Bridging the Gap:

An Analysis of determinants contributing to the Gender Digital Divide in Southern African countries, using the AfroBarometer data (2018)

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Abstract

In this paper, I examine the factors that contribute to the gender digital divide across eleven Southern African countries. The ongoing digitalization of the world presents this divide as a critical challenge that prevents equality in Least Developed Countries. Despite efforts and policies that attempt to address the barriers to female's access and usage of digital resources, a digital gender gap persists. This is largely the case in Southern Africa, where females are shown to be less likely than men to use technologies.

Using the 2018 AfroBarometer data for eleven Southern African countries (Botswana, Lesotho, Madagascar, Malawi, Mauritius, Mozambique, Namibia, South Africa, Zambia, Zimbabwe, and Eswatini), my investigation includes an analysis through descriptive statistics and through empirical methods. My preliminary findings through the descriptive analysis illustrate the diverse range of the divide across the countries. In all eleven countries the difference between males and females in internet usage is evident. Further findings demonstrate the impact of the rural/urban divide on internet usage and how educational levels affect access to computers. My empirical approach was layered: first, a multivariate logistic regression looked at the determinants of internet usage, followed by a nonlinear decomposition technique that broke down these determinants into different effects. The findings from these approaches were consistent with the descriptive statistics. Variables such as education and employment were noted as significant contributing factors. Additionally, these results also identified household size and cultural implications behind the digital divide. The results were in favour of males having greater access to and usage of internet and mobile technology.

To assess the robustness of my results, I have also included a sensitivity analysis of the decomposition results through models that incorporate different assumptions, data variations and an Instrumental Variable technique to check for non-randomness in the sample. These results support the consistency of the baseline models and enhance the robustness of the original decomposition approach used. However, I do acknowledge that the paper does have limitations due to the nature of the data. My suggestion is to investigate the digital divide further through other datasets that are more recent.

Given the results, my recommendations for policy would be to focus on increasing female employment and addressing the skills gap. To bridge the gender digital divide, these should focus on enhancing females' economic empowerment, particularly through education and capability-enhancing opportunities. This is essential to embed equal, inclusive prospects for females.

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Abbreviations

Acronym	Full Name
EM	Employed Male
EW	Employed Woman
GSMA	Global System for Mobile Communications Association
ICT	Information and Communication Technologies
ILO	International Labour Organisation
IMF	International Monetary Fund
ITU	International Telecommunication Union
UM	Unemployed Male
UN	United Nations
UNCTAD	United Nations Conference on Trade and Development
UW	Unemployed Woman
WDR	World Development Report

1. **Introduction**

For an individual to access and utilize the opportunities provided by technology is a capability that is a pivotal determinant of socio-economic advancement in the increasing digitization of society. However, this presents a challenge: not all segments of society have equal prospects to benefit equally from these advancements. The gaps between groups when it comes to technology highlight the complex interplay between physical spaces, virtual environments, and the networks that connect them. A growing concern is the gap that exists, and is increasingly widening, between males and females – this is known as the gender digital divide. In socio-economic landscapes such as Southern Africa, this gap is more pronounced due to the cultural, economic, and institutional factors that combine to create uneven chances.

Despite global efforts towards gender equality in digital usage, females are disproportionately underrepresented in the digital economy. There are barriers that females in developing countries, such as the Southern African region, often face when attempting to bridge this gap at an individual capability. These include cultural norms, unequal access to education, and social restrictions, all of which limit their active participation in local communities, and subsequently, the digital world. In addition to this, Southern Africa already faces significant challenges in terms of technological accessibility; according to the International Telecommunication Union (ITU) only 19% of females use the internet in Least Developed Countries, whereas the percentage of females in developed countries using the internet is much higher at 86% (ITU, 2023). The disproportionate share of females that account for non-Internet users in comparison to males continues to be relatively high. Specifically, the significant gender gap in the African regions is demonstrated by the gender parity score, which is the ratio of females using the Internet (%) divided by males using the Internet (%), of 0.58 for 2019 (ITU, 2019). Since this score is below 1, it represents inequality. This is the lowest of all regions worldwide; for example, worldwide the gender parity score is at 0.90 and the Americas have a score of 0.99 for 2019.

Considering these systemic barriers briefly mentioned above, it becomes evident that these contribute to the reduced participation of females in the digital economy on a regular basis. With reduced access to household finances or resources (CSIS, 2024), economic constraints are one of the leading factors limiting their ability to afford devices and the means to engage actively. Alongside this, the role of cultural norms is critical; females are discouraged from pursuing digital literacy and education due to societal expectations and patriarchal norms (UN Women, 2023). This exposure to digital technologies

is further exacerbated in regions with limited infrastructure, whereby connectivity issues limit even digitally skilled and capable females from access to digital platforms and networks (ITU, 2023). Another noteworthy barrier is that of the safety and privacy concerns of today's digital landscape. The fear of harassment or data misuse discourages many females from participating fully in online spaces, reinforcing the influence of cultural norms mentioned earlier. (UN Women 2023).

To understand why and how these barriers to digital parity between genders persist, this paper aims to examine the persistent gender gap in digital access and use across Southern African countries using the data made available by Afrobarometer from the year 2018 for eleven Southern African countries. As an overview, Chapter 3 uses descriptive statistics to demonstrate the magnitude of the differences in internet usage across an array of factors. This is further broken down by visualizing the rural/urban divide for internet usage as well as how different education levels impact individual access to computers. The preliminary analysis suggests that digital literacy not only has consequences for the employability of an individual, but also shows that digital skills are a key factor that exacerbate the digital gap. Ultimately, the connection between the digital divide and the employment and skills gap.

To gain further insights at an empirical level, two methods are employed. The first approach is through a conventional Multivariate Logistic Regression Model that seeks to discern the determinants of internet usage across the eleven countries. This analysis is extended by using interaction terms for employment and education variables and the 'margins' command to calculate probabilities, followed by the 'lincom' command to allow for comparative predictions. From this, key findings were that age and rural location have an inverse effect on internet usage: individuals who are older or living in more rural conditions are less likely to use the internet. On the other hand, higher education levels and employment levels demonstrate a positive impact on the likelihood for the individual to use the internet across all countries. Most importantly, as the main variable of the internet, being male was shown to have general trends with a higher likelihood for internet usage in comparison to females, except for South Africa and Eswatini. The second approach was a decomposition analysis using the multivariate Oaxaca-Blinder technique developed by Yun (2005). The value of this approach was to highlight and distinguish the effects at an individual level in comparison to external coefficient effects. This analysis emphasized the impact of employment, education, and racial identity when comparing the gap that exists between males and females. Overall, the combination of approaches develops a multifaceted view of the nature of digital exclusion, whereby necessary targeted interventions that take these socio-economic and demographic contexts into account are required to bridge the digital divide.

1.1. Overview of the digital divide

As information is a key resource in networked societies[1] and is utilized in all spheres of the economic and socio-cultural dimensions, this creates a dynamic that reproduces new ways of exclusion and poverty in the generation of social divisions (Wessels, 2014). Variables considered when measuring it include education, ethnicity, gender, geography, and socio-economic positions. The last measure, socio-economic positions, has large and broad implications when understanding this concept: the digital divide is not only a question of online access but also digital skills and literacy (Lupton, 2013; Ragnedda and Muschert, 2013). The different viewpoints of the digital divide place emphasis on different mechanisms: the socio-cultural perspective of the digital divide, which is based upon the purpose, signification, and (re)shaping of digital technology usage and accessibility, and the relational perspective, which looks at the capacities of individuals based on the current circumstances (Castells, 2001).

Less access to and use of media networks and technical skills growth is experienced by those who have less connection to social networks in general (van Dijk, 2005). It is through this lens that the transition towards a digitalized global landscape is seen as playing a critical role in how digital tools can shape future opportunities, capabilities, and social structures (Castells, 2001; De Prato et al., 2014; Webster, 2006). Countries, such as those in Southern Africa, endowed with low levels of economic capital struggle to remove themselves from the current income and wealth disparities, discrimination, and financial or institutional barriers, that disenable individuals from participating in the information economy (Fuchs, 2008). Despite some African economies having a relatively sophisticated market in comparison to others, this has been a driving force behind further embedding digital inequalities and poverty. The limited resources and opportunities available for groups considered marginalized are only accelerated through the unequal distribution and accessibility of technology in society.

Southern Africa's development is hampered by the severe lack of robust education systems, poverty ,and widespread illiteracy. In relating this to overall economic mobility and well-being, technology access and diffusion are essential in increasing the efficiency of market transactions, services, and goods production, thereby enhancing productivity and reducing operational costs (Dewan & Riggins, 2005). When looking at the household level factors and the role of technology, improving accessibility and usage can facilitate communication, learning, and access to services, which in turn enhances labor

[1] The concept of a "networked society," highlights the transformative effects of ICTs on social interactions, economic systems, and cultural dynamics, suggesting a paradigm shift towards interconnectedness and digital dependency (Castells, 2001; Webster, 2014).

productivity and savings capacity by providing more direct channels to financial services and aid. The exclusion of females from accessing and developing digital skills has two main implications: firstly, it is a loss of potential individual capacity and contribution to new ideas; and secondly, there is a direct impact on productivity and GDP growth. If developing countries were to achieve digital gender parity by 2025, this could add $700 billion to GDP growth (McKinsey Global Institute, 2015).

The first constraint on females is the cost of digital devices and internet services, coupled with a lack of financial independence. This places technologies out of reach for many females, which results in their ability to participate in the digital realm being significantly constrained, impacting their educational and economic opportunities (Hilbert, 2011; World Bank, 2012). Another leading barrier is how the cultural and societal norms in many African societies often prioritize men's access to technology and education over their female counterparts. Ultimately these norms can restrict the mobility of females, limit their access to technological training and education, and discourage their participation in the digital world (Johnson, 2016; GSMA, 2020). Lastly, institutional barriers and the underrepresentation of females in decision-making roles for the digital sector exacerbate the lack of gender-sensitive policies and programs in the ICT sector, therefore not encouraging the specific needs and challenges faced by women to be addressed (UNESCO, 2019; ITU, 2020).

2. Literature review

The literature on the digital divide as it pertains to gender dynamics is broad and multi-faceted. Available studies on the gender digital divide in general span issues of physical and psychological accessibility, cultural norms, and economic barriers; moreover, the available literature on the quantitative techniques used to measure this is also varied. Two common approaches observed are comparative statistical analysis, logistic regression analysis, and decomposition analysis. For this reason, this section of the literature review has been divided into two sections:

1) A detailed view of the thematic approaches as understood in a range of literature
2) A review of methodological approaches used to quantify the digital divide.

2.1. Thematic approaches

According to the World Development Report (2016), significant gender disparities in technology usage and employment in the ICT sector persist in many countries; over 1.7 billion females in low- and middle-income countries do not possess mobile phones. On average, females in these countries are 14 percent

less likely to own a mobile phone compared to males. For example, in Africa, females are 50 percent less likely than males to utilize the internet. In addition to ownership and access, females often face constraints in controlling the use of technology, creating an additional barrier (WDR, 2016). A study conducted by researchers in West Africa focused on measuring the gender digital divide in six francophone countries[2] (Hafkin, 2007). They found no gender gap in usage among young females who had received education up to the secondary school level and beyond. This finding suggests that education plays a significant role in addressing the gender gap in internet access and usage (Polat, 2012). However, it is widely acknowledged that females encounter obstacles in accessing education at all stages of life due to factors such as lack of time to attend school, familial and household responsibilities, and socio-cultural norms that prioritize education at a lower level (Pande, 2012). Similarly, according to Melhem, Morrell, and Tandon (2007), females and girls face significant challenges in benefiting from the knowledge society due to their limited access to scientific and technical education, as well as education in general. Across developing countries as a whole, 75% of females are literate in comparison to 86% of males. For instance, in countries like India, only 51% of females possess basic reading and writing skills, while the corresponding figure for males is 75%. Without this fundamental skill, females are unable to engage with the internet and reap its associated advantages (Intel, 2013).

Ample evidence exists in the existing literature to substantiate the presence of a gender digital divide, particularly in the context of Southern African countries. This divide, characterized by disparities in access, use, and impact of Information and Communication Technologies (ICT) between males and females, is a subject of extensive research and debate. Studies by authors such as Hilbert (2011), Gurumurthy & Chami (2014), and Van Dijk (2019) provide a comprehensive overview of how gender inequalities manifest in the digital realm. These inequalities are not only prevalent in terms of access to digital technologies but also in the capacity and opportunities to utilize these technologies effectively. The gender digital divide is further compounded by socio-economic, cultural, and structural factors that disproportionately affect females' engagement with technology. These factors include, but are not limited to, lower levels of digital literacy among females, socio-cultural norms that restrict females' use of technology, and economic barriers that limit females' ability to own and access digital devices. The recognition of this divide sets the stage for a deeper exploration of the specific challenges and barriers faced by females in Southern African countries, highlighting the necessity for targeted interventions to bridge this gap.

[2] Benin, Burkina Faso, Cameroon, Mali, Mauritania, and Senegal

An essential aspect of overcoming existing gender inequalities in these societies hinges on the enhanced ability of females to access and utilize Information and Communication Technologies (ICT). Such access not only offers improved quality of life through greater opportunities (Gurumurthy & Chami, 2014) but also empowers females in domains like employment, education, health, and finance, thereby increasing their agency (Hilbert, 2011). Studies examining gender differences in Internet engagement and access frequently highlight the significant impact of cultural conditioning and socio-demographic factors on females' digital experiences (Pokpas et al., 2019). However, these studies often prioritize statistical data over a nuanced understanding of the socio-cultural factors specifically affecting females' access to and use of technology. This oversight underscores the need for a more focused exploration of the gendered aspects of digital inclusion (Geldof, 2011). In the realm of digital inclusion, social norms often relegate females to roles that impede their active participation in the digital age. The traditional gender roles and household dynamics can significantly hinder females' ease of using technology and developing relevant skills (Galperin & Arcidiacono, 2020). Helsper (2008) defines digital inclusion as the influence of social factors on individuals' engagement with digital resources, emphasizing how socioeconomic dynamics can exacerbate inequalities in access to technological materials (Rashid, 2016). Furthermore, digital inclusion encompasses the ability to acquire digital skills and leverage them for personal development (Van Dijk, 2019).

In terms of the digital inequalities that may exit the usage gap refers to the application of the technology at an individual capacity level. The application of technology, in this regard, can be used for serious purposes, *w*hich have a positive impact on capital and resources, or entertainment purposes with few implications on capital and resources (van Dijk, 2003, 2005; Zillien & Hargitatti, 2009). Understanding how people engage with digital technologies is crucial for comprehending the consequences of unequal access (Zillien & Hargitatti, 2009). Mesch et al. (2012) incorporate theories of social stratification and cultural sociological perspectives by looking at the different accessibilities, usage types and attitudes across ethno-national variations in Israel using multivariate analysis. The findings confirm that ethnic groups (Israeli Jews and Israeli Arabs) were the main cause of digital access inequality, which was also characterized by disparate attitudes and occupational status. Another dimension of inequality in society that may affect internet usage and outcomes is spatial in terms of life in modern society – the location of an individual, such as rural versus urban areas, determines the structural inclination towards growth opportunities and digital penetration (Lupač, 2018). Researchers also recognize the issue of participation at the societal and individual level and how, for those that do engage, advantages are experienced in a

range of areas from academic success and labour market achievement to the uptake of health services (Park, 2017; Morales et al., 2016).

Among the array of available digital divide research, the first group of studies mainly considered demographic variables such as income, race, age, and education (Prieger & Hu, 2008; Fairlie, 2004). However, as the research area has progressed over time, there has been an increasing attention to technology views and human capital (van Deursen & van Dijk, 2019). Along the lines of inequitable access and use of ICTs, the existing disparities between rural and urban areas in access to infrastructure and amenities can contribute to further worsening any prevailing gender discrepancies. To provide a better understanding into the processes through which inequalities are enforced, it is also necessary to look at other factors such as income, level of education, age, and ethnicity since these also impact the dynamics between gender and ICT (Faulkner & Lie, 2007). The local gender dynamics and contexts should be considered foremost when looking at the differences in the number of male and female users (Castells et al., 2007). Although there is evidence from multidimensional models based on international data that differences in internet access across genders may not be as prevalent in younger and more educated individuals, this points to the influence of other variables (Friemel, 2016; Goldfarb & Prince, 2008; Hindman, 2000). Moreover, in continuation of this point about cultural influence and social norms, various authors (Van Dijk & Hacker, 2003; Ritzhaupt at al., 2013) report findings that indicate the impact of race and/or ethnicity on performance in ICT-related tasks.

The existing literature that sheds light on the gendered aspects of the digital divide emphasizes the need for targeted interventions to address the barriers faced by females in accessing and utilizing digital technologies (Huyer & McCann, 2004). Huyer and McCann examine the barriers that contribute to the digital gender divide in developing countries. These barriers include limited access to infrastructure, a lack of digital literacy and skills, socio-cultural norms and stereotypes, and economic disparities. A significant portion of females in developing countries lack access to the internet, according to recent research by Intel (2014) that included 2,200 females and girls from India, Egypt, Mexico, and Uganda. The study revealed that 25% of females in developing nations were without internet connectivity, with even higher rates of 45% observed in Sub-Saharan Africa. The findings underscore the persistent disparity in females' internet access, not only in Africa but also in the Middle East and other developing regions of the world. In their study, Gil et al. (2010) outline four key obstacles that impede females' access to and utilization of ICTs (Information and Communication Technologies): exclusion from technology education and design, constraints on available leisure time, societal norms that favour males, and financial and/or institutional limitations. These barriers may be extended to the perception of ICT

and the impact of this on the gender digital divide. The ITU (2021) presents statistics on gender parity in Africa: in 2021, there were 35% of males using the internet in comparison to 24% of females. However, they do show that this is narrowing over the years 2018 to 2020. The restraints placed on females, such as responsibilities for household work, and unpaid work alongside the expectations in society and unequal control over finances, not only limit employment capacity and growth, but also the ability to make use of ICT (Heintz, 2012).

2.2. Methodological approaches

The study by Bornman (2016) focuses on the information society and the digital divide in South Africa. The research employs longitudinal surveys to gather data and examine the state of digital access and usage in the country. Socio-demographic factors such as age, education, income, and location are analyzed to understand their impact on digital inclusion. Bornman (2016) confirms that although there was a general increase of 3% in Internet usage over the three years, there was also an upward trend in the percentage of those not using the internet. The results also indicated a 3-4% gender gap in computer usage and internet usage. In both cases, the male respondents were the dominant group. There were also reported differences in population groups and education levels. The racial disparity was especially profound with 40.7% of the white population using computers daily compared to less than 10% of the black, coloured and Indian population (Bornman, 2016). Going beyond the statistics in digital usage between females and males in South Africa, Pokpas et al. (2019) examine the mental models to explain the overlapping causes of community and gender on ICT adoption. Diverse perspectives of females from marginalized areas and lower income communities were uncovered by means of semi-structured individual interviews. One of the most noteworthy reasons for the gender disparity in digital use identified amongst those females includes socially constructed norms and behaviors, innate abilities of males, and cultural associations with masculinity (Popkas et al., 2019). Other constraints include the rural socio-demographics of females as more are located rurally in relation to work opportunities, as well as the time-consuming responsibilities of womanhood, such as domestic, community and productive work (Deen-Swarray et al, 2012). However, more digitally proficient and educated females contribute to the underlying reason to lack of education for females on the importance of technological skills and opportunities in digital access.

Looking at disaggregated micro-level data in at Sub-Saharan Africa (SSA) allows for individual-level inter-country probability data to be examined. This is preferable to macro-level records that give a vague and broad outline of the gender Digital Divide in Africa. Alozie and Akpan-Obong (2019) examine the

individual-level dynamics determining this ICT use gender divide in six SSA countries. Out of these six countries[3], respondents from South Africa reported the highest usage of the internet, where the actual gender gap is marginally in favour of females when it comes to smartphone ownership (Alozie & Akpan-Obong, 2019). Guha and Mukerji (2021) examine India, another developing nation with persistent inequalities in society and technological access, through the prism of a demand-supply framework to assess and determine the size of the digital divide. This study particularly contributes to understanding the heterogeneity at the district level in a country and how to implement a method of studying the relevant dataset, for which a form of a demand equation was applied to two ICT instruments. These two instruments included the share of households with computers and the Internet and the share of households with mobile phones. From the estimated multivariate econometric model of the digital divide determinants, their results indicated that there exists a rural-urban divide, but also that districts with a greater proportion of young and educated people, as well as a greater social status for females have a greater circulation of internet access through computers and mobile phones. Moreover, internet access is also greater with higher degrees of supply side access such as urbanization and better broadband network service (Guha & Mukerji, 2021).

The majority of the methodological approaches adopted for estimating the digital divide are based on individuals and their characteristics, which is gathered by means of survey research containing information on individual properties. The bulk of research on the usage of technology is based on the differences in usage types, skills and content types that is accessed (Zillien & Marr, 2012). Davison and Cotton (2003) carried out one example of a study that looked at the various uses of technology. The research indicated that the type of connection (such as broadband or dial-up) resulted in different utilization habits, implying ease of access is a strong determinant. In the hope of finding explanations on the aggregate level, these survey responses are studied using multivariate analyses. Looking at the ICT provision in five developing countries and how this differs across genders, Rashid (2016) employs data from a user survey based on public access to ICT. His study was based on the concept of digital inclusion, from which different measurement indicators were derived as well as a Pearson correlation coefficient and a linear regression model. Most notably, the findings presented that in two of the five countries, namely Ghana and Bangladesh, there exists digital exclusion of females; the determinants contributed to this were lower education and income levels.

[3] The six study countries included Uganda, Ghana, Kenya, Senegal, Nigeria and South Africa.

Similarly, a study by Ono and Zavodny (2006) examines the cross-country differences in information technology (IT) usage by looking at related determinants (sex, age, education and income groups) and how this has evolved over time within and across the five chosen developed countries (Singapore, South Korea, Japan, Sweden and the U.S.). The main goal was to grasp the reach of inequality in and amongst these different determinant groups. In all three Asian countries, females are less likely to make use of a home computer despite owning one. Overall, their results indicate that younger males who are well educated are more likely to use computers and the Internet in all five countries. Using a measure of correlation with inequality, they also found that the greater the inequality in gender, income and education, the closer the association with digital equality gaps in all three factors. Wasserman and Richmond-Abbott (2005) make use of a multivariate analysis in a study that looks at socioeconomic status and social, racial, and geographic variables to explain how these impact the differences in web use amongst males and females in the United States of America.

They found little significant variation in internet use based on gender but found that there was a significant education and income level gap.

Researchers typically choose their methodological approach based on the datasets available for their study. Decomposition analysis is a technique that Oaxaca (1973) and Blinder (1973) invented and later modified for non-linear models like probit or logit. This approach aims to dissect the underlying factors contributing to the gender digital gap. Jiang and Luh (2016) successfully applied this regression-based decomposition method to discern the differences in internet usage between males and females and to identify the key contributing factors. Wasserman and Richmond-Abbott (2005) also employed a similar technique, using factor analysis to uncover latent factors that explain observed correlations among variables. Prior to conducting regression analysis, Park et al. (2015) demonstrated how this technique, also known as latent variable analysis, helped characterize the digital divide through a composite index. In their study, they calculated an internet knowledge score based on four categories. Similarly, Raihan et al. (2021) also perform a Blinder-Oaxaca decomposition analysis of the gender divide in technology in Bangladesh, but rather than employing a linear model, they are able to overcome the limitations[4] through a two-step estimation for a non-linear model as proposed by Fairlie (1999). The technique

[4] The decomposition relies on observed characteristics to explain the differences in outcomes between the groups. If there are important unobserved characteristics that differ between the groups and are correlated with the outcome variable, the decomposition may suffer from omitted variables bias.

entails a two-fold decomposition estimated by probit models (Fairlie, 1999)[5]. Galperin and Arcidiacono (2020) use this decomposition technique to examine the effect of the digital gender gap on employment patterns and labour force participation across Latin American countries. The computer and internet (CI) usage of each group consists of two elements: the first being the differences in socio-demographic characteristics and then, secondly, the difference in factors contributing to the actual usage output. In other words, these two components refer to the endowment effect and the coefficient effect, respectively.

Multivariable logit regression is another econometric technique employed across various studies based on differences in internet use, which is used to estimate the probability of internet use based on the effect of individual and household-level demographics. Reddick et al. (2020) use this method to predict the digital divide by looking at the accessibility of broadband internet connectivity in San Antonio. Their results illustrate that females are less likely to report having broadband access than males, using the odds ratio as a means of comparison.

Although there are many studies on the gender digital divide that explore different themes and methods, there is still room to build on the data type and approaches used. This study uses Afrobarometer data, which has not previously been applied to this specific question, focusing on eleven Southern African countries. It also introduces Oaxaca-Blinder decomposition analysis alongside multivariate logistic regression—techniques that have not been used before in this regional context. This combination allows for a more detailed exploration of how individual and household characteristics shape the gender digital divide in Southern Africa. Unlike the other studies discussed above, which often focus on national-level indicators and longitudinal-type data, the analysis done in this paper reveals that employment and educational attainment are among the key drivers of the divide in Southern Africa. In addition, the results highlight that unexplained factors, such as socio-economic and demographic variables, play a significant role. This approach, being the first to use the AfroBarometer data in the decomposition technique alongside other econometric analyses for this region, not only captures individual experiences and behaviors but also provides fresh insights into the socio-cultural dynamics influencing digital inclusion in these countries.

[5] By estimating non-linear models separately for each group, Fairlie's approach allows for a more accurate decomposition of the differences in outcomes. It takes into account any non-linear relationships that may exist between the observed characteristics and the outcomes.

3. DATA AND METHODS

This section introduces the approach through three distinct subsections: "Data," "Variables and Descriptive Statistics," and "Understanding the Skills & Digital Gap." It establishes the framework for the study, presenting the data, variables, and overarching objectives that guide the exploration of the intricacies and implications of the digital divide. The investigation encompasses independent variables related to demographics and socio-economic aspects, such as age, gender, education, employment, rural location, shelter type, household size, and income. Descriptive statistics offer a comprehensive overview of variable distribution and characteristics – this explores the divide in digital skills, investigating the requisite competencies for navigating the digital landscape.

3.1. Data Sources and Sample

The cross-sectional survey data used in this study was collected from the AfroBarometer survey (http://www.afrobarometer.org) conducted in 2018 and covering 34 different countries across the African region. Afrobarometer is a non-partisan survey research network operating across Africa, dedicated to gathering dependable data on the perceptions and assessments of democracy, governance, and quality of life among Africans (Krönke, 2020). The main reason for choosing AfroBarometer data is because the data assesses various aspects of the digital divide in the questionnaires and responses undergone. The survey responses provide insights into assessing access to devices and network services, utilization rates, and variations in the everyday use of the Internet among individuals and states. For this study, the data gathered from eleven Sub-Saharan African countries[6] (SSA) was used. The purpose of only including SSA countries is to focus on the regions that are geographically linked and allow for spatial interdependence. Typically, samples taken within each country consist of approximately 1200 cases. To achieve a representative cross-section of all citizens that were 18 years and older in each country, random selection methods were used at the stages of sampling. Each survey employed clustering, stratification, and multistage area probability sampling methods, allowing for countrywide and nationwide probability samples of the chosen countries (Afrobarometer, 2017). The stratifications were based on geographic units, such as the main sub-national unit of province or state, and by rural or urban areas, with the main objective of achieving a probability with equal demographic division and scale to the actual population size. This means that a proportionally greater probability of being selected was allocated to more populated geographic units. Additionally, to make sure that no specific racial or

[6] South Africa, Botswana, Namibia, Mozambique, Zambia, Zimbabwe, Malawi, Mauritius, Madagascar, Lesotho, Eswatini

language groups were left out, the correct method of area stratification was used. This involved using primary sampling units and secondary sampling units (which were only needed in some rural areas) to pick sampling start points and then households at random (Afrobarometer, 2018). Fieldworkers conducted in-person interviews with each respondent in a randomly chosen household for these surveys. These surveys involved personal interviews that were conducted by fieldworkers, in which the individual respondent in each household was randomly selected. However, this selection alternated between male and female to achieve gender balance in the given responses.[7]

In the survey questionnaire, there are four relevant questions asked about technology that can be used for analysis in this paper[8]. The first two are Question 89D and Q89F, "Do you own a computer?" and "Do you own a mobile?', respectively. Follow-up questions to this were (Q91B) "How often do you use the internet?" and (Q91A) "How often do you use a mobile phone?" with answers ranging from Everyday/A few times a week/A few times a month/Less than once a month/Never. These were coded into binary responses so that (1) Everyday, (2) A few times a week, and (3) A few times a month were combined to form a positive "yes" (1) and (4) Less than once a month and (5) Never to form "no" (0). Independent variables included in the analysis are individual and country-specific factors that are expected to impact ownership and use of technologies, such as age, gender, education, employment, rural location, type of shelter, household size, and whether the individual receives a regular cash income every month. Race and the state of living conditions are also included in the descriptive analysis.

3.2. Variables And Descriptive Statistics

The main variables of interest for this study are mobile use and computer use, which can be seen as two ways of defining digital access and capabilities. In Table 1, the entire sample and each country is made up of a total of 14,116 adults with a roughly even distribution of males and females.

[7] In the case of over or under-sampling for the household size, there are two types of weights included: "Withinwt" was created for national-level statistics, whereas the "Combinwt" was created for the merged datasets with different to compare the cross-national differences of the descriptive statistics. This cross-national weight was employed in the following descriptive statistics section to come, wherein the national sample of each country is standardized to equal sizes.

[8] One main drawback of this dataset is that there is no variable that contains information on the exact amount of digital use (such as data downloaded or hours used). However, it does not contain categorical variables on computer and mobile use. This means that instead of precise point estimates of differences as comparisons between countries, this can rather be interpreted as common patterns of usage or access.

Table 1. Sample composition of the countries

Respondents	All	Males	Females
All	14, 116	7,082	7,034
South Africa	1,724	869	855
Botswana	1,112	557	555
Namibia	1,142	567	575
Mozambique	2,065	1,049	1,016
Zambia	1,158	584	574
Zimbabwe	1,176	588	588
Malawi	1,121	558	563
Mauritius	1,125	562	563
Madagascar	1,179	592	587
Lesotho	1,150	575	575
eSwatini	1,164	581	583

Source: Merged Round 6 data (36 countries) (2016). (n.d.). https://www.afrobarometer.org/survey-resource/merged-round-6-data-36-countries-2016/

Table 2 presents the descriptive statistics of the variables of interest for this study. This was based on the determinants outlined by previous studies mentioned in Chapter 2. These include individual characteristics such as education and age, as well as household and locational factors. As expected from stratified random sampling in Southern Africa, the average age for males (39.4) is slightly higher compared to that of females (38.4) and it is far more likely that a man is employed in the Southern African region. Additionally, it is clear from the data that males have a significant advantage over females in terms of education, with a higher likelihood that females have received no or only informal education. Although this evens out at primary and secondary levels, the gap increases at higher levels as males are more likely to have completed some tertiary or graduate education. *Access to cash* is a proxy variable that looks at how often the individual has gone without a cash income. In this case, females have a greater likelihood of being without access to cash relative to males, on average.

Table 2. Summary statistics of variables

Variable	All Mean	Male Mean	Female Mean
Computer own ("Access"==1)	0.281	0.306	0.254
Mobile own ("Access"==1)	0.843	0.856	0.827
Individual characteristics			
AGE	38.89	39.371	38.403
EMPLOYED	0.319	0.382	0.257
LANGUAGE			
English	0.026	0.025	0.025
European	0.031	0.032	0.029
African	0.932	0.929	0.930
Other	0.011	0.012	0.009
EDUCATION			
No education/informal	0.268	0.252	0.284
Primary	0.343	0.331	0.357
Secondary	0.241	0.255	0.227
(Some) Tertiary	0.094	0.103	0.085
Graduate	0.051	0.057	0.046
RACE			
Black African	0.899	0.900	0.898
White	0.011	0.012	0.011
Coloured/Mixed	0.037	0.037	0.038
Arab/Lebanese	0.001	0.001	0.001
Asian	0.050	0.049	0.050
Household characteristics			
Rural	0.594	0.595	0.594
Household size	3.201	3.214	3.189
Access to electricity	0.458	0.462	0.456
LIVING CONDITIONS			
Bad	0.476	0.479	0.473
Okay	0.195	0.193	0.197
Good	0.328	0.327	0.329
SHELTER			
Formal	0.645	0.652	0.638
Informal	0.334	0.327	0.341
Unit Dwelling	0.020	0.019	0.020

Source: Merged Round 6 data (36 countries) (2016). (n.d.). https://www.afrobarometer.org/survey-resource/merged-round-6-data-36-countries-2016/

3.3. Understanding the skills & digital gap

When looking at the gender dynamics within a country and the different attitudes towards technology uptake, the various studies discussed above attribute the skills gap to the disproportionate employment of females. Females are often thought to be relegated to more part-time, nonstandard jobs that do not result in digital training or exposure to ICT (Helsper, 2012). As presented in Table 3, which makes use of International Labour Organization data[9], there are large gaps between females and males in terms of the workforce. Males make up a larger portion of the labour force in each country and also have a much higher unemployment rate in each case. Moreover, on average, males have longer work hours. Cultural and institutional factors give rise to these disparities. This brings about two points to note for this paper: as the family roles for females that are based on social norms persist, the more severe the constraint on their labour force participation (Popkas et al, 2021); secondly, discrimination against females in Southern African countries is highly detrimental to their ability to gain access to labour opportunities, and subsequently, access and usage of technology (Fuchs & Novak, 2008).

Table 3. Employment categories by gender in selected Southern African countries

Country	Labour force participation rate %		Employment rate %		Unemployment rate %		Weekly hours	
	Male	Female	Male	Female	Male	Female	Male	Female
South Africa	57.4	44.1	41.5	30.4	27.7	31.0	42.0	36.9
Botswana	65.6	56.5	45.6	42.0	24.2	25.6	47.9	43.6
Namibia	62.7	55.4	49.5	45.1	21.1	18.6	45.0	41.1
Mozambique	80.1	78.1	77.6	75.3	3.1	3.7	32.8	24.8
Zambia	43.7	27.2	38.5	22.7	11.9	16.4	43.1	36.9
Zimbabwe	52.7	34.7	44.3	28.4	16.0	17.9	39.6	32.6
Malawi	56.9	41.3	48.0	40.6	1.0	1.6	33.7	26.7
Mauritius	85.0	58.3	78.5	52.4	7.6	10.2	38.5	34.2
Madagascar	89.2	83.6	87.6	82.1	1.8	2.8	35.2	31.2
Lesotho	55.0	45.2	42.6	35.1	22.6	22.3	51.2	48.1
eSwatini	55.9	47.1	44.1	35.6	21.0	24.4	46.7	40.5

Source: Country profiles - ILOSTAT. (n.d.). ILOSTAT. https://ilostat.ilo.org/data/country-profiles/. Retrieved for years 2018 except for Mozambique and Madagascar (2015)

In Table 4 and Table 5 below are the preliminary results about whether they use the internet on their mobile phones (given that they own one) and whether they have access to a computer, respectively. In

[9] The reason the data from the International Labour Organization is incorporated here is to illustrate the trends of gender labour across the respective countries of interest for this study.

Table 4, internet usage is relatively low throughout and across all eleven countries, with Mauritius and South Africa showing the highest figures of 62.75% and 68.33%, respectively. In most countries, there is a gender gap that favours males in internet use. This is consistent in all countries aside from Madagascar and South Africa, where the results indicate a gap that favors females.

Table 4. Gender differences in usage of mobile phones for mobile phone owners

Country	All (%)	Men(%)	Women(%)	Difference (Men-Women)
All	28,0	30,6	25,4	5,15
Botswana	38,2	43,9	32,4	11,5
eSwatini	30,4	34,9	25,9	9,0
Lesotho	14,8	15,6	14,0	1,5
Madagascar	6,8	6,9	6,8	0,1
Malawi	6,1	6,6	5,6	0,9
Mauritius	68,0	72,0	64,1	7,9
Mozambique	21,9	23,7	20,0	3,6
Namibia	37,6	39,8	35,4	4,3
South Africa	46,6	50,7	42,4	8,2
Zambia	14,1	16,4	11,8	4,5
Zimbabwe	20,9	23,3	18,5	4,7

Table 5. Gender differences in access to internet usage

Country	All (%)	Men(%)	Women(%)	Difference (Men-Women)
All	52,2	53,3	51,0	2,4
Botswana	59,1	62,9	55,2	7,8
eSwatini	58,6	60,8	56,3	4,5
Lesotho	38,9	39,5	38,3	1,2
Madagascar	35,8	35,6	36,0	-0,4
Malawi	40,7	45,6	33,2	12,5
Mauritius	61,8	62,9	60,6	2,3
Mozambique	45,5	45,5	45,5	0,0
Namibia	58,2	61,8	54,7	7,1
South Africa	68,3	68,0	68,7	-0,6
Zambia	40,4	41,4	39,2	2,1
Zimbabwe	43,9	45,2	42,6	2,6

Source: Merged Round 6 data (36 countries) (2016). (n.d.). https://www.afrobarometer.org/survey-resource/merged-round-6-data-36-countries-2016/

When looking at the gender differences in computer access, shown in Table 5 below, there are very low scores in computer accessibility throughout the eleven countries. For both females and males, this ranges

from a low of 6,2% in Malawi to 68,1% in Mauritius. Across all study countries, only 28,1% reported access to a computer, on average. This points out that the larger problem of the existing digital inaccessibility is more entrenched in developing SSA countries, such as Malawi, and relative to more industrialized African nations (Fuchs, C. & Horak, 2008). In contrast to the scores reported on mobile internet usage (Table 4), all of these results indicate computer access in favour of males. The largest gender gap is seen at 11.5 percentage points in Botswana, whereas the lowest gap is at 0.12 percentage points in Madagascar.

In Table 6. and Table 7, the descriptive reports for the frequency of mobile use and the frequency of internet use, by gender, are included. In terms of everyday mobile use, the percentage score for the average across all countries is relatively high at 78,7%. In terms of individual countries, this ranges from a high of 95,1% in Mauritius to a low of 6.02% in Madagascar. The largest gender difference in everyday mobile use is seen at 17.28 percentage points in Malawi, which is in favour of males. Namibia displays the lowest gender difference of only 0,6% points. Overall, the data reported in this table suggests that a large proportion of Southern Africa has access to and uses mobile devices. However, when looking at the use of the internet, these results are very low across the eleven countries, with only 32,1% indicating everyday use. Mauritius reports the highest percentage of everyday use at 56,3%, which is considerably higher than Madagascar with only 8.48% reporting everyday use of the internet. The gender gap is also more obvious when looking at internet usage: on average across all countries, there is a difference of 4.98 percentage points in everyday use. Moreover, in Zambia, Malawi, and Botswana, there is roughly a 12-percentage point gap between females and males who never use the internet, where the percentage of males is far less than that of females.

Table 6. Gender differences in the frequency of mobile use

	All (%)	Men(%)	Women(%)	Difference (Men-Women)
All Countries				
Everyday/few times a week	78,77	81,06	76,46	4,6
Few times a month/less than once	3,73	3,19	4,26	-1,07
Never	17,50	15,74	19,28	-3,54
South Africa				
Everyday/few times a week	93,50	94,35	92,75	1,6
Few times a month/less than once	1,81	1,15	2,46	-1,31
Never	4,70	4,60	4,80	-0,2
Botswana				
Everyday/few times a week	93,17	93,90	92,43	1,47
Few times a month/less than once	1,89	1,62	2,16	-0,54
Never	4,95	4,49	5,14	-0,65
Namibia				
Everyday/few times a week	93,70	94,00	93,39	0,61
Few times a month/less than once	2,28	1,76	2,78	-1,02
Never	14,19	4,23	3,83	0,4
Mozambique				
Everyday/few times a week	80,24	84,75	75,59	9,16
Few times a month/less than once	5,57	4,67	6,50	-1,83
Never	14,19	10,58	17,91	-7,33
Zambia				
Everyday/few times a week	75,47	79,62	71,25	8,37
Few times a month/less than once	5,18	3,94	6,45	-2,51
Never	19,34	16,44	22,30	-5,86
Zimbabwe				
Everyday/few times a week	86,48	88,95	84,01	4,94
Few times a month/less than once	5,53	3,74	7,31	-3,57
Never	7,99	7,31	8,67	-1,36
Malawi				
Everyday/few times a week	56,74	65,41	48,13	17,28
Few times a month/less than once	9,28	8,62	9,95	-1,33
Never	33,99	25,97	41,92	-15,95
Mauritius				
Everyday/few times a week	95,11	95,55	94,67	0,88
Few times a month/less than once	0,71	0,89	0,53	0,36
Never	4,18	3,56	4,80	-1,24
Madagascar				
Everyday/few times a week	6,02	6,43	5,62	0,81
Few times a month/less than once	3,05	3,55	2,56	0,99
Never	90,92	90,03	91,82	-1,79
Lesotho				
Everyday/few times a week	86,70	87,48	85,91	1,57
Few times a month/less than once	3,83	3,65	4,00	-0,35

Never	9,48	8,87	10,09	-1,22
Eswatini				
Everyday/few times a week	92,7	93,98	91,42	2,56
Few times a month/less than once	1,37	1,38	1,37	0,01
Never	5,93	4,65	7,20	-2,55

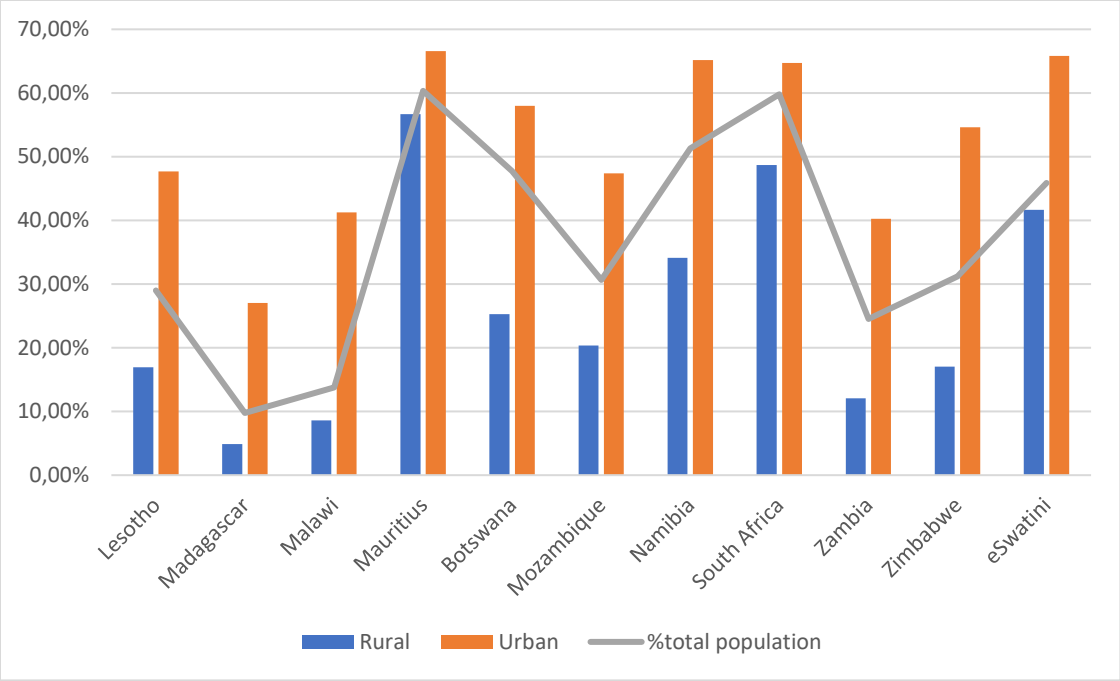
Table 7. Gender differences in the frequency of internet use

	All (%)	Men(%)	Women(%)	Difference (Men-Women)
All Countries				
Everyday/few times a week	32,14	34,62	29,64	4,98
Few times a month/less than once	8,49	9,38	7,61	1,77
Never	59,37	56,00	62,75	-6,75
Botswana				
Everyday/few times a week	41,37	45,96	36,76	9,20
Few times a month/less than once	10,16	12,03	8,29	3,74
Never	48,47	42,01	54,95	-12,94
eSwatini				
Everyday/few times a week	41,24	45,78	36,71	9,07
Few times a month/less than once	6,01	5,16	6,86	-1,70
Never	52,75	49,05	56,43	-7,38
Lesotho				
Everyday/few times a week	25,48	26,96	24,00	2,96
Few times a month/less than once	5,31	4,87	5,74	-0,87
Never	69,21	68,17	70,26	-2,09
Madagascar				
Everyday/few times a week	8,48	9,46	7,50	1,96
Few times a month/less than once	2,81	3,04	2,56	0,48
Never	88,71	87,50	89,95	-2,45
Malawi				
Everyday/few times a week	12,31	17,38	7,28	10,10
Few times a month/less than once	2,85	4,30	1,42	2,88
Never	84,83	78,32	91,30	-12,98
Mauritius				
Everyday/few times a week	56,27	57,12	55,42	1,70
Few times a month/less than once	7,64	8,36	6,93	1,43
Never	36,09	34,52	37,66	-3,14
Mozambique				
Everyday/few times a week	25,42	26,79	24,02	2,77
Few times a month/less than once	10,31	11,25	9,35	1,90
Never	64,26	61,96	66,63	-4,67
Namibia				
Everyday/few times a week	43,35	46,21	40,52	5,69

Few times a month/less than once	13,57	14,64	12,52	2,12
Never	43,08	39,15	46,96	-7,81
South Africa				
Everyday/few times a week	53,25	54,89	51,58	3,31
Few times a month/less than once	10,67	11,28	10,06	1,22
Never	36,08	33,83	38,36	-4,53
Zambia				
Everyday/few times a week	20,55	24,83	16,20	8,63
Few times a month/less than once	7,60	9,42	5,75	3,67
Never	71,85	65,75	78,05	-12,30
Zimbabwe				
Everyday/few times a week	21,85	23,12	20,58	2,54
Few times a month/less than once	13,95	16,33	11,56	4,77
Never	64,20	60,54	67,86	-7,32

Looking at the comparison between urban and rural areas in Figure 1, which depicts a bar graph comparing the percentage of internet use in rural versus urban areas across all countries studied, it is evident that urban areas have a higher percentage of internet use compared to rural areas in every country listed. This supports the notion of a digital divide in terms of geographic location, from a internal country perspective as well as a cross-country comparison. However, this rural/urban divide varies; Madagascar has the highest discrepancy between urban and rural internet use, with urban areas reaching 27% while rural areas are at 4,9%. Mauritius shows the smallest gap, with urban internet use at 66,5% and rural at 56,7%. On the other hand, countries such Eswatini, Zambia, and South Africa have relatively high internet use in urban areas (above 50%), but significantly lower in rural areas. A reliable and functional electricity grid is one of many factors that can have an impact on this. According to the Economic Development in Africa Report (UNCTAD, 2021), the failure of markets to function efficiently and implement ICT reform is often the root of the lack of institutional endowments in African countries (Salemink, Strijker, & Bosworth, 2017). In contrast, countries such as Mauritius and South Africa have implemented policies to counteract this and thus illustrate a more even divide, where there is only a slightly higher percentage score indicating the average individual use of the internet. The literature highlights how some government policies that prioritize the externalities of digital development which is shown to positively impact rural areas (Riddlesden & Singleton, 2014). What this specifically pertains to is digital literacy skills. Digital literacy not only has repercussions for the employability of an individual, but it also impacts the learning externalities in the community (Kandri, 2019). Ultimately, these preliminary findings highlight the connection between the digital divide and the employment and skills gap and supports the need for further investigation.

Figure 1. Rural versus urban divide of Internet use by country

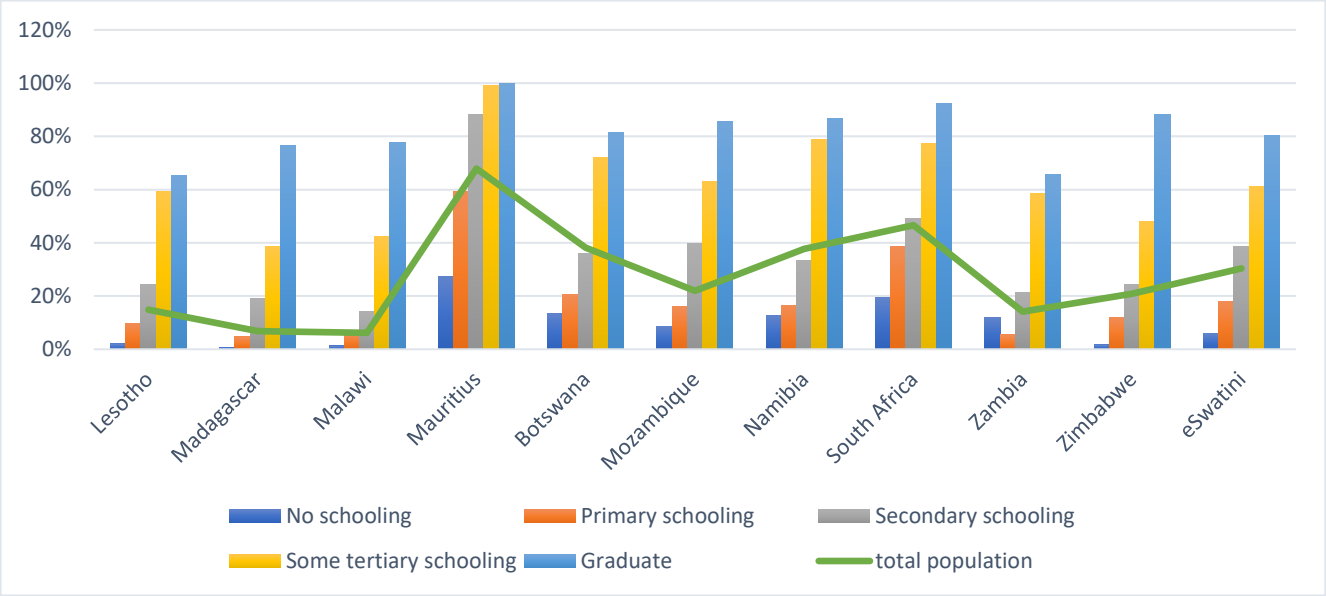


Source: Merged Round 6 data (36 countries) (2016). (n.d.). https://www.afrobarometer.org/survey-resource/merged-round-6-data-36-countries-2016/

In terms of device ownership and accessibility, as well as digital literacy, across these eleven countries, a pattern is becoming clear: the proportion of African adults in SSA with the ability to use digital devices, let alone could do so, is low and there exist significant hurdles in overcoming the current barriers. One factor to consider is education and, in effect, an individual's technological competency. Figure 2 depicts the percentage of people with various educational levels (no schooling, some tertiary schooling, primary schooling, graduate, secondary schooling) and their access to computers in the countries of interest. This is compared to the total population average that has access to computers; highlighting the general pattern that is country specific. The key takeaway is that computer access increases with higher levels of education in every country: for individuals with a level of education greater than or equal to tertiary schooling, there is a greater access. It essentially also demonstrates that access to computers for those with little to no education is limited. At most, 19% and 27 of uneducated individuals in South Africa and Mauritius have access to a computer, whereas in poorer, less developed countries such as Malawi and Madagascar, an extremely low proportion can access computers (less than 1%) This is confirmed by the literature which shows that South Africa and Mauritius have relatively higher GDP per capita compared to many other African countries (IMF, 2019) and thus reinforces literature that indicates individuals with higher education levels may have more skills and opportunities to use digital technologies. (Van Dijk, 2006). Economic prosperity often translates into better infrastructure, including telecommunications and

internet connectivity. This economic disparity is further embedded by the fact that those individuals with access to these forms of development and economic opportunities can afford better access to technology (Norris, 2001; Ragnedda and Muschert, 2013).

Figure 2. Individual education levels and access to computers (%), by country



Source: Merged Round 6 data (36 countries) (2016). (n.d.). https://www.afrobarometer.org/survey-resource/merged-round-6-data-36-countries-2016/

4. Methodology and approach

In Chapter 3 above, the descriptive analytics illustrate the large differences in individual and household variables across the eleven countries that contribute to the explanation of the group differences in mobile, computer, and internet usage and access, where term usage means that this occurs frequently, more than once a month. However, these differences between groups can't tell us what each person's contribution is. More specifically, the above analysis doesn't give us a direct and clear way to tell if differences between people within and across each country have an effect on gender differences in the digital divide.

Two empirical strategies are employed for this study, as this will provide more in-depth analysis and understanding of the factors determining the digital differences across gender. The main method of analysis is through the decomposition technique – this is because the decomposition method is primarily used to analyze and explain the sources of gaps between different groups, such as gender or race (Fairlie, 2005; Oaxaca & Blinder, 1973; Yun, 2004). Moreover, the decomposition method offers a more detailed breakdown of the gender gap than logistic regression. It allows for a quantifiable contribution of different

factors, such as differences in education, experience, or occupational choices, to the overall gender gap. This breakdown provides a nuanced understanding of the factors driving inequality and can inform policy interventions aimed at reducing disparities. Overall, the nonlinear Oaxaca-Blinder decomposition developed by Yun (2004) is a powerful tool for understanding and analyzing differences in outcomes between groups and can provide a more accurate and nuanced analysis of the underlying factors driving these differences.

4.1. Model 1: Multivariate logistic regression

The first method is a standard multivariate logit regression, shown by equation (1) below. The model, in log odds form, is derived as follows:

(1) $\mathrm{P(y = 1|X)} = \frac{e^{X'\beta}}{1+e^{X'\beta}}$

(2) $\mathrm{P(y = 0|X)} = 1 - \frac{e^{X'\beta}}{1+e^{X'\beta}}$

(3) $\log\left(\frac{P(y=1|X)}{1-(P(y=1|X)}\right) = \beta 0 + \beta_1 x_1 \cdot + .. + \beta_k \cdot x_k$

Where:

Where:

- $P(y=1)$ is the probability of an individual using the Internet or Mobile
- $\beta 0$ is the intercept term.
- $\beta 1, \beta 2, \ldots, \beta k$ are the coefficients corresponding to the demographic variables.
- X1,X2 ,…,X*k* represent the individual and household-level demographic variables (such as age, employment, education, etc.).

This is used to study how the likelihood of individuals using the specific technology defined (internet or mobile) is impacted by the various individual and household-level demographics.

To enhance this analysis, further comparison of the predicted probabilities of internet use across different groups is included. The output from the Logistic Regression Model that includes interaction terms between employment status, and education level is first used to derive the probabilities by using the margins command to calculate adjusted predictions at specific values, which is then followed by lincom

which is used to compute the differences in these predictions. For instance, *lincom 1.edu#1.male - 0.edu#1.male* calculates the difference in the probability of internet use between males with higher education and males with less education. Similarly, comparisons were made between different combinations of education and employment status among females, and between males and females, to understand the interaction effects on internet use. Essentially, the aim is to analyze how the outcome varies by education or employment and gender for each country. This allows for comparative results that show how the likelihood of internet use changes with education and employment status within each gender group. As shown in equation (2) below, an interaction contrast variable between employment and gender is computed to illuminate the differences in digital adoption (mobile or computer) for males and females based on the effect of employment. This will be denoted by an interaction contrast (IC) that can be defined as:

$$IC = [Pr(EM) - Pr(UM)] - [(Pr(EW) - Pr(UW)] \quad (2)$$

The interaction contrast measures the difference in the probability of internet use due to education level among employed females. A positive value suggests that higher education increases the probability of internet use, whereas a negative value suggests the opposite. Here the four groups are given: employed females (EW), unemployed females (UW) and educated versus uneducated (WE and WU). For this paper, uneducated has been coded as being less than only having secondary schooling. This allows for the different model predictions to highlight whether employment status and education are factors.

4.2. Model 2: Oaxaca-Blinder decomposition analysis

The nonlinear Oaxaca-Blinder decomposition is a statistical technique used to analyze differences in the mean outcomes of two groups, such as differences in wages between males and females or differences in test scores between different racial groups (Fairlie, 2005). It extends the traditional Oaxaca-Blinder decomposition method by allowing for nonlinear relationships between the covariates and the outcome variable.

The traditional Oaxaca-Blinder decomposition divides the difference in mean outcomes between two groups into two main parts: the explained component, also called the "endowment effect," which is the part of the difference that can be explained by differences in "endowments" (like education and experience) between the groups; and the unexplained component, also called the "coefficient effect," which is the part of the difference that can't be explained. Similar to the methodology used by Galperin and Arcidiacono (2021) in their study, I analyze the determinants of the gender digital divide in Southern

African countries. This framework categorizes covariates into two groups for a comprehensive analysis: personal factors (such as age, employment status, educational attainment, and racial identity) and external factors (including household type, rural versus urban location, and income consistency). This bifurcation, which follows Galperin and Arcidiacono's methodology, is essential for analyzing the individual and contextual influences on digital access and usage. Personal factors focus on intrinsic individual characteristics, while external factors encapsulate the broader socio-economic and environmental contexts, offering a holistic view of the multifaceted nature of the digital divide.

The nonlinear Oaxaca-Blinder decomposition extends this approach by incorporating nonlinear relationships between the covariates and the outcome variable. This allows for a more flexible and accurate analysis of the factors that contribute to the differences in mean outcomes between the two groups (Yun & Powers, 2011). It can be hard to figure out how to break down nonlinear models into their two parts, the endowment effect and the coefficient effects, because the contributions from each variable do not add up to the whole. This is because the linear prediction is not equal to the conditional expectation.

Fairlie (2005) proposes a solution to this using the logit function. His technique also involves the ordering of replacement randomization and sequential covariate replacement. Accordingly, Fairlie's technique proposes that the described portion of the decomposition gap as a contribution of each observable variable is the same as the difference between the average predicted probability from replacing the distribution of males with that of females, all else constant (Acosta-Ballesteros, J. et al, 2021). This technique essentially makes use of covariate grouping where the average decomposition results are drawn randomly from 1000 replications of randomized variable ordering; this is advantageous since population sub-groups are included and eliminates the chance of path dependence (Fairlie & Robb, 2007). This issue of *path dependence* is due to the sensitivity of the decomposition results to the ordering of the variables. The results of decomposition analysis using Fairlie's technique are included in the appendix to show the effect of this. One advantage of this technique is that it allows for analysis across the countries; however, looking at Southern Africa as a whole, it does not allow for the coefficient effects corresponding to each specific variable to be identified (Acosta-Ballesteros, J. et al, 2021) – therefore, the decomposition technique by Yun (2004) has been employed for the main analysis.

It is necessary to use Yun's (2004) method, which is a more general approach, because the outcome of interest is binary (using a computer or a cell phone), so the model's functional form needs to be considered. For instance, taking a dependent variable that is either a linear or non-linear function of

independent variables in some linear combination, one can derive the difference of this dependent variable in the first moment (the mean difference between two groups). This can be written as:

$$Y = F(X\beta)$$

Where F is a once differentiable function and a mapping to the linear combination of $(X\beta)$ to Y; the letters Y, X and (β) are an $N\ x\ 1$ vector, a matrix of independent variables and a vector of coefficients, respectively. Then, one can write the decomposed first moment difference of Y as: (with $\bar{}$ being representative of the average of the sample). A description of the decomposition of differences in probabilities for binary models is as follows:

$$\overline{Y_M} - \overline{Y_F} = \hat{\Delta} = \left(\overline{\emptyset(X_{\iota M}\widehat{B_{lM}})} - \overline{\emptyset(X_{\iota F}\widehat{B_{lM}})}\right) + \left(\overline{\emptyset(X_{\iota F}\widehat{B_{lM}})} - \overline{\emptyset(X_{\iota F}\widehat{B_{lF}})}\right)$$

Where the difference in coefficient effects and the difference in endowment effects are the decomposition of the difference equation of male and female probabilities. In this equation, $\overline{Y_M}\ and\ \overline{Y_F}$ are the average of the probability of internet or mobile usage for males and females respectively. The first term on the right-hand side of the equation represents the explained component, which is the difference in mean outcomes that can be attributed to differences in the covariates. The second and third terms represent the unexplained component for the second and first groups, respectively.

One of the merits of the nonlinear Oaxaca-Blinder decomposition is improved accuracy as it allows for a more accurate estimation of the differences in outcomes between groups when the relationship between the outcome and the explanatory variables is not linear. Another merit is flexibility, wherein a wider range of model specifications and functional forms can be used, which can better capture the complex relationships between the outcome and the explanatory variables. Lastly, the nonlinear Oaxaca-Blinder decomposition can give a better analysis when the data doesn't follow the rules of linear regression, like when it is heteroscedastic, multicollinear, or not normal (Powers & Yun, 2009). Moreover, the limitation of the reference-dependent problem of the decomposition technique can be overcome; each dummy variable can be defined in such a way to correspond to each level of the factor itself, which is then included as a complete set using the "normal()" command options. Because the countries have been grouped together, the "norm" function is also valuable in effectively treating them as fixed effects by holding their values constant at specified levels. Here, the coefficients estimated by the logistic regression model add up to zero across the levels of the respective dummy variable. What this means now is that if a different reference category were to be chosen, it would not change the effects and intercept of the respective variable results.

5. Empirical Analysis

5.1. Multivariate logistical regression analysis

This sub-chapter presents the results from the multivariate logit model(s), as depicted in equation (2) in Chapter 4. These results are estimates of the likelihood of whether an individual will use the internet, shown in 8, or mobile, Table 9 in the appendix, conditional on the observable characteristics. It is first worth noting that there were omissions for the binary variable *African* and *English*. This is due to the sample contained in each country, whereby for some, there were very few individuals of a non-African race as well as very few English speakers.

The logistic regression is corrected for survey sampling properties, whereby weighting has been accounted for using the survey data weights available in the dataset. The results are reported in log odds ratio for ease of interpretation. Looking at the anticipated predicted likelihoods, most of the effects are as expected across the eleven countries. An individual's age (aside from Zimbabwe) and residing in a rural location are inversely related to the likelihood of an individual using the Internet. This is evident from the negative coefficients observed for older age groups and rural residents across most countries. For instance, in the age group 50-60, the results show significant negative coefficients in all countries, such as -2.206 for Botswana and -2.768 for Eswatini, indicating a lower likelihood of internet usage among older populations. Similarly, the negative coefficients for 'Rural' in countries like Madagascar (-0.774) and Malawi (-0.502) suggest that rural residents are less likely to use the internet compared to their urban counterparts.

On the other hand, the probability of using the internet increases with higher levels of education, if the individual received a cash income over the past month, and with employment. This is reflected in the positive coefficients for higher education levels, such as tertiary schooling, which show strong positive associations in all countries. Additionally, positive coefficients like 0.629 for Botswana and 0.807 for Malawi show that having a job or receiving income correlates with higher internet usage. Living in a traditional hut is associated with a decreased likelihood of the individual's use of the internet, in comparison to those living in a formal housing structure. The negative coefficients for 'Traditional' shelter, such as -0.562 for Botswana and -1.013 for Eswatini, support this observation. Household size is mainly expected to increase the probability of internet use; however, this is not consistent throughout all the countries; South Africa, Lesotho, and Eswatini report negative expected likelihoods, as seen in the coefficients for household size.

Table 8. Likelihood of Internet usage by country (log odds coefficient)

VARIABLES	Botswana	eSwatini	Lesotho	Madagascar	Malawi	Mauritius	Mozambique	Namibia	South Africa	Zambia	Zimbabwe
AGE Group (18-20)											
20-30	0,196	-0,442	0,0474	-0.986*	-0,51	-2.170*	-0.338*	-0,233	-1.002**	-0,196	-0.541*
	(-0.404)	(-0.495)	(-0.322)	(0,521)	(-0.404)	(0,116)	(0,191)	(0,276)	(0,435)	(0,379)	(0,318)
30-40	-0.704*	-1.553***	-0.719**	-1.031*	-1.187***	-2.970***	-1.047***	-1.280***	-1.890***	-0.944**	-0.567*
	(-0.410)	(0,493)	(0,341)	(0,529)	(0,436)	(1,126)	(0,212)	(0,287)	(0,433)	(0,414)	(0,332)
40-50	-1.452***	-2.621***	-1.257***	-2.295***	-1.347***	-3.707***	-2.012***	-1.152***	-2.239***	-1.344***	-1.734***
	(-0.460)	-0,52	(-0.361)	(0,604)	(0,522)	(1,119)	(0,291)	(0,324)	(0,445)	(0,478)	(0,372)
50-60	-2.206***	-2.768***	-2.729***	-2.642***	-1.972***	-4.562***	-2.128***	-2.014***	-3.139***	-2.706***	-1.467***
	(-0.506)	(-0.56)	(-0.465)	(0,696)	(0,588)	(1,126)	(0,418)	(0,432)	(0,465)	(0,660)	(0,420)
60+	-2.685***	-3.076***	-2.679***	-2.617***	-1.874***	-4.842***	-2.899***	-2.149***	-3.677***	-2.832***	-4.234***
	(-0.569)	(-0.602)	(-0.478)	(0,703)	(0,668)	(1,115)	(0,561)	(0,446)	(0,489)	(0,640)	(0,833)
Male(=1)	0,257	0.368**	0,0836	0,224	0.815***	0,092	0.286**	0.430***	0,019	0.727***	0.371**
	(-0.189)	(-0.178)	(-0.168)	(0,270)	(0,266)	(0,204)	(0,137)	(0,157)	(0,143)	(0,216)	(0,167)
EMPLOYMENT (Unemployed)											
Looking	-0,121	-0,334	-0,269	0,226	0,463	0,564	-0,0852	-0,0292	-0,118	0,353	0,0924
	(-0.223)	(-0.273)	(-0.212)	(-0.447)	(-0,349)	(-0,379)	(-0,155)	(-0,206)	(-0,200)	(-0,265)	(-0,204)
Part-time	0.701*	0,033	0,156	0.613*	0,201	0,549	0.677***	0,089	0,172	(0,057)	0.932***
	(-0.386)	(-0.320)	(*-0.275)	(-0.357)	(-0,409)	(-0,401)	(-0,203)	(-0,302)	(-0,253)	(-0,346)	(-0,279)
Employed	0.629**	0.789**	0.694**	0,047	0.807**	0.809***	1.062***	0.693***	0.515**	1.033***	0,292
	(-0.281)	(-0.310)	(-0.283)	(-0.333)	(-0,345)	(-0,236)	(-0,250)	(-0,221)	(-0,229)	(-0,290)	(-0,270)
Received income	0.457**	0.541***	0.415**	1.192***	0,376	0,250	0.588***	0,201	0.324**	0.374*	0,048
	(-0,212)	(-0.179)	(-0,175)	(-0.299)	(-0,274)	(-0,326)	(-0,129)	(-0,167)	(-0,147)	(-0,219)	(-0,205)
African Race(=1)	-	-0,476	0,758	0,194	-	-0,195	-1,221	-0,263	-0.388*	-	-
	-	(-0.917)	(-0,987)	(-0,758)	-	(-0,238)	(-0,858)	(-0,316)	(-0,229)	-	-
English(=1)	-	2.699***	-	-	-	-	-	0.787***	0,382	0.689*	0,411
	-	(-0.839)	-	-	-	-	-	(-0,280)	(-0,260)	(-0,411)	(-1,432)
EDUCATION (No education)											
Primary schooling	1.466***	1.086***	1.297***	2.628***	1.307***	1.329***	0.849***	1.003***	0.586**	1.233***	1.009**
	(0,298)	(0,395)	(0,317)	(0,752)	(0,367)	(0,366)	(0,180)	(0,334)	(0,276)	(0,385)	(0,463)
Secondary schooling	3.038***	2.149***	2.436***	3.968***	2.111***	2.812***	1.792***	1.638***	1.628***	2.709***	2.033***
	(0,336)	(0,378)	(0,312)	(0,783)	(0,392)	(0,410)	(0,209)	(0,323)	(0,278)	(0,394)	(0,457)
Tertiary schooling	3.412***	2.982***	2.946***	5.330***	4.146***	4.604***	2.196***	3.130***	2.170***	4.108***	2.919***
	(0,419)	(0,427)	(0,436)	(0,834)	(0,574)	(0,744)	(0,269)	(0,384)	(0,339)	(0,443)	(0,499)
Graduate	3.869***	3.756***	3.506***	5.821***	4.481***	5.365***	2.558***	3.784***	3.264***	4.319***	4.673***
	(0,484)	(0,490)	(0,476)	(0,959)	(1,348)	(1,065)	(0,510)	(0,552)	(0,469)	(0,646)	(0,924)
SHELTER (Formal house)											
Traditional	-0.562**	-1.013**	-0,406	-1.124***	-0,482	0,632	-1.042***	-0.767***	-0.699***	-1.094***	-0.964***
	(-0,263)	(-0,400)	(-0,340)	(-0,282)	(-0,301)	(-0,515)	(-0,136)	(-0,175)	(-0,186)	(-0,311)	(-0,241)
Dwelling structure	0,393	0,069	0,743	0,931	2.371**	0,765	0,799	0,824	-0.791***	1.597***	1,592
	(-0,429)	(-0,351)	(-0,582)	(-0,734)	(-1,020)	(-0,687)	(-0,817)	(-0,504)	(-0,280)	(-0,544)	(-0,992)
Rural(=1)	-0.454**	-0.698***	-0.511**	-0.774***	-0.502*	-0.428**	-0.804***	-0.663***	-0.411***	-0.628***	-1.114***
	(-0,198)	(-0,220)	(-0,233)	(-0,275)	(-0,284)	(-0,204)	(-0,132)	(-0,173)	(-0,157)	(-0,231)	(-0,185)
Household size	(0,006)	0.0703*	0,002	0,088	0,041	0,023	0,011	0.0669*	-0.0862**	0,036	0.181***
	(-0,055)	(-0,037)	(-0,043)	(-0,120)	(-0,050)	(-0,079)	(-0,027)	(-0,035)	(-0,041)	(-0,040)	(-0,046)
Constant	-1.691***	-0,409	-1,678	-3.332***	-2.466***	1,857	0,56	-0,491	1.690***	-2.847***	-1.687***
	(-0,535)	(-1,120)	(-1,102)	(-1,110)	(-0,557)	(-1,240)	(-0,897)	(-0,513)	(-0,554)	(-0,579)	(-0,593)
Observations	1,137	1,110	1,146	1,175	1,115	1,072	2,045	1,138	1,720	1,152	1,172

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1. Reference groups in brackets next to headings of categorical variable names. Survey data weights used "Combinwt"

Looking at the main question about whether being male influences digital use, it is clear that the direction and significance vary by country. Being male in all countries aside from South Africa and Eswatini has a positive impact on the likelihood of internet usage. However, this is only reported to be significant at the 5% level for Botswana, Malawi, Namibia, and Zambia, as indicated by the coefficients (e.g., 0.257 for Botswana and 0.815 for Malawi). This aligns with the literature by Alozie & Akpan-Obong (2017), which illustrates the varying levels and differences of the gender digital divide across six African countries, noting that South Africa did indicate to have a slight advantage for females. Similarly, Hilbert (2011) has highlighted the complexities of the digital divide, where factors like gender, age, education, and socio-economic status interplay differently across regions and countries.

To better understand the factors driving the digital divide, researchers examine how model predictions of internet use among females vary by employment status and education level. This inquiry is grounded in a general hypothesis about the role of education in moderating the relationship between employment and internet use. Specifically, it posits that higher education levels in females are likely to increase internet usage, regardless of their participation in the labor force, as highlighted by Dettling (2017). This approach aims to unravel the nuanced interplay between education, employment status, and digital engagement among females. The two groups were categorized as follows: higher education, which was grouped as those with completed secondary schooling and above, and lower education, grouped as lower than secondary schooling. From Table 9 below, in both cases of high and lower education levels, when a woman is employed (EW), it has a significant effect on increasing the likelihood of using the internet in comparison to those unemployed (UW). This magnitude is mostly larger for those females who have received a higher education, as is noticeable in countries such as Botswana, Mauritius, Lesotho, and Eswatini. In Mauritius, the difference is predominantly evident as the probability of using the internet when employed is increased by 7 percentage points for those with less education. This largely coincides with Figure 2 above, whereby those with education levels above secondary schooling were shown to have greater access to and usage of the Internet.

However, these results are inconclusive – amongst the eleven countries below, six illustrate that the education effect does not necessarily moderate the impact of employment on internet use amongst females. For instance, in South Africa, the probability of internet use among employed females with higher education is 13.8%, compared to 13.0% for those with less education, showing a smaller interaction contrast. This could suggest a relatively uniform impact of employment on internet use across education levels. In contrast, in Mauritius, females with less education have a significantly higher probability (17.8%) of using the internet when employed compared to those with higher education

(9.0%), indicating a negative interaction contrast. This larger gap could be influenced by factors such as the availability of internet access, cultural influences, or economic factors that disproportionately benefit less educated employed females.

The literature supports these findings, which highlight the role of education in shaping internet usage patterns, particularly the impact of educational attainment on females' internet access in various socio-economic contexts. However, the results also present some contradictions to the general literature, especially in cases like Malawi and Mauritius, where educated females are less likely to use the internet compared to their male counterparts. This suggests that while education is generally a positive determinant of internet usage, its impact can vary significantly based on specific socio-economic and cultural contexts within different countries.

Table 9. Predicted probability of internet use among females by education levels and employment across countries

	(A) Higher education [Pr (EW) - Pr (UW)]	(B) Less education [Pr (EW) - Pr (UW)]	Interaction contrast\ (A-B)
South Africa	0.138***	0.130***	0.081*
	(0.009)	(0.010)	(0.009)
Botswana	0.101***	0.154***	-0.052***
	(0.010)	(0.011)	(0.007)
Namibia	0.124***	0.097***	0.027***
	(0.009)	(0.010)	(0.007)
Mozambique	0.121***	0.091***	0.024*
	(0.010)	(0.009)	(0.005)
Zambia	0.077**	0.032***	0.043***
	(0.012)	(0.007)	(0.007)
Zimbabwe	0.118***	0.054***	0.064***
	(0.012)	(0.007)	(0.007)
Malawi	0.068***	0.064***	0.005
	(0.012)	(0.008)	(0.011)
Mauritius	0.090***	0.178***	-0.088***
	(0.008)	(0.012)	(0.009)
Madagascar	0.017*	0.029***	-0.017*
	(0.012)	(0.004)	(0.010)
Lesotho	0.119***	0.168***	-0.049***
	(0.009)	(0.012)	(0.008)
eSwatini	0.132***	0.146***	-0.014**
	(0.010)	(0.009	(0.005)

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

In Table 8, the differences between males and females for the predicted probabilities in internet use by employment status are presented along with the calculated interaction contrast. Being employed has varying additive effects on the probability predicted for females in comparison to males in each country. In countries such as Zambia, Zimbabwe, Malawi, Mauritius, Madagascar, and Lesotho, this employment effect is larger for females compared to males, most of which are significant at the 5% level. Malawi has the largest difference, wherein the probability of females using the internet is increased by 57 percentage points compared to 47 percentage points for males (which results in a 10 percentage point difference that is highly significant). Looking at the other countries, the range of this difference is from about 1.2 percentage points (Eswatini) to about 8 percentage points (Mauritius).

Furthermore, when examining the additive effect of education on internet usage, the results are revealing. For instance, in South Africa, the predicted probability of internet use for educated males is 47.8% (significant at the 0.1% level), while for females, it is 46.6% (also significant at the 0.1% level), with an interaction contrast of 1.2 percentage points. This pattern is observed across various countries, with Botswana showing a notable difference where educated females have a 4 percentage point higher probability of using the internet compared to educated males. However, in countries like Malawi and Mauritius, the effect of education is inversely related, with females showing a lower probability of internet use compared to males by 7.4 and 8.7 percentage points, respectively. These findings indicate that, firstly, employment is a strong and significant contributing factor in predicting internet usage amongst both males and females and, secondly, in most countries, females are significantly and more greatly impacted by this effect.

Table 10. The differences between the effects of employment on the probability of internet use by gender across countries

	(A) Males	(B) Females	Interaction contrast\ (A-B)
	[Pr (EM) - Pr (UM)]	[Pr (EW) - Pr (UW)]	
South Africa	0.478***	0.466***	0.012***
	(0.010)	(0.008)	(0.005)
Botswana	0.541***	0.501***	0.040***
	(0.007)	(0.010)	(0.003)
Namibia	0.492***	0.480***	0.011***
	(0.008)	(0.008)	(0.003)
Mozambique	0.486***	0.86**	-0.008
	(0.008)	(0.009)	(0.004)
Zambia	0.431***	0.417***	0.014***
	(0.011)	(0.014)	(0.007)
Zimbabwe	0.436***	0.429***	0.007
	(0.011)	(0.013)	(0.005)
Malawi	0.395***	0.471***	-0.074***
	(0.016)	(0.020)	(0.009)
Mauritius	0.395***	0.481***	-0.087***
	(0.013)	(0.011)	(0.066)
Madagascar	0.314***	0.313***	-0.024***
	(0.018)	(0.013)	(0.007)
Lesotho	0.499***	0.533***	-0.033***
	(0.008)	(0.008)	(0.005)
eSwatini	0.470***	0.473***	-0.003***
	(0.008)	(0.008)	(0.003)

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

5.2. Oaxaca-Blinder decomposition analysis

The underlying concept of the second empirical strategy demonstrates the outcome of interchanging the characteristics of one group (male) with that of another group (female) – this is known as the two-fold decomposition analysis since two components are obtained, the explained and unexplained. The analysis bifurcates the observed differences into two components: the explained (endowment effect) and the unexplained (coefficient effect). The endowment effect represents the hypothetical scenario where females possess the same characteristics as males, while the coefficient effect reflects the differential impact of these characteristics on the digital divide. A negative coefficient effect estimate indicates that

if that coefficient factor were equalized across males and females, there would be an expected increase in the gender gap; whereas a positive characteristic effect estimate indicates that the gender gap in the digital divide is expected to reduce if females were equal to males in the distribution of that factor variable. In Table 12. And Table 13, the observed male-female differences in internet use and mobile use have been decomposed using a logit regression model with a set of predictors that included the variables of interest that are hypothesized for this study to affect the gender digital divide.

Looking at the results displayed in Table 12, the corrected total effect (raw difference) can be decomposed into an endowment effect and the coefficient effect. The result indicates that the differences in effects account for 56.05% in the prevalence of the digital gap, with differences in racial identity and education accounting for most of this. The decomposition results reveal that the combined effects of various socio-economic and demographic factors account for approximately 56.05% of the observed digital divide. This significant percentage underscores the multifaceted nature of the digital gap, driven by complex interactions between these factors. Supporting literature on this topic further reinforces these findings. For instance, a study by Chib and Harris (2012) highlights how socioeconomic factors, including education and race, significantly influence the digital divide in Africa. Additionally, Hilbert (2011) emphasizes the role of gender, showing that females in several African countries face more significant barriers to internet access than males, often due to lower levels of education and socio-economic status.

To gain insights into these gender differences, it is necessary to look at each contribution of the independent variable in terms of the endowment effect (characteristic) and coefficient effect. A particularly salient factor under the endowment effects is the 'Employed' variable. With a significant estimate of 0.011, it indicates that employment status is a crucial determinant in bridging the digital divide. This finding is consistent with the broader literature, including the work of Galperin and Arcidiacono (2021), who emphasize the role of employment in digital inclusivity. This illustrates that employment contributes positively to the endowment effect and accounts for 17.50% of the corrected total effect. In other words, the digital gender gap in internet usage can be closed by increasing female employment.

Other significant variables to note are the education level dummies, all of which contribute positively to the endowment effect. The 'No Education' dummy variable emerges as a predominant factor, contributing 22.52% to the corrected total effect. This suggests that educational disparities, particularly the absence of basic education, play a significant role in perpetuating the gender digital divide. The

analysis suggests that if females were afforded opportunities comparable to their male counterparts, even in the absence of formal education, we could expect a reduction of approximately 16% in the gender digital gap. This finding points to the necessity of policy interventions that focus not only on educational attainment but also on creating equitable opportunities in the digital realm. This is in alignment with the literature, wherein studies by Hafkin (2007) and Polat (2012) highlight the profound impact of educational disparities and socio-economic factors on technology usage and employment in the ICT sector. Moreover, another large indicator to consider is whether the individual had received a cash income in the past month, which relates to financial status. This can be interpreted as if females had the same consistency in income/earnings as males over the past month, the overall gender gap in internet usage would decrease by 5.64%. The logistic regression results also directly complement these findings; specifically, that higher levels of education, consistent income, and employment are positively associated with increased internet usage. This is in line with the literature that suggests females' economic empowerment is a pivotal element in increasing their digital engagement (Intel, 2013; Gil et al., 2010).

Moreover, the analysis of age groups and other demographic factors like household type and rural versus urban location, although not the primary focus of this study, reveals additional layers of the digital divide. For instance, younger age groups show varying impacts on internet usage, indicating that digital inclusion efforts might need to be tailored according to different age demographics. Lastly, to conclude, addressing racial disparities within gender groups is paramount. A reduction in these disparities could potentially decrease the female-male internet usage gap by approximately 51%, highlighting the intersectionality of race and gender in the context of digital access.

Table 11. Decomposition of gender differences in internet usage

Difference	Estimate	Percent Contribution
Raw Difference	-0.00648	-
Unexplained: characteristics	0.0340***	50.16
Explained: coefficients	0.0338***	49.84
	Due to differences in Characteristics	Due to the difference in Coefficients
Variables	Estimate (%)	Estimate (%)
Personal factors		
18-20 years old	-0.00135***	0.0001
	(-0.002)	(-0.001)
20-30 years old	-0.00392***	0.0010

	(-0.003)	(-0.003)
30-40 years old	-0.000936***	-0.0026
	(-0.002)	(-0.003)
40-50 years old	-0.00120***	0.0003
	(-0.005)	(-0.002)
50-60 years old	-0.000463***	-0.0031
	(-0.007)	(-0.002)
60+ years old	-	-
	-	-
Employed	0.0110***	-0.0022
	(-0.002)	(-0.003)
Received cash income	0.00340***	0.0033
	(-0.000)	(-0.004)
English speaking	0.0001	-0.0009
	(-0.000)	(-0.001)
No education	0.0134***	0.0105***
	(-0.000)	(-0.004)
Primary schooling	0.00316***	0.0008
	(-0.000)	(-0.004)
Secondary schooling	0.00106***	0.0016
	(-0.000)	(-0.003)
Some tertiary schooling	0.00319***	-0.00299**
	(-0.000)	(-0.001)
Graduate schooling	0.00395***	-0.0005
	(-0.000)	(-0.001)
Identifies as African race	-0.000130***	0.0329*
	(-0.000)	(-0.018)
External factors		
Formal house	0.000760***	-0.011
	(-0.000)	(-0.008)
Informal/traditional hut	0.00144***	0.0019
	(-0.000)	(-0.005)
Unit dwelling	0.0004*	0.0003
	(-0.000)	(-0.000)
Rural location	0.000168***	-0.0092
	(-0.002)	(-0.007)
Household size	0.000137*	0.0195**
	(-0.007)	(-0.009)
Constant	-0.0058 (0.027)	

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

A first glimpse of the results of the decomposition analysis presented in Table 10 reveals that a substantial portion of the gender gap is attributed to the endowment effect, which accounts for a notable

66.42% of the contribution. This suggests a significant disparity in the inherent characteristics between genders, such as socio-economic and demographic factors, that if equalized, could markedly reduce the gender gap in mobile usage, resonating with findings from ITU (2021) and Heintz (2012) regarding the economic barriers females face in accessing ICTs. On the other hand, the explained characteristics, or the coefficient effect, contribute to 67.91% of the difference (33.58% of the total contribution), indicating that how these characteristics influence mobile usage varies significantly between males and females. This finding is consistent with patterns observed in the Internet usage results, although the magnitude of the discrepancy is more pronounced in the context of mobile usage.

As seen as one of the major contributing factors throughout the literature and the preliminary results, the impact of education is worth noting. The 'No education' variable, with its positive and significant impact, underscores the critical role of educational attainment in bridging the gender digital divide. The substantial contribution of this variable to the gender gap (17.8%) aligns with existing literature, which emphasizes the transformative power of education in enhancing digital access (UN Females, 2021). This is further confirmed by the negative coefficient effect of the 'Identifies as African race' variable, highlighting racial disparities and their influence on mobile usage opportunities, thus supporting previous hypotheses (GSM Association, 2022). The coefficient effect of household size, which is shown to be highly significant at the 5% level with an estimate of 0.0195, implies that the impact of the household size on internet usage is gendered. This suggests that policies aimed at increasing internet usage for females should consider the dynamics of household size and its interaction with gender. Another insight to consider is that of cultural factors captured in the coefficient effect of “identifies as African race”, which is associated with a slightly positive but significant contribution to the gender gap in internet usage. This suggests that gendered norms surrounding cultural expectations, access to resources, or societal roles affect internet usage differently for African men and women.

The analysis of the endowment effects in the context of the gender digital divide in mobile usage presents a complex and somewhat inconsistent picture when compared to the previous chapters, specifically the results identified from the logistic regression. This inconsistency may be attributed to the endowment effects encapsulating the influence of unobserved variables, which introduces a degree of ambiguity in the interpretation. Specifically, variables such as age and formal housing, which exhibit negative signs, suggest that younger females and those residing in formal housing are more inclined to use mobile devices. This observation implies that aligning the effects of these variables for females with those for males could potentially lead to an increase in the gender digital gap, estimated at 2.02% for age and 0.09% for housing conditions. Such findings underscore the intricate interplay of demographic factors

in determining mobile usage patterns across genders. On the other hand, the positive impact of receiving cash income on females' mobile usage stands out as a significant factor. This aspect of the analysis suggests that bolstering females' economic empowerment might be a crucial strategy in narrowing the gender gap in mobile usage. The substantial contribution of this variable, accounting for 8.8% in reducing the gender gap, highlights the critical intersection of economic factors and digital access. This aligns with broader discussions in the literature regarding the pivotal role of financial inclusion in facilitating digital empowerment, suggesting that targeted economic interventions could be instrumental in bridging the digital divide between genders.

Table 12. Decomposition of gender differences in mobile usage

Difference	Estimate	Percent Contribution
Raw Difference	0.0375***	-
Unexplained: characteristics	0.0249***	66.42
Explained: coefficients	0.0126***	33.58
	Due to differences in Characteristics	Due to the difference in Coefficients
Variables		
Personal factors		
18-20 years old	0.0001	0.0006
	(-0.000)	(-0.002)
20-30 years old	-0.000415**	0.0038
	(-0.000)	(-0.005)
30-40 years old	-0.000600***	0.0051
	(-0.000)	(-0.004)
40-50 years old	-0.0001	-0.0025
	(-0.000)	(-0.003)
50-60 years old	-0.0030	-0.00427*
	(-0.000)	(-0.002)
60+ years old	-	-
	-	-
Employed	-0.0017	0.0019
	(-0.001)	(-0.005)
Received cash income	0.00247***	0.0088
	(-0.000)	(-0.007)
English speaking	0.0001	-0.0007
	(-0.000)	(-0.003)
No education	0.00506***	0.0178
	(-0.000)	(-0.013)

Primary schooling	0.00172***	0.0033
	(-0.000)	(-0.010)
Secondary schooling	0.000917**	0.0027
	(-0.000)	(-0.007)
Some tertiary schooling	0.000633*	-0.0071
	(-0.000)	(-0.005)
Graduate schooling	0.00196***	0.0000
	(-0.000)	(-0.004)
Identifies as African race	-0.005***	-0.0337
	(-0.000)	(-0.039)
External factors		
Formal house	0.000883***	0.001
	(-0.000)	(-0.013)
Informal/traditional hut	0.00134***	-0.0045
	(-0.000)	(-0.007)
Unit dwelling	0.0020	0.0002
	(-0.000)	(-0.001)
Rural location	0.006***	0.0006
	(-0.000)	(-0.011)
Household size	0.0292***	0.0148
	(-0.000)	(-0.012)
Constant	0.0186 (0.0531)	

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

5.3. Limitations and robustness checks

The decomposition method has many advantages in that it allows one to examine the factors that contribute to gaps in internet and mobile usage (in other words, digital devices) by gender. However, despite this, it is necessary to point out that this study has several limitations that require further investigation and sensitivity analysis before delving into policy renormalizations that arise from the results insights.

5.3.1. Sensitivity analysis of decomposition results

Sensitivity analysis is a statistical technique that will allow one to assess the robustness of their results by examining how sensitive the results are to different assumptions or variations in the data. In the context of the Yun (2004) decomposition, sensitivity analysis can be used to evaluate how sensitive the results of the decomposition are to different assumptions about the omitted variables. Moreover, this can provide some additional insights into the determinants of the digital gender gap.

Presented in the Appendix, the first three models included in this analysis look at variations of definitions and subsamples of the sample. The first set of models is based on the binary outcome of internet usage, and the second set relates to the binary outcome of mobile usage. Model I's alternative operationalization of the digital divide through internet access[10], rather than usage, aligns with the literature suggesting that access is a more encompassing measure of digital engagement (Hargittai, 2003). It captures not only usage but also the potential for use, which is essential in understanding the gender divide. Model II considers restricting the age group to those between the years of 18 and 55 - de Haan (2004) that technological readiness is not uniformly distributed across age groups. Model III examines the employed subset of the population, offering insights into the intersection of employment and digital engagement. This perspective is particularly relevant, given the increasing importance of digital literacy in the job market (van Deursen & van Dijk, 2014).

The methodological changes in Models IV to VI, including the swapping of reference categories and normalization orders, test the sensitivity of the results to these assumptions. The stability of significant estimates across these models suggests robust findings, consistent with the literature that emphasizes the importance of methodological rigor in decomposition analysis (Jann, 2008). The application of probability sample weights in Model VII addresses potential biases and reinforces the findings' generalizability. This step is in line with the renormalizations by Solon, Haider, and Wooldridge (2015) to account for complex survey design features in regression analysis.

The last three models are constructed to look at some changes to methodological approaches. Model IV shows the changes when adjusting the reference group category (where male equals 0 is now the reference group and female equals 1 is the comparison group), whereas Model VI checks whether the order of switching the reference binary variables in the normalization procedure alters the results. This is done by adjusting the variable informal first instead of second in the order. This changes the reference group for the category of variables. Finally, in Model VII, the probability sample weights for within-country differences provided by the dataset have been employed to correct for imperfections in the sample, such as bias and unequal probabilities.

In general, the results in the first column of Model I (for internet usage only) where internet access has been used instead are relatively inconsistent with those from the baseline model, wherein differences can

[10] Specifically, instead of using the binary variables *internet usage* as in the previous sections, a variable *internet access* has been created to re-define the opportunities to technology that may differ between males and females. In this case, 1 denotes access to internet, and 0 denotes no access, as provided by the dataset used.

be found in the magnitude of the estimates. Moreover, the directions of the estimates of the coefficient effect for Age, Employed, African, and Household size are opposite. This suggests that the direction of change has an opposite causal impact on reducing/increasing the gender divide. One can also note that the characteristic effect for the age variable is larger, whereas the coefficient effect is smaller. The model estimates produced for this alternative variable imply the potential endogeneity of the internet access variable. Some magnitude differences are also clear in the defined age group of 18 to 55 years old (Model II); however, these are more consistent in terms of direction for the more significant variables (such as cash income, education levels, and identified as African race). One can deduce from this model definition that it excludes those who may be deemed as technologically advanced, which is why age has a more powerful explanatory estimate in the baseline model.

The results in Model III for both internet usage and mobile usage indicate that there are some differences compared to those obtained in the main analysis. It is important to note that the proportion of the gap explained by identifying as African race is larger when we consider only those employed, as might be expected. Across all models, No Education, however, is the factor that largely explains the gender digital divide regardless of employment status, explaining most of the percentage of it in all subsamples. Moreover, the different distribution of males and females across education levels widens the gap to a larger extent when comparing the total sample (both employed and unemployed) to the subsample of only employed. Additionally, only in the sample of those employed, does the impact of being in a rural location differ from that of the original sample – specifically, the gender gap in internet usage would reduce (-0.013) if females had males' returns in the same rural locations. In comparison, the coefficient estimate for rural locations in the baseline model was negligible.

Looking at the first two models, Model II and Model VI, for mobile usage, the similarities and differences are consistent with the trends captured for the same models estimated for internet usage. The results for Model II demonstrate estimates that are relatively consistent in both magnitude and direction to the baseline model estimates. It is noteworthy that the proportion of the gap explained by the coefficient effects of No Education is larger (by 29 percentage points) when considering the defined age group. Moreover, a notable difference in Model III is Rural Location: the significance and magnitude of the characteristic effect is larger, and the coefficient effect has a larger contribution (56% higher) to the portion of the gender gap. Considering Received Cash Income, which now has an opposite (negative) impact for the characteristic estimate, meaning that if females and males were distributed equally across income-earning positions, the gap would now be reduced (maintaining female characteristics). In

general, the results for Mobile Usage Model II and Model III bring forward the same conclusions as that for Internet Usage.

With regards to the last three models for Internet Usage and Mobile Usage, small differences with the baseline model are evident in the coefficient and characteristic effects, specifically for Model V and Model VI. Across the estimates for both effects, the directions and magnitudes are relatively consistent throughout – this demonstrates that the procedure of the baseline model is robust to the methodological changes they include. However, when considering the estimates for Model IV where the reference groups are swapped, one would expect the directions to be interchanged. The Model IV results support that this is indeed the outcome.

Lastly, an issue that must be addressed and investigated is the nature of non-random sampling in the population studied: for an individual to access and use the internet, it is required that they have a device on which they can do so. Given this requirement, those who own a device may result in the non-random nature of the sample used in this study. Table 19 addresses this by investigating sample selection bias through means of an instrumental variable technique[11]. This is done by generating a binary instrumental variable "reliable_electricity"[12] that indicates whether electricity is available less than most of the time or equal to all of the time. Computer ownership is assumed to be influenced by the nature of electricity being reliable (and thus indirectly internet use). However, this does not directly affect internet use aside from through computer ownership, meeting the criteria for a good instrument. This technique aims to assess the impact of isolated, exogenous part of the variation in computer ownership on internet use, which provides a way to estimate the causal effect of the endogenous variable, computer ownership, on the outcome of internet use as if the variable were randomly assigned.

As a robustness check these results from the IV model are compared to that of the baseline logistic regression of internet use. The analysis of the results for the non-random sampling check supports the original findings in that the demographic and individual factors consistently influence the original results: firstly, age is negatively correlated with internet use in both models. For example, the 50-60 age group in Zimbabwe shows a marked decrease in usage with coefficients of -2.206*** in the sensitivity

[11] This is done through a two stage approach: For each country specified, a logistic regression models computer ownership as a function of the instrument (reliable_electricity) and other control variables. Then it predicts the fitted probability of owning a computer (device_ownership_fitted). This captures the exogenous variation in computer ownership explained by reliable_electricity, which is then used as explanatory variable in another logistic regression modeling internet use alongside the same set of controls.

[12] This chosen instrument satisfies the two key conditions: it is be correlated with the endogenous explanatory variable (computer ownership) and is not correlated with the outcome's error term.

analysis compared to -2.183*** in the original. Gender is more variable in the IV model; however, in both models males are significantly more likely to use the Internet. Consistent with the baseline model is the educational attainment variable, which emerges as a strong predictor of internet usage - individuals with higher education levels are consistently more likely to use the internet across all countries. Lastly, economic status, illustrated by the income variable, also positively influences internet use across both models. The consistent patterns as seen in the IV model in comparison to the baseline model highlight the role of these variables in determining internet use. In conclusion, while the IV model supports the original findings, the first-stage device ownership variable provides valuable insights into the direct impact of having a device on internet usage.

5.3.2. Limitations

The normalization process in the nonlinear decomposition model, while instrumental in mitigating the issues of reference coefficients, carries its own set of limitations that are worth acknowledging. Fortin, Lemieux, and Firpo (2011) and Kim (2013) discuss the challenges that arise from normalization procedures, particularly when comparing results across different studies. One of the primary concerns is that the results of the decomposition may be sample-specific, thereby limiting the meaningfulness of cross-study comparisons. This specificity arises because the dominant group's regressor coefficients are assumed to be standard, which may not hold across different populations or contexts. Moreover, the method used to average the normalization approach is sensitive to the number of groups and the methods of grouping. Such sensitivity can influence the decomposition outcomes, potentially skewing the interpretation of the factors contributing to the digital gender divide (Jann, 2008).

The use of AfroBarometer survey data introduces another set of limitations. This is mainly due to that the data used was collected pre-Covid. Given the rapid digital transformation spurred by the pandemic, the landscape of digital access in African economies has likely evolved significantly (Qiang et al., 2021). This shift could manifest in either the amplification or reduction of the gender digital divide. A consideration of this is the disproportionate impact of the pandemic on females, who often bear the brunt of increased care responsibilities, possibly affecting their digital engagement and proficiency (World Bank, 2020). For instance, the expansion of broadband access and technological availability may have bridged some gaps. However, the pandemic has also been shown to exacerbate existing inequalities, potentially worsening the digital divide for marginalized groups (UNCTAD, 2021; Onkokame & Gillwald, 2021).

Furthermore, the dataset does not provide a comprehensive view of internet access quality, digital literacy and skills, frequency of usage, and income levels, which are critical dimensions of digital engagement (ITU, 2020; World Wide Web Foundation, 2020). The absence of these measures in the data potentially underestimates the extent of the digital gender divide. Direct measures of the frequency of internet use, for instance, could reveal a more pronounced divide, aligning with findings from other research that emphasize the multidimensional nature of digital inequality (van Deursen & van Dijk, 2014).

6. Conclusion and Recommendations

6.2 Concluding Remarks

This paper intended to contribute to the understanding of the complex factors behind the digital divide, specifically in Southern African countries. The years preceding the COVID-19 pandemic demonstrated that a gender digital divide was present in Southern African countries. The vast array of literature that defines and exemplifies views and methods to understand this divide have been proven valuable in unpacking the existence of digital gender inequalities. These tools can be applied to more recent data to unpack whether the same patterns are still prevalent today. The main outcome of this paper is that within and across the eleven countries, the digital gender gap exists: males are more likely to use the Internet and mobiles. The magnitude of this divide varies across the countries. Madagascar and Malawi are shown to have the poorest outcomes, whereas the results Mauritius and South Africa indicate greater gender equality. In reference to the determinants of the digital gap, the key findings of this paper indicate the strong relationship between education and employment in widening the divide. Very little or no education was shown to be a large contributor, wherein females are less likely to have access to or usage of technology. Another noteworthy outcome was how employment also has a negative impact in enforcing the divide. These can be considered as remnants of a more patriarchal society embedded in cultural norms. Cultural identity and household size were also found as key contributors: the impact of the household size on internet usage is an effect that impacts the gap, as well as the individual identifying as Africa. Overall. this study contributed to the literature on the differences between the influences of individual and household factors on digital access across genders in Southern African countries, using data collected by AfroBarometer.

Using empirical methods utilized in previous digital divide and gender inequality literature, this study sought to disentangle the effects of individual and household characteristics when determining the

factors contributing to the gender digital divide in eleven Southern African countries, looking at the year 2018. This was primarily achieved by using the Yun Decomposition technique, which was supplemented by the multivariate logistic regression analysis. These results highlighted that these factors are significantly influenced by a myriad of socioeconomic and demographic factors. Overall, the results illustrate that approximately 56% of this divide can be attributed to variations in educational attainment and employment. These factors shape digital access at an individual level across the eleven countries studied. Employment status emerges as a crucial factor, accounting for 17.5% of the digital divide. When looking at the gender gap presented in mobile usage, it is clear that similar trends and factors are highlighted as main contributions to the current scenario. A considerable portion of this gap is due to unexplained traits, such as socioeconomic and demographic variables. However, explained traits, notably education and racial identity, play a significant role, accounting for 67.9% of the variation in mobile usage. This suggests that enhancing females' economic empowerment, particularly through cash income, could be pivotal in reducing the gender gap in mobile phone usage. Overall, females often face greater barriers to internet access and mobile usage in comparison to males, which is further exacerbated by disparities in educational levels and socioeconomic status.

6.2. Recommendations

Based upon the findings of this paper, it is evident that policymakers need to consider the role access to digital devices and skills has in promoting gender equality. Despite the attempts made by researchers and policymakers to address equitable access and usage of technology, these efforts have been insufficient. There is an urgent need for governments, nations, and industry to take serious steps towards a new paradigm, whilst also keeping in mind the interlinking concerns of the socio-economic status and new emerging technologies. The following insights can be considered as recommendations going forward:

- It is crucial to promote education and equal access to digital resources. This is confirmed by the research that has shown that there are significant gender disparities in technology usage and education. It has been found that females are less likely to own mobile phones and use the internet compared to males (ITU, 2019). In addition to this, women often encounter socio-cultural obstacles when trying to access educational opportunities (World Bank, 2016). Despite efforts to empower African girls with coding and tech skills being made through initiatives like the African Girls Can Code Initiative, other factors such as ingrained gender roles and expectations may

prohibit the success of this. This initiative was specifically led by UN Females in collaboration with the African Union Commission and the International Telecommunication Union and aimed to integrate ICT, gender, and coding into national curricula across the continent (ITU, 2018). To improve this, an approach that takes local ideologies into account may be considered with the help of local communities.

- To improve economic mobility for females, policies that aim to enhance female employment opportunities alongside technical training must be considered. This can be seen as a means for females to gain financial independence and also opens doors to digital involvement and the enhancement of skills. For example, implementing policies that promote female entrepreneurship in the technology sector, as suggested by Webb (2008) in Information Technologies and International Development, can play a crucial role in increasing the representation of women in the digital workforce. In addition, collaborations between the government and private sector can play a crucial role in developing specialized training and mentorship initiatives that empower women with essential digital skills.

- And lastly, it is crucial to consider the discrepancies in digital access that highlight the wider socio-economic gaps, particularly in Sub-Saharan Africa where there are obstacles related to digital infrastructure, expensive data costs, and unreliable electricity (The World Bank, 2021). This is in alignment with the findings of the 2018 African Economic Outlook, which highlight the high internet and call charges in Africa compared to other regions. Revealed in this is that the cost of data in Africa accounts for approximately 18% of the average income for a regular citizen, while in Asia it is only 3% (African Development Bank Group, 2018). To address this issue, African nations must explore the possibility of establishing cross-border collaborations with a wide range of stakeholders. This would help in developing digital infrastructures that are more inclusive and accessible to all (UNCTAD, 2019).

Overall, policy design should be made with the local context and preferences in mind and should emphasise community economic and behavioural factors that influence gender opportunities. The African governments must adopt a suitable shift towards navigating the gender gap, especially regarding technology.

APPENDIX

Table 14. Decomposition of gender differences in Internet and Mobile usage using Fairlie's technique

	Internet Usage	Mobile Usage
Male digital engagement rate	0.403	0.839
Female digital engagement rate	0.341	0.79
Gender gap	-0.061	-0.039
Total explained	-0.029	-0.013
Contributions from differences		
Age	0.00723***	0.00197***
	(-0.001)	(-0.001)
Employed	-0.0115***	0.00145*
	(-0.002)	(-0.001)
Received cash income	-0.00259***	-0.00194***
	(-0.000)	(-0.000)
Household size	0.006	-0.0848***
	(-0.000)	(-0.000)
English speaking	0.0001	0.0001
	(-0.0001)	(-0.0001)
Rural living	0.000251	-0.000382
	(-0.0002)	(-0.0002)
Education	-0.0195***	-0.00915***
	(-0.001)	(-0.001)
Race	-0.000646**	0.0001
	(-0.0002)	(-0.0002)
Living situation	-0.00228***	-0.00425***
	(-0.001)	(-0.001)
Observations	14 008	14 008

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

Table 15. Robustness checks: Models I-III for Internet Usage

	Model I		Model II		Model III	
Difference	Estimate	Percent Contribution	Estimate	Percent Contribution	Estimate	Percent Contribution
Raw Difference	0.0503***	-	0.0678***	-	0.0453***	-
Unexplained: characteristics	0.0146**	29.070	0.0340***	49.840	0.0390***	86.100
Explained: coefficients	0.0356***	70.930	0.0338***	50.160	0.00629***	13.900
	Due to difference in Characteristics	Due to difference in Coefficients	Due to difference in Characteristics	Due to difference in Coefficients	Due to difference in Characteristics	Due to difference in Coefficients
Variables	Estimate (%)	Estimate (%)	Estimate (%)	Estimate (%)	Estimate (%)	Estimate (%)
Personal factors						
18-20 years old	-0.000866***	0.000	-0.00135***	0.000	0.00166***	0.000338
	(0.000)	(-0.001)	(0.000)	(-0.001)	(0.001)	(-0.001)
20-30 years old	-0.00294***	0.000	-0.00392***	0.001	-0.00469***	0.00454
	(0.000)	(-0.003)	(0.000)	(-0.003)	(-0.002)	(-0.004)
30-40 years old	-0.00112***	-0.003	-0.000936***	-0.003	-0.00328	-0.000769
	(0.000)	(-0.002)	(0.000)	(-0.003)	(-0.002)	(-0.003)
40-50 years old	-0.000756**	-0.001	-0.00120***	0.000	-0.000869	0.000297
	(0.000)	(-0.002)	(0.000)	(-0.002)	(-0.001)	(-0.002)
50-60 years old	-0.000387***	-0.002	-0.000463***	-0.003	0.00131***	-0.00351
	(0.000)	(-0.002)	(0.000)	(-0.002)	(0.000)	(-0.002)
60+ years old	0.001	0.001			0.001	0.001
	(0.000)	0.000			(0.000)	(0.000)
Employed	0.0142***	0.002	0.0110***	(-0.002)		
	(-0.002)	(-0.003)	(-0.002)	(-0.003)		
Received cash income	0.00284***	-0.002	0.00340***	0.003	-0.000547***	0.00103
	(0.000)	(-0.004)	(0.000)	(-0.004)	(0.000)	(0.004)
English speaking	0.000	-0.001	0.000	-0.001	0.000	-0.000914
	(0.000)	(-0.001)	(0.000)	(-0.001)	(0.000)	(-0.001)
No education	0.0120***	0.0114***	0.0134***	0.0105***	0.0153***	0.0149***
	(0.000)	(-0.004)	(-0.000)	(-0.004)	(-0.004)	(-0.005)
Primary schooling	0.00284***	0.001	0.00316***	0.001	0.00431***	0.000565
	(0.000)	(-0.003)	(0.000)	(-0.004)	(-0.001)	(-0.005)
Secondary schooling	0.00106***	0.000	0.00106***	0.002	0.00255***	-0.000227
	(0.000)	(-0.002)	(0.000)	(-0.003)	(-0.001)	(-0.003)
Some tertiary schooling	0.00314***	-0.002	0.00319***	-0.00299**	0.00306***	-0.00197*
	(0.000)	(-0.001)	(0.000)	(-0.001)	(-0.001)	(-0.001)
Graduate schooling	0.00327***	-0.001	0.00395***	0.000	0.00304***	-0.000295
	(0.000)	(-0.001)	(0.000)	(-0.001)	(-0.001)	(-0.001)
Identifies as African race	-0.00073***	0.012	-0.000130***	0.0329*	-0.00460**	0.0503**
	(0.000)	(-0.015)	(0.000)	(-0.018)	(-0.002)	(-0.023)
External factors						
Formal house	0.000600***	-0.010	0.000760***	-0.011	-0.000958	-0.00726
	(0.000)	(-0.007)	(0.000)	(-0.008)	(-0.001)	(-0.009)
Informal/traditional hut	0.00151***	0.001	0.00144***	0.002	-0.00345***	0.00627
	(0.000)	(-0.004)	(0.000)	(-0.005)	(-0.001)	(-0.006)
Unit dwelling	0.00056**	0.000	4.16e-06*	0.000	-0.001	0.000
	(0.000)	0.000	(0.000)	(0.000)	(0.000)	(-0.001)
Rural location	0.000133***	0.002	0.000168***	-0.009	-0.00654***	-0.0140*
	(0.000)	(-0.005)	(0.000)	(-0.007)	(-0.002)	(-0.008)
Household size	0.000202***	0.0148**	0.000137*	0.0195**	0.0464	0.0109
	(0.000)	(-0.007)	(0.000)	(-0.009)	(-0.001)	(-0.009)
Observations	14, 089	14, 089	14, 089	14, 089	9,578	9,578

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

Table 16. Robustness checks: Models IV-VI for Internet Usage

	Model IV		Model V		Model VI	
Difference	Estimate	Percent Contribution	Estimate	Percent Contribution	Estimate	Percent Contribution
Raw Difference	0.0678***		0.0678***		0.0664***	
Unexplained: characteristics	0.0318***	46.960	0.0340***	49.840	0.0364***	54.720
Explained: coefficients	0.0360***	53.040	0.0338***	50.160	0.0301***	45.280
	Due to difference in Characteristics	Due to difference in Coefficients	Due to difference in Characteristics	Due to difference in Coefficients	Due to difference in Characteristics	Due to difference in Coefficients
Variables	Estimate (%)	Estimate (%)	Estimate (%)	Estimate (%)	Estimate (%)	Estimate (%)
Personal factors						
20-30 years old	0.00126***	-0.0001	-0.00135***	0.0001	-0.00130***	0.0004
	(-0.000)	(-0.001)	(-0.000)	(-0.001)	(-0.000)	(-0.001)
30-40 years old	0.00357***	-0.0010	-0.00392***	0.0010	-0.00420***	0.0036
	(-0.000)	(-0.003)	(-0.000)	(-0.003)	(-0.000)	(-0.004)
40-50 years old	0.00116***	0.0024	-0.000936***	-0.0026	-0.00138***	0.0007
	(-0.000)	(-0.003)	(-0.000)	(-0.003)	(-0.000)	(-0.003)
50-60 years old	0.00121***	-0.0004	-0.00120***	0.0003	-0.00114***	0.0007
	(-0.000)	(-0.002)	(-0.000)	(-0.002)	(-0.000)	(-0.002)
60+ years old	0.000330***	0.0032	-0.000463***	-0.0031	-0.000797***	-0.00530**
	(0.0000)	(-0.002)	(0.0000)	(-0.002)	(-0.000)	(-0.002)
Employed	-0.0119***	0.0034	0.0110***	-0.0022	0.0111***	-0.0033
	(-0.002)	(-0.005)	(-0.002)	(-0.003)	(-0.002)	(-0.003)
Received cash income	-0.00282***	-0.0037	0.00340***	0.0033	0.00336***	0.0011
	(-0.000)	(-0.005)	(-0.000)	(-0.004)	(-0.000)	(-0.005)
English speaking	-0.000169**	0.0009	0.0001	-0.0009	0.0009***	-0.0001
	(-0.000)	(-0.001)	(-0.001)	(-0.001)	(-0.000)	(-0.001)
No education	-0.0146***	-0.00938***	0.0134***	0.0105***	0.0117***	0.0108**
	(-0.000)	(-0.004)	(-0.000)	(-0.004)	(-0.000)	(-0.005)
Primary schooling	-0.00303***	-0.0008	0.00316***	0.0008	0.00366***	-0.0001
	(-0.000)	(-0.004)	(-0.000)	(-0.004)	(-0.000)	(-0.004)
Secondary schooling	-0.000750**	-0.0018	0.00106***	0.0016	0.00106***	0.0000
	(-0.000)	(-0.003)	(-0.000)	(-0.003)	(-0.000)	(-0.003)
Some tertiary schooling	-0.00394***	0.00372**	0.00319***	-0.00299**	0.00281***	-0.0023
	(-0.000)	(-0.002)	(-0.000)	(-0.001)	(-0.000)	(-0.001)
Graduate schooling	-0.00391***	0.0006	0.00395***	-0.0005	0.00343***	-0.0005
	(-0.000)	(-0.001)	(-0.000)	(-0.001)	(-0.000)	(-0.001)
Identifies as African race	0.000165***	-0.0337*	-0.000130***	0.0329*	-0.000158***	0.0219
	(-0.000)	(-0.019)	(0.0000)	(-0.018)	0.0000	(-0.021)
External factors						
Formal house	-0.00110***	0.0117	0.000760***	-0.0112	0.000818***	-0.0051
	(-0.000)	(-0.009)	(-0.000)	(-0.008)	(-0.000)	(-0.009)
Informal/traditional hut	-0.00146***	-0.0018	0.00144***	0.0019	0.00126***	0.0050
	(-0.000)	(-0.005)	(-0.000)	(-0.005)	(-0.000)	(-0.005)
Unit dwelling	0.0000	-0.0003	0.0004*	0.0003	-0.0001	-0.0001
	(0.0000)	(-0.000)	(0.0000)	(-0.000)	(0.0000)	(-0.001)
Rural location	-0.000126***	0.0094	0.000168***	-0.0092	-0.000206***	-0.0061
	(0.0000)	(-0.007)	(0.0000)	(-0.007)	(0.0000)	(-0.007)
Household size	0.0001	-0.0201**	0.000137*	0.0195**	0.0001	0.0153*
	(-0.000)	(-0.009)	(-0.000)	(-0.009)	(-0.000)	(-0.009)
Observations	14,089	14,089	14,089	14,089	14,089	14,089

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

Table 17. Robustness checks: Models II-II for Mobile Usage

	Model IV		Model V		Model VI	
Difference	Estimate	Percent Contribution	Estimate	Percent Contribution	Estimate	Percent Contribution
Raw Difference	0.0678***		0.0678***		0.0664***	
Unexplained: characteristics	0.0318***	46.960	0.0340***	49.840	0.0364***	54.720
Explained: coefficients	0.0360***	53.040	0.0338***	50.160	0.0301***	45.280
	Due to difference in Characteristics	Due to difference in Coefficients	Due to difference in Characteristics	Due to difference in Coefficients	Due to difference in Characteristics	Due to difference in Coefficients
Variables	Estimate (%)	Estimate (%)	Estimate (%)	Estimate (%)	Estimate (%)	Estimate (%)
Personal factors						
20-30 years old	0.00126***	-0.0001	-0.00135***	0.0001	-0.00130***	0.0004
	(-0.000)	(-0.001)	(-0.000)	(-0.001)	(-0.000)	(-0.001)
30-40 years old	0.00357***	-0.0010	-0.00392***	0.0010	-0.00420***	0.0036
	(-0.000)	(-0.003)	(-0.000)	(-0.003)	(-0.000)	(-0.004)
40-50 years old	0.00116***	0.0024	-0.000936***	-0.0026	-0.00138***	0.0007
	(-0.000)	(-0.003)	(-0.000)	(-0.003)	(-0.000)	(-0.003)
50-60 years old	0.00121***	-0.0004	-0.00120***	0.0003	-0.00114***	0.0007
	(-0.000)	(-0.002)	(-0.000)	(-0.002)	(-0.000)	(-0.002)
60+ years old	0.000330***	0.0032	-0.000463***	-0.0031	-0.000797***	-0.00530**
	(0.0000)	(-0.002)	(0.0000)	(-0.002)	(-0.000)	(-0.002)
Employed	-0.0119***	0.0034	0.0110***	-0.0022	0.0111***	-0.0033
	(-0.002)	(-0.005)	(-0.002)	(-0.003)	(-0.002)	(-0.003)
Received cash income	-0.00282***	-0.0037	0.00340***	0.0033	0.00336***	0.0011
	(-0.000)	(-0.005)	(-0.000)	(-0.004)	(-0.000)	(-0.005)
English speaking	-0.000169**	0.0009	0.0001	-0.0009	0.0009***	-0.0001
	(-0.000)	(-0.001)	(-0.001)	(-0.001)	(-0.000)	(-0.001)
No education	-0.0146***	-0.00938***	0.0134***	0.0105***	0.0117***	0.0108**
	(-0.000)	(-0.004)	(-0.000)	(-0.004)	(-0.000)	(-0.005)
Primary schooling	-0.00303***	-0.0008	0.00316***	0.0008	0.00366***	-0.0001
	(-0.000)	(-0.004)	(-0.000)	(-0.004)	(-0.000)	(-0.004)
Secondary schooling	-0.000750**	-0.0018	0.00106***	0.0016	0.00106***	0.0000
	(-0.000)	(-0.003)	(-0.000)	(-0.003)	(-0.000)	(-0.003)
Some tertiary schooling	-0.00394***	0.00372**	0.00319***	-0.00299**	0.00281***	-0.0023
	(-0.000)	(-0.002)	(-0.000)	(-0.001)	(-0.000)	(-0.001)
Graduate schooling	-0.00391***	0.0006	0.00395***	-0.0005	0.00343***	-0.0005
	(-0.000)	(-0.001)	(-0.000)	(-0.001)	(-0.000)	(-0.001)
Identifies as African race	0.000165***	-0.0337*	-0.000130***	0.0329*	-0.000158***	0.0219
	(-0.000)	(-0.019)	(0.0000)	(-0.018)	0.0000	(-0.021)
External factors						
Formal house	-0.00110***	0.0117	0.000760***	-0.0112	0.000818***	-0.0051
	(-0.000)	(-0.009)	(-0.000)	(-0.008)	(-0.000)	(-0.009)
Informal/traditional hut	-0.00146***	-0.0018	0.00144***	0.0019	0.00126***	0.0050
	(-0.000)	(-0.005)	(-0.000)	(-0.005)	(-0.000)	(-0.005)
Unit dwelling	0.0000	-0.0003	0.0004*	0.0003	-0.0001	-0.0001
	(0.0000)	(-0.000)	(0.0000)	(-0.000)	(0.0000)	(-0.001)
Rural location	-0.000126***	0.0094	0.000168***	-0.0092	-0.000206***	-0.0061
	(0.0000)	(-0.007)	(0.0000)	(-0.007)	(0.0000)	(-0.007)
Household size	0.0001	-0.0201**	0.000137*	0.0195**	0.0001	0.0153*
	(-0.000)	(-0.009)	(-0.000)	(-0.009)	(-0.000)	(-0.009)
Observations	14,089	14,089	14,089	14,089	14,089	14,089

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

Table 18. Robustness checks: Models IV-VI for Mobile Usage

	Model II		Model III	
Difference	Estimate	Percent Contribution	Estimate	Percent Contribution
Raw Difference	0.0375***		0.0274***	
Unexplained: characteristics	0.0249***	66.420	0.0250***	91.070
Explained: coefficients	0.0126***	33.580	0.00245**	8.930
	Due to difference in Characteristics	Due to difference in Coefficients	Due to difference in Characteristics	Due to difference in Coefficients
Variables	Estimate (%)	Estimate (%)	Estimate (%)	Estimate (%)
Personal factors				
20-30 years old	0.002	0.00	(0.000)	0.00
	(0.000)	(-0.002)	(0.000)	(-0.004)
30-40 years old	-0.000415**	0.00	-0.000121*	0.00
	(0.000)	(-0.005)	(0.000)	(-0.008)
40-50 years old	-0.000600***	0.01	-0.000973**	0.01
	(0.000)	(-0.004)	(0.000)	(-0.007)
50-60 years old	0.000	-0.003	0.000	-0.005
	(0.000)	(-0.003)	(0.000)	(-0.005)
60+ years old			0.000	-0.007
			(-0.000)	(-0.005)
Employed	-0.002	0.002		
	(-0.001)	(-0.005)		
Receives cash income	0.00247***	0.009	-0.000147***	0.006
	(0.000)	(-0.007)	(0.000)	(-0.011)
No education	0.00506***	0.018	0.00260***	0.031
	(0.000)	(-0.013)	(-0.001)	(-0.031)
Primary schooling	0.00172***	0.003	0.00102***	0.000
	(0.000)	(-0.010)	(0.000)	(-0.022)
Secondary schooling	0.000917**	0.003	0.000955*	0.005
	(0.000)	(-0.007)	(-0.001)	(-0.014)
Some tertiary schooling	0.000633*	-0.007	0.000	-0.010
	(0.000)	(-0.005)	(0.000)	(-0.009)
Graduate schooling	0.00196***	0.000	0.000659**	0.001
	(0.000)	(-0.004)	(0.000)	(-0.004)
Identifies as African race	-0.0005***	-0.034	0.000	0.021
	(0.000)	(-0.039)	(0.000)	(-0.079)
External factors				
Formal house	0.000883***	0.001	-0.000572***	0.004
	(0.000)	(-0.013)	(0.000)	(-0.024)
Informal/traditional hut	0.00134***	-0.0045	-0.000965***	-0.003
	(0.000)	(-0.007)	(0.000)	(-0.016)
Unit dwelling	0.000	0.000234	0.000	0.000
	(0.000)	(-0.001)	(0.000)	(-0.001)
Rural location	0.006***	0.000589	-0.000678**	0.016
	(0.000)	(-0.011)	(0.000)	(-0.024)
Household size	0.000292***	0.0148	0.000752**	0.020
	(0.000)	(-0.012)	(0.000)	(-0.022)
Observations	14,089	14,089	9,578	9,578

Table 19. Instrumental Variable model (Electricity and Device Ownership)

VARIABLES	Botswana	eSwatini	Lesotho	Madagascar	Malawi	Mauritius	Mozambique	Namibia	South Africa	Zambia	Zimbabwe
device_ownership_fitte	3.567***	3.775***	-0.423	2.469*	1.968	9.250***	5.589***	3.038***	3.225**	-2.274	2.749***
	(1.021)	(1.154)	(1.741)	(1.324)	(1.463)	(2.400)	(2.114)	(0.635)	(1.402)	(2.097)	(1.060)
AGE Group (18-20)	0.190	-0.427	0.0442	-0.109	-0.943*	-0.300	-2.261**	-0.0789	0.235	-1.375**	0.138
20-30	(0.385)	(0.499)	(0.321)	(0.400)	(0.531)	(0.441)	(1.127)	(0.201)	(0.351)	(0.567)	(0.423)
	-0.681*	-1.230**	-0.732**	-0.0455	-0.966*	-0.623	-2.795**	-0.684***	-0.680*	-2.298***	-0.551
30-40	(0.395)	(0.507)	(0.342)	(0.436)	(0.534)	(0.475)	(1.133)	(0.226)	(0.395)	(0.584)	(0.458)
	-1.421***	-2.449***	-1.291***	-1.189**	-2.159***	-1.281**	-3.896***	-1.774***	-0.562	-2.623***	-0.580
40-50	(0.452)	(0.527)	(0.381)	(0.488)	(0.614)	(0.587)	(1.135)	(0.306)	(0.421)	(0.577)	(0.550)
	-2.278***	-2.488***	-2.797***	-1.175**	-2.442***	-1.547**	-4.821***	-1.781***	-1.641***	-3.619***	-1.926***
50-60	(0.514)	(0.572)	(0.544)	(0.468)	(0.707)	(0.628)	(1.145)	(0.431)	(0.456)	(0.649)	(0.709)
	-2.672***	-2.812***	-2.712***	-3.595***	-2.487***	-1.683**	-4.495***	-2.459***	-1.553***	-4.148***	-2.183***
60+	(0.574)	(0.607)	(0.477)	(0.937)	(0.703)	(0.738)	(1.121)	(0.573)	(0.511)	(0.660)	(0.659)
	0.184	-0.00385	0.109	0.308*	0.273	0.801***	-0.314	0.204	0.252	0.158	0.760***
Male(=1)	(0.190)	(0.210)	(0.204)	(0.170)	(0.278)	(0.277)	(0.223)	(0.140)	(0.171)	(0.219)	(0.219)
EMPLOYMENT (Unemployed)	-0.0571	0.176	-0.297	0.306	0.251	0.788**	0.786*	0.101	0.0949	-0.364	0.346
Looking	(0.222)	(0.318)	(0.250)	(0.236)	(0.457)	(0.349)	(0.401)	(0.160)	(0.214)	(0.303)	(0.267)
	0.906**	0.359	-0.196	0.959***	0.638*	0.645	0.466	0.559***	-0.199	0.245	0.0297
Part-time	(0.371)	(0.336)	(0.334)	(0.284)	(0.363)	(0.397)	(0.428)	(0.209)	(0.334)	(0.260)	(0.355)
	0.447	0.878***	0.686**	0.249	0.107	1.113***	0.509*	1.068***	0.349	0.483**	0.889***
Employed	(0.294)	(0.317)	(0.289)	(0.276)	(0.341)	(0.355)	(0.265)	(0.260)	(0.263)	(0.231)	(0.303)
	0.175	0.389**	0.437**	-0.185	0.996***	-0.450	-0.703	0.411***	0.179	0.488**	0.104
Received income	(0.240)	(0.189)	(0.190)	(0.246)	(0.318)	(0.379)	(0.468)	(0.137)	(0.167)	(0.218)	(0.247)
	1.284***	0.853**	1.350***	0.787*	2.593***	1.188***	0.306	0.768***	0.909***	0.725**	1.139***
	(0.300)	(0.395)	(0.368)	(0.449)	(0.747)	(0.370)	(0.535)	(0.179)	(0.331)	(0.290)	(0.381)
	2.436***	1.496***	2.565***	1.635***	3.737***	1.542***	0.348	1.041***	1.216***	2.121***	2.241***
	(0.379)	(0.419)	(0.586)	(0.451)	(0.814)	(0.436)	(1.015)	(0.268)	(0.343)	(0.511)	(0.444)
	1.844***	1.216*	3.165***	2.123***	4.738***	1.579*	1.674	0.863**	1.491*	3.161***	2.964***
	(0.566)	(0.679)	(0.950)	(0.575)	(0.962)	(0.938)	(1.252)	(0.389)	(0.761)	(0.939)	(0.600)
EDUCATION (No education)	2.133***	1.566**	3.788***	3.016**	4.602***	-1.354		0.657	1.915**	4.663***	2.775***
Primary schooling	(0.692)	(0.781)	(1.213)	(1.216)	(1.362)	(2.048)		(0.640)	(0.913)	(1.285)	(0.859)
	-0.202	-0.201	-0.421	-0.857***	-0.946***	-0.130	0.163	-0.636***	-0.0572	-1.122***	-0.793**
Secondary schooling	(0.274)	(0.440)	(0.347)	(0.249)	(0.294)	(0.313)	(0.542)	(0.160)	(0.350)	(0.416)	(0.315)
	-0.766	-0.229	0.793	-1.065	-1.475*	-2.233	2.003***	-0.881	-0.800	-1.138***	1.441***
Tertiary schooling	(0.489)	(0.359)	(0.649)	(0.960)	(0.870)	(1.470)	(0.774)	(0.907)	(0.541)	(0.419)	(0.554)
	-0.232	-0.173	-0.558*	-0.322	-0.476	0.287	-0.0671	-0.564***	-0.498***	-0.616**	-0.406
Graduate	(0.202)	(0.260)	(0.331)	(0.458)	(0.347)	(0.360)	(0.253)	(0.145)	(0.192)	(0.242)	(0.248)
	-0.0528	0.0266	0.00454	0.121**	0.00274	-0.0200	-0.271*	-0.0255	0.00166	-0.0574	0.0297
	(0.0547)	(0.0410)	(0.0521)	(0.0567)	(0.141)	(0.0553)	(0.141)	(0.0276)	(0.0440)	(0.0495)	(0.0400)
African Race(=1)		-0.539	0.630		0.678		0.943**	-0.906	-0.0351	-0.338	
		(0.860)	(1.092)		(0.820)		(0.480)	(0.775)	(0.323)	(0.230)	
English(=1)		2.338***		0.475					1.018***	0.876*	0.616
		(0.849)		(1.449)					(0.292)	(0.514)	(0.449)
Constant	-1.860***	-1.272	-1.493	-2.589***	-4.095***	-3.605***	1.281	-0.608	-1.840**	2.577**	-3.397***
	(0.533)	(1.113)	(1.346)	(0.832)	(1.206)	(0.652)	(1.250)	(0.852)	(0.836)	(1.028)	(0.625)
Observations	1,137	1,110	1,146	1,172	1,175	1,115	1,001	2,045	1,138	1,720	1,152

Notes: Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

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