}{1+\exp(z)} = \Lambda(z) \tag{4}$$

which lies in the interval between 0 and 1 for all real numbers z. $\Lambda(z)$ is a cumulative logistic function for a standard logistic random variable. The Equation (4) can be interpreted as the probability of *mpo* equaling "1" (success or owning a mobile phone). From this we can now derive the inverse of the logistic function $\Lambda(z)$ *logit* or *ln (odds)* to get the linear expression:

$$logit[\Lambda(z)] = ln\left(\frac{\Lambda(z)}{1-\Lambda(z)}\right) = \alpha + \beta x. \tag{5}$$

By rewriting Equation (5), we get our final econometric logit model to be estimated

$$\ln{(odds)_i} = \alpha + \beta_k x_{ik} + \cdots + \beta_k x_{ik}, \;\; k = 0,1,\dots,m \;\; i = 0,1,\dots,n\,. \tag{6}$$

Equation (6) states that dependent variable (DV) refers to the logit of mobile phone ownership for a particular observation i in the sample. The coefficient β_k measures *ceteris paribus* effect of one-unit change of x_{ik} on the DV. Predicted probabilities can be calculated by using equation (4).

eISSN: 2453-6571, cdISSN: 1339-5076
ISBN: 978-80-554-1375-4

III. Results

Our strategy was to perform logit model across whole sample for Nigerian market to determine the coefficients values. Coefficients of the logit model were estimated with Maximum Likelihood Estimation (MLE) using described equations (1)-(6) from our statistical software. Table 3 presents the main results.

Final model consisted of total 22 variables and a constant term. The weighted analysis was performed on total of 1552 observations.

It is important to note that, since our dependent variable *mpo* is at the individual level, we had to use individual weights in our calculations in order to gross up the data to national level. This resulted with the target population of 90 595 137 individuals which were 15 years old or older in 2011-2012.

The critical *F value* is 16.79 with (22, 40) degrees of freedom. Probability of observing as extreme or more extreme F value is 0.000, given that the null hypothesis is true.

Main results suggest that most variables are statistically significant based on *p* values either at 1%, 5% or 10% level. However, this is not the case with certain variables. For example, variable *location* (urban/rural) is not statistically significant ($p = 0.865$) and has no effect on probability of mobile phone ownership. Similarly, other electricity sources (e. g. solar) does not contribute to the model significantly ($p = 0.958$).

TABLE IV. Estimated Logit Model For Nigerian Market

MODEL	Coef.	Lin. Std. Err.	t	P>t	[95% Conf. Interval]	
intercept	-1.291	0.708	-1.82	0.073	-2.708	-0.126
rural	-0.069	0.407	-0.17	0.865	-0.884	0.745
main electricity grid	0.850	0.329	2.58	0.012	0.190	1.509
generator	1.817	0.434	4.18	0.000	0.947	2.687
other	-0.028	0.536	-0.05	0.958	-1.100	1.044
female	-0.534	0.273	-1.95	0.055	-1.080	0.012
age	-0.017	0.008	-2.04	0.046	-0.034	-0.0003
primary	0.808	0.496	1.64	0.109	-0.184	1.801
secondary	1.720	0.542	3.17	0.002	0.636	2.804
tertiary: diploma /certificate	1.803	0.471	3.83	0.000	0.860	2.745
tertiary: bsc/ba	1.879	0.934	2.01	0.049	-0.010	3.747
unpaid housework	0.993	0.385	2.57	0.012	0.222	1.765
Retired	2.289	0.860	2.66	0.010	0.569	4.009
unemployed	1.048	0.518	2.02	0.047	0.012	2.085
disabled and unable to work	0.708	0.977	0.72	0.472	-1.247	2.663
employed	1.436	0.424	3.38	0.001	0.587	2.284
self-employed	1.179	0.314	3.75	0.000	0.550	1.808
reading_with difficulty	0.822	0.512	1.61	0.113	-0.201	1.846
reading_not at all	0.851	0.866	0.98	0.330	-0.880	2.583
writing_with difficulty	-0.088	0.421	-0.21	0.835	-0.930	0.754
writing_not at all	-1.763	0.829	-2.13	0.038	-3.422	-0.105
eng_yes	0.430	0.433	0.99	0.324	-0.436	1.298
disposable income	0.0008	0.00001	4.52	0.000	0.00004	0.0001
Model summary						
Number of strata	2			**Numb. Of obs.**	1552	
Number of PSU	63			**Population size**	90 595 137	
				Design df	61	
				F (22, 40)	16.79	
				Prob > F	0.000	

In addition, variables regarding literacy (reading with difficulties, reading not at all, writing with difficulties, and English reading and writing skills) and are not statistically significant.

Considering other statistical significant variables, there is a gender gap in mobile phone ownership with *female*'s coefficient of -0.534 meaning they are less likely than males to own a mobile phone.

With respect to education, the higher degree an individual has, they are more likely to own a mobile phone. Interestingly, results report that monthly disposable income does not contribute significantly to the propensity of owning a mobile phone.

Furthermore, results report that *age* (-0.017) doesn't have significant effect on probability of mobile phone ownership. From the group of variables regarding main activity during last six months, *retired* people are more likely (2.289) to have mobile phones than student/pupils. They are followed by *employed* (1.4363) and *self-employed* (1.179) individuals.

IV. Discussion

Some previous digital divide policies in Nigeria, such as *Growth Enhancement Support* (GES) when government introduced mobile phone subsidy to farmers in 2012 may not yield desired results. It was argued by [6] that they should first explore main socio-economic factors responsible for mobile phone ownership and then decide when and to whom to subsidize mobile phone. Identification of these factors may, in turn, facilitate the development of more coherent policies.

In this study we explored the impact of socio-economic factors on the probability of mobile phone ownership in Nigeria. We used national representative dataset from the *DataFirst*, based on RIA Africa ICT access and usage survey for period 2011-2012 [15], [16].

We used a binary logit model that had been used in previous research for similar purposes, such as [11] and [18]. The model's “quality” indicators suggest that the model shows good fit to the data. Additionally, the type of variables included in the model is justified. The variables representing socio-economic factors included in the model were adopted from [11] and [18] and most of them are statistically significant.

Another important aspect is the ratio of the number of observations and number of variables included in the model. The literature suggests that the minimum number of observations per variable for logit model should be 10 – 20 in order to achieve empirical validity [19]. This was indeed the case with our model resulting with approximately 67 observations per each variable.

The direction and magnitude of estimated coefficients seems reasonable. Importantly, a variable *location* denoting geographic area of residence for an individual (rural or urban) is statistically significant and does not contribute to the model [6]. Namely, this is consistent with the theory from analysis [6] arguing that the farmer will not buy a mobile phone with no obvious direct benefit. In other words, the farmer will not spend a certain amount of money to buy a mobile phone and on recurring costs that follow if the benefit doesn't outweigh the cost. Therefore, poverty cannot be taken exclusively as a cause of not owning a mobile phone in Nigeria.

Results suggest presence of gender gap in mobile phone ownership. Nigerian females are less likely to own mobile phones than males. Such results are consistent with the studies [11], [20], [21], and [22]. These studies argue that mostly men are early-adopters when new technology is being introduced. Additionally, gender gap decreases eventually as technology becomes more and more prevalent.

Another important socio-economic factor affecting the probability of mobile phone ownership is *age*. The results show that age has negative and mild effect on the *log odds* of mobile phone ownership. Namely, several studies [11], [23], and [24] suggest that the sign of correlation between odds of mobile phone ownership and age should be positive. This is something that can be implied from the variables referring to the main activity last 6 months. Coefficients values suggest that retired are more likely to own mobile phones than the youngest - pupils and students.

One more important socio-economic factor to consider is education, and its certain aspects deserve attention. Our results have confirmed previous claims from [11] that individuals with higher education degree are more likely to own a mobile phone. This can be interpreted by the fact that if someone is more educated, they will have less training costs and will be able to see the benefits of having a mobile phone more quickly [11].

Variable *income* suggests an interesting thing. Despite its positive sign which seems reasonable, the magnitude of its effect on the log odds of owning a mobile phone is very moderate. This can be interpreted from three aspects. First, in our research, we did not use a variable that would refer to the total monthly income but exclusively to the monthly amount which remains available to the individual. Second, it could be argued that the effect of variable *income* is moderate because monthly amount available is insufficient to own a cell phone. Thirdly, there is always a possibility that a person is moonlighting and receiving a salary, thus not reporting it in the survey.

Socio-economic factor *English reading/writing skills* suggest that knowing how to read and write in English is not statistically significant. In other works, log odds of owning a mobile phone and English literacy are not correlated. This aligns with similar study conducted in Gabon [11] where authors obtained statistical insignificance of the same variable. This may suggest that there isn't enough content in English that would attract potential mobile phone owners.

Similarly, if individuals do not know how to write it is very unlikely that they will own mobile phones. This may suggest the need to work harder on writing skills which are inevitable when using a mobile phone.

V. Conclusion

Careful *ex-ante* evaluation of socio-economic factors affecting the mobile phone ownership can be used to improve effectiveness of digital divide policies. This is because, as shown, certain socio-economic factors may have different effects from those that seemed reasonable at first and may be specific to individual countries, such as Nigeria.

As our results demonstrate, urban or rural *location* is not correlated with the probability of mobile phone ownership, as well as other electricity sources (e.g. solar), disability and inability to work, literacy problems. On the other hand, the main aspects of socio-economic factors which stimulate the most mobile phone ownership in Nigeria are housings that are connected to the main electrical grid or have a generator, individuals with tertiary level of education, retired, employed, and self-employed.

Further research is needed to avoid inefficient policies. An important issue to resolve for future studies is not only socio-economic factors affecting the first-order digital divide, but also the second-order digital divide. Another aspect would be to repeat such analysis with newer data set. This, in turn, would enable to analyze if certain policies yielded desired results and measure evolution of individual's behavior over time.

Our results may pave the road to more extensive studies in the future. The results may help authorities and policy makers to make coherent and efficient ICT policies and strategies in Nigeria and other similar countries, especially on African continent.

Acknowledgment

Present paper has made use of data "Africa - RIA Household and Small Business Access and Usage Survey 2011-2012", produced by *Research ICT Africa* and provided by *DataFirst*, Cape Town, South Africa.

References

[1] L. Hosman, E. Fife, "The use of mobile phones for development in Africa: top-down-meets-bottom-up partnering," The Journal of Community Informatics, vol. 8(23), 2012.

[2] United Nations. (2012). *Annual report 2011/2012*. Available at: http://www.undp.org/content/dam/undp/library/corporate/UNDP-in-action/2012/English/UNDP-AnnualReport_ENGLISH.pdf

[3] H. Geser, (2004). *Towards a sociological theory of the mobile phone*. Available at: http://socio.ch/mobile/t_geser1.pdf

[4] J. Patterson, (2016). *Africa's mobile subscriptions grow fastest globally*. Available at: http://www.thisisafricaonline.com/News/Africa-s-mobile-subscriptions-grow-fastest-globally?ct=true?utm_campaign=TIA+e-newsletter+March+2016+1st+issue+-+post-download+version&utm_source=emailCampaign&utm_medium=email&utm_content=

[5] M. Ragnedda, G. W. Muschert, "The Digital Divide: The Internet and social inequality in international perspective (Routledge Advances in Sociology)", 1st edition, 2015.

[6] E. Ojameruaye (2013, January, 28). *A commentary of mobile šhones subsidy for poor rural farmers in Nigeria*. Available at: http://chatafrik.com/articles/nigerian-affairs/a-commentary-of-mobile-phones-subsidy-for-poor-rural-farmers-in-nigeria#.VtAUtOY70kl

[7] E. Hargittai, “Second-Level Digital Divide: Differences in People's Online Skills,” First Monday, vol. 7(4), 2002.

[8] N. Mumporeze, M. Prieler, “Gender digital divide in Rwanda: A qualitative analysis of socioeconomic factors,” Telematics and Informatics, doi: https://doi.org/10.1016/j.tele.2017.05.014, in press 2017.

[9] C. Fuchs, E. Horak, “Africa and the digital divide,” Telematics and Informatics, vol. 25(2), pp. 99-116, 2008.

[10] M. Kasusse, “Bridging the digital divide in Sub-Saharan Africa: The rural challenge in Uganda,” The International Information & Library Review, vol. 37(3), pp. 147-158, 2005.

[11] T. Penard, N. Poussing, G. Zomo Yebe, P. Nsi Ella, “Comparing the determinants of Internet and cell phone use in Africa: Evidence from Gabon,” Digiworld Economic Journal, no. 86, pp. 65-83, 2012.

[12] I. Brännström, “Gender and digital divide 2000–2008 in two low-income economies in Sub-Saharan Africa: Kenya and Somalia in official statistics,” Government Information Quarterly, vol. 29(1), pp. 60-67, 2012.

[13] A. Chabossou, C. Stork, M. Zahonogo, “Mobile Telephony Access and Usage in Africa,” Proceeding ICTD'09, Proceedings of the 3rd international conference on Information and communication technologies and development, pp. 392-405, Doha, Qatar — April 17 - 19, 2009.

[14] GSMA (2013). *Sub-Saharan Africa mobile economy 2013*. Available at: https://www.gsma.com/mobileeconomy/archive/GSMA_ME_SubSaharanAfrica_2013.pdf

[15] Statistics South Africa, “Africa - RIA Household and Small Business Access and Usage Survey 2011-2012”, [dataset]. Pretoria. Statistics South Africa [producer], 2012. Cape Town. DataFirst [distributor], 2012.

[16] Research ICT Africa. Household and Small Business Access & Usage Survey 2011. Available at: http://www.researchictafrica.net/docs/Survey%20Methodology%202011:12.pdf

[17] J. M. Wooldridge, “Introductory Econometrics: A Modern Approach,”, 6th Edition, 2015.

[18] M. C. Tran, A. B. Labrique, S. Mehra, H. Ali, S. Shaikh, M. Mitra, P. Christian, K. Jr West, “Analyzing the mobile “Digital Divide”: Changing determinants of household phone ownership over time in rural Bangladesh,” JMIR Mhealth Uhealth, vol.3(1), 2015.

[19] D. Hosmer, S. Lemeshow, R. Sturdivant, “Applied logistic regression,” 3rd Edition, Hoboken, NJ: John Wiley & Sons, 2013.

[20] A. Gillwald, A. Milek, C. Stork, "Towards evidence-based ICT policy and regulation gender assessment of ICT access and usage in Africa," Research ICT Africa , vol. 1, Policy Paper 5, 2010.

[21] P. Schumacher, J. Morahan-Martin J. "Gender, Internet and computer attitudes and experiences," Computers in Human Behavior, vol. 17(1), pp. 95-110, 2001.

[22] B. Bimber, "Measuring the Gender Gap on the Internet," Social Science Quarterly, vol. 81(3), pp. 868-876, 2000.

[23] B. Oyelaran-Oyeyinka, C. N. Adeya, "Dynamics of adoption and usage of ICTs in African universities: A study of Kenya and Nigeria," Technovation, vol. 24(10), pp. 841-851, 2004.

[24] R. E. Rice, J. E. Katz, "Comparing Internet and mobile phone usage: Digital Divides of usage, adoption, and dropouts," Telecommunications Policy, vol. 27(8-9), pp. 597-623, 2003.