

The Impact of Mobile-Based Digital Technology Adoption on Poverty Reduction: Insights from Ethiopia

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Abstract

Ethiopia, a country with inadequate infrastructure, is making efforts to expand mobile phone access and services, as this technology has the potential to address existing gaps caused by infrastructural deficiencies. The aim of this study is to analyse the impact of the adoption of mobile-based digital technologies (MBDTA) on poverty reduction in the Hadiya zone, Ethiopia. A multistage sampling technique was used to select a random sample of 278 respondents, and an endogenous switching regression model was employed to address selection bias. The results of the Alkire and Foster (2011) approach indicate that 68% of respondents were multidimensionally poor, and the adjusted multidimensional poverty rate was 47.1%, with 34.2% for adopters and 65.4% for non-adopters. The findings of ESR indicate that MBDTA has a significant negative impact on multidimensional poverty. The impact of these technologies on poverty reduction varies significantly across different districts within the study area. This implies that MBDTA can substantially alleviate poverty in the study area. Policymakers should address the barriers that limit MBDTA, such as access to mobile internet and mobile money platforms, as these tools are crucial for alleviating multidimensional poverty.

1 Introduction

Recently, information and communication technologies (ICTs) have received due attention from scholars and policymakers worldwide due to their socio-economic importance (Yang et al., 2021). As recognised by the Sustainable Development Goals (SDGs), ICTs are an important component of all economic activities today, including the creation of jobs, the provision of government services, financial inclusion, and efficient information and smooth communication (Aker & Mbiti, 2010; Balgobin & Dubus, 2022; Prieto-Egido et al., 2023). Given their accessibility and convenience, mobile-based digital technologies (MBDTs) are well-suited tools to achieve these goals in countries where physical infrastructure remains limited (Aker et al., 2016; Alam et al., 2019; Mothobi & Grzybowski, 2017). MBDTA can be defined as the uptake and integration of mobile internet and mobile banking into everyday life, facilitating access to institutions, markets, and services.

Ethiopia, a country with inadequate infrastructure, is making efforts to expand mobile phone access and services, as this technology has the potential to address existing gaps caused by infrastructure deficiencies. One such effort is a series of actions in ICT policy, particularly sector privatisation and telecom reform since 2020, which facilitated the entry of Safaricom, leading to improved operational efficiency (Shahid et al., 2023). Such initiatives are essential tools for poverty alleviation through MBDTA, with relevance that extends beyond Ethiopia's borders and aligns with the SDG 1 (Kikulwe et al., 2014; UN, 2023; Yang et al., 2021). Enhancing the understanding of the relationship between MBDTs and poverty in Ethiopia is crucial for bridging infrastructural gaps by connecting marginalised poor communities to markets, services, and information (Aker & Mbiti, 2010; Mothobi & Grzybowski, 2017). MBDTA enables individuals to diversify their income sources, helping them manage risk and maintain economic stability, thereby reducing poverty.

Existing studies have primarily focused on China, while there have been few studies in Africa analysing the link between MBDTA and poverty (Kikulwe et al., 2014; Leng et al., 2020; Ma et al., 2020; Munyegera & Matsumoto, 2016). There has been limited empirical evidence emphasizing the poverty reduction effects of MBDTA in Sub-Saharan Africa (SSA), particularly in Ethiopia. Existing studies have predominantly emphasized objective outcome variables, such as income, health, education, and living standards, often overlooking subjective variables such as happiness and satisfaction in poverty assessments despite its ability to provide valuable insights into welfare implications (Alkire & Seth, 2015; Ma et al., 2020). Furthermore, it is crucial to analyse the heterogeneous impact of MBDTA across various demographic groups of the population. This study adopted a multidimensional poverty approach to capture the diverse deprivations experienced by households.

Hadiya zone, located in Central Ethiopia, is one of the zones where area-specific research on integrating MBDTs into poverty reduction is lacking. This gap is particularly significant given Ethiopia's unique socioeconomic and demographic conditions compared to other countries. This zone is particularly well suited for this study, as most households rely heavily on mobile phones, not only to facilitate business transactions that form an integral part of their livelihoods, but also to maintain communication with family members and relatives both domestically and abroad (Adugna, 2019). However, there are notable variations in MBDTA for poverty reduction efforts (Smidt & Jokonya, 2022; Warner et al., 2023). In light of the aforementioned gaps and discussion, three critical policy questions emerge. Does the adoption of mobile-based digital technology translate into poverty alleviation? What do socio-economic, demographic, institutional, and contextual factors contribute to the differing impacts of poverty? How can government policies be designed to ensure that MBDTA effectively translates into poverty alleviation?

The study contributes to policy and academic debates in three important ways. Firstly, we provide pragmatic evidence to policymakers by analysing the impact of MBDTA on household poverty. This finding reinforces Ethiopia's current ICT policy efforts by deepening the understanding of poverty reduction effects of MBDTA and informing broader regional strategies. Secondly, we used a comprehensive measure of the impact MBDTs on poverty using both objective and subjective measures, which could provide deeper insights than the existing literature. To this end, the study employed a novel ESR model that addresses endogeneity issues from observable and unobservable factors, unlike existing literature that mainly uses the PSM model (Mora-Rivera & García-Mora, 2021; Ogutu et al., 2014). By so doing, the study seeks to fill the existing literature gaps since there are few studies that have been done in SSA and specifically in this Hadiya zone. Finally, we analysed the heterogeneous impact of MBDTA on poverty reduction across different districts using ATT of ESR in the study area.

2 Review of the Literature

2.1. Theoretical perspectives of MBDTA and poverty

Poverty is the inability of households to meet their fundamental necessities due to a lack of resources. It is acknowledged that poverty is a multifaceted concept encompassing both monetary and non-monetary dimensions, commonly known as multidimensional poverty (OPHI, 2024). Monetary poverty is defined as having insufficient income to buy necessities for survival, whereas non-monetary poverty is defined as having insufficient access to private property, social isolation, low educational attainment, and poor (Jansen et al., 2015).

The relationship between MBDTA and poverty reduction can be understood through several theoretical perspectives. One of the most prominent is the Technology Adoption and Diffusion Theory, which emphasises how innovations spread across populations and the conditions under which they are embraced (Rogers, 1995). In the context of poverty, mobile phones serve as transformative tools by lowering transaction costs, improving information flows, and enhancing financial inclusion (Aker & Mbiti, 2010; Suri & Jack, 2016). The speed and breadth of diffusion in many low-income communities suggest that MBDTs can overcome barriers that traditionally limit the poor from participating fully in economic and social systems (Munyegera & Matsumoto, 2016).

Another relevant lens is Sen's Capability Approach, which links poverty not only to a lack of income but also to constraints on individuals' freedoms and opportunities (Knech, 2014; Sen, 2006). In this context, MBDTs serve as capabilities enhancing tools by facilitating individuals' access to education, healthcare, financial services, and social networks that were previously out of reach (Mukong & Nanziri, 2021; Munyegera & Matsumoto, 2016). Thus, MBDTA address both the income and non-income dimensions of poverty.

From the perspective of Institutional and Governance Theories, the impact of MBDTs depends on the broader ecosystem of policies, infrastructure, and regulatory frameworks (Gegenhuber et al., 2022). While mobile tools have the potential to bridge gaps in service delivery, their success in alleviating poverty often hinges on the effectiveness of institutions in creating enabling environments (Galperin & Fernanda Vicens, 2017). A study indicates that weak governance structures such as insufficient investment in ICT infrastructure or inadequate regulatory support can limit access and exacerbate inequalities (Park, 2017).

Another perspective is Information Economics, which highlights how information and knowledge influence economic decisions and behaviours (Stiglitz, 2000). Complementing this theory, MBDTA facilitates access to information, economic opportunities, and financial services that help alleviate poverty (Atta-Ankomah et al., 2024; Haile et al., 2019; Sharma & Díaz Andrade, 2023). Finally, the inclusive growth framework emphasises that growth must be inclusive and benefit the entire population, including marginalised groups (World Bank, 2008). MBDTA supports this by connecting individuals to institutions and services in areas where institutional reach is limited (Mothobi & Grzybowski, 2017). Together, these theoretical perspectives illustrate that MBDTs are not merely tools of communication but are embedded in broader socio-economic systems that shape their potential for poverty reduction.

2.2. Review of empirical literature

Poverty remains a critical concern for both scholars and policymakers in developing nations (Asiimwe *et al.*, 2025; Esrael *et al.*, 2025; Ruja *et al.*, 2024). In these contexts, efforts to address poverty commonly focus on enhancing capabilities through technology adoption, market-based approaches, improving good governance, and implementing community-based micro-finance (Balasubramanian *et al.*, 2023; Bonga and Bonga, 2024; Mupaso *et al.*, 2023; Ruja *et al.*, 2024; Singh and Chudasama, 2020).

In this regard, the Ethiopian government has undertaken several strategies to alleviate poverty, including the Agriculture Growth Programme, Productive Safety Net Programme, Ethiopian National Adaptation Plan, and Sustainable Land Management Framework (Bahru and Zeller, 2022; Golrokhian *et al.*, 2016; Haregeweynet *et al.*, 2023; Pittore *et al.*, 2025). These initiatives underpin poverty alleviation for the country (Bahru and Zeller, 2022; Golrokhian *et al.*, 2016; Tadesse, 2023). While these initiatives are important to alleviate poverty, the integration of these initiatives with the ICTs has excellent potential to alleviate poverty in developing nations including Ethiopia (Beuermann *et al.*, 2012; Kikulwe *et al.*, 2014; Matsuura-Kannari *et al.*, 2024). For example, the adoption of mobile tools such as mobile money enables remote access and lowers transaction costs, while also enhancing social security by helping households sustain consumption during periods of income shocks (Riley, 2018). MBDTA are also essential for enhancing the transparency of ICT among different individuals and organisations, including producers and consumers, as well as facilitate accessible and affordable financial services (Atta-Ankomah *et al.*, 2024; Furuholt and Matotay, 2011).

Since poverty reduction is a key development agenda for low income countries (Palmer-Jones & Sen, 2003), interest among scholars has steadily increased focusing on linking MBDTs to diverse development agendas such as household welfare (Beuermann *et al.*, 2012), productivity and efficiency of agriculture (Ogutu *et al.*, 2014) and livelihoods diversification (Matsuura-Kannari *et al.*, 2024). A study conducted by (Dzator *et al.*, 2023) reveals that imports of ICT items and the penetration of mobile phones contribute to poverty alleviation in SSA. According to a study by Mora-Rivera and García-Mora (2021) show that poverty reduction effects of the internet are more pronounced in rural areas than in urban areas in Mexico. In rural China, Yang *et al.* (2021) found that mobile internet usage significantly and negatively impacts multidimensional poverty.

Evidence from the Global South reveals that mobile phones and mobile-based services can contribute to increasing household consumption of goods (Beuermann *et al.*, 2012), promote digital financial services (Munyegera and Matsumoto, 2016), improve ICTs (Alam *et al.*, 2019) and contribute to household income (Hübler and Hartje, 2016). However, according to Adebayo and Adeniyi (2024), the MBDTA by households could increase poverty if it diverts funds from other household essentials such as food toward communications. Akin to this, a study done in Africa indicates that in nations with poor economies, mobile phone ownership facilitates violent conflict and riots leading to disruption of business operations (Ackermann *et al.*, 2021).

There is limited empirical evidence highlighting the poverty reduction effects of MBDTA in Sub-Saharan Africa, particularly in Ethiopia. Despite the promising role of MBDTA in poverty alleviation, Ethiopia

remains underrepresented in the literature assessing its socio-economic impacts, Ethiopia remains underrepresented in the literature assessing its socio-economic impacts (Beuermann et al., 2012; Kikulweet et al., 2014; Matsuura-Kannari et al., 2024). In addition, existing studies often overlook critical dimensions such as gender disparities in MBDTA, rural-urban differences in digital infrastructure, and other socio-economic factors that influence the effectiveness of MBDTA in poverty alleviation efforts within the country (Warner et al., 2023). Due to a wider gender gap, limited mobile network coverage in rural areas, and low digital literacy, Ethiopia lags other East African countries in MBDTA adoption (Jeffrie et al., 2024). Moreover, existing studies have primarily focused on objective poverty indicators, such as income, health, education, and living standards, often overlooking subjective dimensions like happiness and satisfaction, despite their critical implications for welfare (Alkire and Seth, 2015; Ma et al., 2020b). Finally, there is a lack of localized studies that capture the heterogeneous effects of MBDTA on poverty alleviation, despite poverty being a critical issue in the country.

Mobile-based digital tools have a positive potential impact on various objective and subjective dimensions of poverty in Ethiopia in multiple ways. For instance, the mobile internet can help increase household incomes by facilitating access to employment opportunities (Hübler and Hartje, 2016). The consumption of a diverse range of goods and services by households has grown significantly in Kenya because of mobile money adoption (Suri and Jack, 2016). The findings indicate that the impact of mobile-based digital tools could be more significant for those with stable electricity compared to those with poor electricity conditions. Regarding the subjective dimension of poverty, mobile-based digital technologies can enhance communication and interaction between individuals at a low cost, which can expand personal online social networks and contribute to increased satisfaction and happiness among households (Yang et al., 2021).

2.3. Review of econometric approaches

Propensity score matching (PSM) and endogenous switching regression (ESR) are econometric models and can be employed to estimate the effect of a binary endogenous variable on outcome variables (Mtenga et al., 2024; Wossen et al., 2017). The potential drawback of PSM is that it only deals with endogeneity problems resulting from observable factors (Wossen et al., 2017). This study employs the ESR model instead of PSM for three key reasons. First, the ESR is the appropriate model when there is no panel dataset (in the cross-sectional dataset) (Ma & Abdulai, 2016). Second, it deals with potential endogeneity resulting from observable and unobservable factors (Yang et al., 2021). Lastly, the model enables us to compute the average impact (ATT) of MBDTA on poverty reduction (Wossen et al., 2017).

2.4. Conceptual Framework

As shown in Fig. 1, several factors influence the MBDTA and their impact in reducing poverty. These factors encompass demographic (age, gender, and family size), socioeconomic (such as education), institutional (distance to market) and situational factors (geographical location). The MBDTA impacts income, health, public services, happiness, and satisfaction, which is crucial to reduce poverty.

Source: Own design based on literature (2025)

3 Research Methodology

3.1 Area description

The Hadiya zone in central Ethiopia is where this study was carried out. It is the administrative hub of the Central Ethiopia Region and is situated 232 km from Ethiopia's capital, Addis Ababa. Figure 2 shows the location of the study zone where the research was conducted. The zone shares borders with Kembata Tembaro (KT) to the South, the Dawro Zone to the Southwest, the Omo River to the West, which separates it from the Yem zone and the Oromia region, Gurage to the North, Siltie to the Northeast, and Halaba zone to the east. Land use in the area is primarily agricultural, with significant areas allocated to crop cultivation. This includes staple crops such as maize, teff and wheat, as well as cash crops such as coffee and khat. According to the Hadiya Zone Plan and Development Department, the zone is home to 1,969,866 residents as of fiscal year 2021–2022. Of these, 990,271 are women and 979,595 are men. A total of 346,958.5 hectares of land are covered by the 316 kebeles that comprise the Zone's rural districts. In this area, 68.1% of the land is classified as moderately undulating (*Woyinadega*), 12.9% as low altitude (*Kola*) and 19% as high altitude (*Dega*). The annual rainfall distribution varies between 801 and 1,400 millimetres, while the altitudinal variance spans from 800 to 2,970 metres. The livelihood of society in the zone depends on on-farm (crop production and livestock rearing), off-farm (agricultural employment), and non-farm employments (trade, construction work, civil servants, and others).

3.2 Data

The present study used data collected from respondents for the study. Qualitative and quantitative data were obtained through interviews and discussion with respondents, as well as from published articles and reports. The primary data includes variables on digital abilities, access to digital devices, the necessary infrastructure for digital activities, household characteristics, access to digital services, and geographical location. Primary data were collected in 2024 directly from respondents through face-to-face interviews using tablets equipped with Kobo Toolbox software. Structured survey instruments were administered by trained enumerators to ensure consistency and data quality. Key informant interviews (KII) and focus group discussions (FGD) strengthen the study by adding depth, context, and triangulation. A total of 12 focus group discussions were held with participants of 6–10 per group, purposively selected based on predefined criteria to capture variation in age, gender and other livelihood profiles across kebeles. Also, 12 key informant interviews were held with government officials, agricultural extension agents and representatives from the telecom and financial sectors to get in-depth insights into socio-economic conditions relevant to MBDTA in the study area. Relevant secondary data were sourced from reports, original articles, and reviews.

For the study, multistage sampling technique were employed to select respondents aged 18 years and older within the study area. In the first stage, three rural districts—Ameka, Gombora, and Lemo—were randomly selected, while Hossana town was purposively included to represent the urban setting of the study zone. In the second stage, three local administrations (Kebeles, which are subdivisions of districts

or towns) were randomly selected from each chosen district. Finally, a total of 278 respondents were selected using a simple random sampling technique, with the sample size determined based on Yamane’s (1967) formula.

The formula,
$$n = \frac{N}{1+N (e)^2} \dots\dots\dots 3.1$$

Where n is the sample size, N is the population size, and e is the level of precision it takes 5%.

3.3 Method of data analysis

3.3.1 Definition of variables

Table 1 reveals the relationship between explanatory and dependent variables that describe how mobile-based digital technology influences poverty.

Table 1
Description of the dependent and explanatory variables used for the study

No.	Variable	Variable definition	Variable description	Expected sign
1	MBDTA	Mobile-based digital technology adoption	1 = adopters of mobile-based digital technology, 0 = otherwise	-
2	Age	Age of the respondent	Continuous	+
3	Gender	Gender of the respondent	1 = men, 0 = women	+/-
4	Education	Education level of respondent	0 = no education, 1 = primary, 2 = secondary, 3 = diploma and 4 = degree and above	+
5	DSMT	Distance to nearest markets	Distance to nearest markets in minutes of walking time	-
6	Family size	Family size in number	Family size in number excluding child and elders	+
7	Geographical location	Geographical location	1 = urban residents and 0 = rural residents	+
8	Land	Land	1 = have access to land and 0 = no	+

The measurements used in this study incorporate both objective and subjective well-being, each weighed equally in the assessment, as presented in Table 2. Objective well-being includes income, where individuals earning less than 1.9 United States dollars per day are considered as economically deprived. Regarding nutritional status, individuals who consume fewer than five of the ten essential food groups recommended by the Food and Agriculture Organization experience nutritional deficiencies. Reliable access to electricity is critical; households experiencing daily electricity interruptions are considered

deprived of electricity utility. Subjective well-being indicators of poverty capture personal perceptions, with self-reported happiness and satisfaction scores below 3 points indicating emotional and psychological challenges. Together, these indicators provide a balanced and multidimensional perspective on poverty and quality of life by integrating tangible material conditions with personal experiences. For the analysis, equal weights were assigned to each dimension. In support of this, Alkire and Foster (2011) argue that assigning equal weights is appropriate because it provides a practical and transparent solution that avoids arbitrary preferences across dimensions. Our dependent variable is a multidimensional poverty index, which was employed in the econometric model.

Table 2
Dimensions, indicators, deprivation cutoff, and relative weight of outcome variables

Objective wellbeing	Dimension	Indicator	Deprivation cutoff	Relative weight
	Income	Per capita income	Income per capita below the national poverty threshold (1.9 USD)	1/5
	Health	Nutrition	An individual consumes less than or equal to 5 of 10 possible food groups ^a	1/5
	Public service	Conditions of electricity	Those who face daily electricity interruption	1/5
Subjective wellbeing	Happiness	Self-reported happiness	Self-reported scores of happiness is below 3 points	1/5
	Satisfaction	Self-reported overall satisfaction	Self-reported score of satisfaction is below 3 points	1/5
Notes: The indicators are highly similar to the ones used by Yang et al. (2021), except some other indicators such public services and nutrition. ^a To achieve the minimum dietary diversity score, 5 of 10 food groups are recommended (FAO & FHI 360, 2016).				

3.4 Measuring multidimensional poverty

We followed the necessary procedures to measure multidimensional poverty (Alkire & Foster, 2011; Yang et al., 2021). Initially, a $n \times d$ matrix is represented by the formula $y = Y_{ij}$ where Y_{ij} is individual's value in dimension j , n is the sample size and d is the number of welfare dimensions. Secondly, determining each dimension's cutoff value and Z_i is vector of deprivation cutoff for j dimension. $\rho(y_i; z) = 1$ if the person is multidimensionally poor and $\rho(y_i; z) = 0$ otherwise. Thirdly, we construct a deprivation matrix $g^0 = |g_i^0|$ that represents the 0–1 matrix of deprivations associated with y , where g_{ij}^0 (individual i deprivation vector) is specified as $g_{ij}^0 = 1$ when $y_{ij} < z_i$ while $g_{ij}^0 = 0$ otherwise. Fourth, we establish poverty threshold (k) and represent a column vector c that contains deprivation counts derived from the matrix g^0 , where i^{th} entry $c_i = |g_i^0|$ denotes the count of deprivations that individual i has experienced. After all these steps, it is possible to calculate head count ratio:

$$H = q/n \dots\dots\dots 3.2$$

Where q represents the count of multidimensionally poor individuals, identified using the dual cutoff approach, and n is the sample size.

To capture the intensity of multidimensional poverty beyond the headcount ratio, Alkire & Foster (2011) proposed an adjusted multidimensional poverty incidence, defined as follows.

$$M_0 = HA; A = \frac{|c_i(k)|}{nd} \dots\dots\dots 3.3$$

Where, A represents the mean deprivation share among those who are considered multidimensionally poor; $\frac{c_i(k)}{d}$ is the share of deprivation by poor individuals. Therefore, the mean deprivation among multidimensionally poor is presented $A = \frac{|c_i(k)|}{nd}$

3.5 Empirical model specification

An ESR model was used to analyse the impact of MBDTA on poverty reduction. The model helps us understand how the poverty reduction effects of MBDTA differ between adopters and non-adopters in two steps. First, it estimates why individuals choose to adopt or not adopt MBDTs. Second, it estimates the impact of MBDTA on poverty. In this study, MBDT adopters are individuals that decide to adopt MBDTs, while non-adopters are those that are not adopters of the technologies.

In the first step of the ESR model, the researchers used the probit model to estimate each person's decision on MBDTA. The following is an expression of an individual's MBDTA decision:-

$$U_i^* = X_i\beta + \mu_i, U_i = 1 \text{ if } U_i^* > 0, 0 \text{ otherwise} \dots\dots\dots 3.4$$

Where, U_i is a binary variable and $U_i = 1$ if the individual are adopters of MBDTs and 0 for non-adopters; X_i is a vector of individual characteristics; β is vector of the parameters to be estimated and μ_i is an error term.

In the second stage, two regime equations are specified explaining the outcome of interest for mobile-based digital technologies adopters and non-adopters.

$$\text{Regime 1: } Y_{1i} = X_i\beta_{i1} + \epsilon_{i1} \text{ if } U_i = 1 \dots\dots\dots 3.5$$

$$\text{Regime 2: } Y_{0i} = X_i\beta_{i0} + \epsilon_{i0} \text{ if } U_i = 0 \dots\dots\dots 3.6$$

where Y_{1i} and Y_{0i} are outcomes for adopters and non-adopters of MBDTA, respectively. X_i represents vector of exogenous variables that influence outcome variables; β_{i1} and β_{i0} are parameters to be estimated. ϵ_{i1} and ϵ_{i0} are the error terms associated with outcome variables.

To address the issue of selection bias, the variable X_i specifications in (3.5) and (3.6) take observable factors into account. Nevertheless, a correlation between the error terms in the selection and outcome

equations could still be created by unobservable factors i.e. $\text{corr}(\mu_i, \varepsilon_{i1}) \neq 0$. Selectivity bias arising from unobserved variables would be confirmed if the correlation coefficients, $\rho_{\mu 0}$ and $\rho_{\mu 1}$, are statistically significant throughout the estimation process (Mtenga et al., 2024). This provides more evidence that the ESR model is appropriate. The ESR model can address the selection bias issue resulting from unobservable factors as a missing variable problem through estimating the Inverse Mills Ratios (IMRs) λ_{i1} and λ_{i0} as follows:

$$Y_{1i} = X_i\beta_{i1} + \sigma_{\mu 1}\lambda_{i1} + \gamma_{i1} \text{ if } U_i = 1 \dots\dots\dots 3.7$$

$$Y_{1i} = X_i\beta_{i1} + \sigma_{\mu 0}\lambda_{i0} + \gamma_{i0} \text{ if } U_i = 0 \dots\dots\dots 3.8$$

Where λ_{i1} and λ_{i0} are control for selection bias resulting from unobservable factors; γ_{i1} and γ_{i0} are error terms that have zero mean; $\sigma_{\mu 1}$ and $\sigma_{\mu 0}$ are covariance terms. This is adapted from (Lokshin & Sajaia, 2004), which supports the simultaneous estimation of the selection and outcome equations. In ESR, the correlation coefficients ($\rho_{\mu 1} = \sigma_{\mu 1} / \sigma_{\mu} \sigma_{\varepsilon 1}$ and $\rho_{\mu 0} = \sigma_{\mu 0} / \sigma_{\mu} \sigma_{\varepsilon 0}$) represent the error terms in the selection Eq. 3.4 and the error terms of outcome equations of 3.5 and 3.6.

If $\rho_{\mu 1} > 0$, indicating negative selections, it implies that individuals with below-average outcomes will most likely choose to adopt the MBDTs. When $\rho_{\mu 0}$ ($\rho_{\mu 0}$) or $\rho_{\mu 1}$ ($\rho_{\mu 1}$) exhibit alternative signs, indicates that individuals choose to adopt MBDTs based on perceived comparative advantage, in which MBDT adopters have above-average outcomes by adopting, while those who do not adopt them have below-average outcomes by not adopting the technologies.

Using the ESR framework, the average treatment effect on the treated (ATT) can be estimated by contrasting the expected results of the counterfactual group with those of MBDT adopters (Ma & Abdulai, 2016).

ATT is expressed as:

$$ATT = E(Y_{i1} | D = 1) - E(Y_{i0} | D = 1) \dots\dots\dots 3.9$$

Where $E(Y_{i1} | D = 1)$ denotes the expected economic wellbeing outcome of mobile-based digital technology adopters; and $E(Y_{i0} | D = 1)$ represents the counterfactual of MBDT adopters, which indicates the probable income outcome of adopters if he/she had not adopted the MBDTs.

To address endogeneity, an instrumental variable (IV) was selected, considering the possibility of causal relationships between dependent and independent variables. Given the reverse causation between the MBDTA and poverty reduction, social networks were included as an instrumental variable to address the endogeneity issue. We used the logit model for analysing the effect of social networks on MBDTA to evaluate the validity of the instrument. The relationship between social networks and multidimensional poverty indicators was examined using the ordinary least squares model. The findings show that the social network significantly and positively influences MBDTA, but it has no significant effect on

multidimensional poverty. These findings support the choice to employ the social network variable as a valid instrument.

4 Results and Discussions

This section presents descriptive statistics and econometric analyses for the variables specified relevant to the study. The descriptive statistics provide a summary of variables. An econometric model, such as the ESR, was used to analyse the impact of the MBDTA on poverty reduction.

4.1 Descriptive statistics

The descriptive statistics for the variables used in this study are presented in Table 3. The results indicate that the respective age distributions of adopters and non-adopters were 41.51 and 47, indicating that older respondents have less likelihood of adopting MBDTs. Males exhibit greater engagement with these technologies, with about 93% of them being adopters. Regarding education, respondents with higher levels of education were more likely to adopt MBDTs compared to their less educated counterparts. The average distance to the nearest market indicates that most adopters of MBDTs live near to market areas. Adopters of these technologies tend to have smaller family sizes, with an average of 5.18 compared to 6 for non-adopters. Individuals residing in rural areas, which are far from urban centres were falling behind in the adoption of MBDTs.

Table 3
Descriptive statistics for the explanatory variables used

Variable	Adopters	Non- adopters	Difference	t-statistics
Age	41.51	47	-5.5 ***	-4.8
Agesquared	1847.4	2288.9	-441.5 ***	-4.08
Gender	0.93	0.5	0.43 ***	11.3
Education	3	1.46	1.54 ***	14
DSMT	22	30	-8 ***	-4.64
Family size	5.18	6	-0.82 ***	-4.53
Geography	2.6	2.2	0.4 ***	3.45

Source: Survey data (2025). *** mean significant at levels of 0.01

4.2 Econometric analysis

4.2.1 Deprivation level and contribution of each outcome variable to poverty

The findings presented in Table 4 emphasise that the condition of electricity was the most significant driver of poverty, accounting for 29%. This underscores the need to address root causes of power outages affecting residents in the study area. This aligns with the study by Atta-Ankomah et al. (2024) who underscore electricity as key mobile money adoption in Ghana. Following the condition of electricity, individual income levels, which contribute 26.4%, were a significant factor that led to poverty in the study area. This finding aligns with Esrael et al. (2025). Thenutrition contributes 15.9% to poverty, highlighting that a significant portion of the population does not receive adequate nutrition as recommended by FAO & FHI 360 (2016). The dimensions of happiness and satisfaction contribute 14.4% and 14.3%, respectively, highlighting their importance in enhancing household welfare. This finding corroborates the study by Yang et al. (2021).

Table 4 Deprivation and share of each indicator to multidimensional poverty index			
Wellbeing	Indicator	Deprived (%)	share of each indicator
Objective	Income	64.2	0.264
	Public service (electricity)	87.5	0.29
	Health (nutrition)	38.3	0.159
Subjective	Happiness	33.76	0.144
	Overall Satisfaction	33.75	0.143

Source: Survey data (2025). Note: Deprived: the % of individuals whose indicator values are below the threshold.

4.2.2 Multidimensional poverty index

The results of the multidimensional poverty index were presented in Table 5. The multidimensional poverty headcount ratio was 0.68, indicating that about 68% of individuals are considered multidimensionally poor. The headcount ratios for adopters and non-adopters of MBDTs were 0.519 (51.9%) and 0.88 (88%), respectively, indicating that adopters are 41% less likely to be multidimensionally poor compared to non-adopters. The intensity of poverty was 0.693 with the value of 0.659 and 0.743 for adopters and non-adopters respectively indicating poor individuals are deprived in 69.3% of weighted indicators used in multidimensional index.

The adjusted multidimensional poverty for the total sample was 0.471, with rates of 0.342 for adopters and 0.654 for non-adopters of MBDTs. This indicates that adopters are 48% less likely to experience multidimensional poverty compared to non-adopters, underscoring the potential of MBDTA in reducing poverty. This finding aligns with study by Yang et al. (2021). The multidimensional poverty headcount ratio and the incidence of multidimensional poverty were higher than income poverty, as illustrated in Table 4. This indicates that relying solely on income poverty as a measure of poverty will underestimate the incidence of poverty. The result aligns with the study by Mahadevan & Jayasinghe (2020).

The findings, which emphasise the potential of MBDTA in reducing poverty, strongly align with SDG 1 (no poverty) and SDG 5 (gender equality). Given that non-adopters experience higher levels of poverty than adopters, it is important for Ethiopia's digital strategy to target non-adopters' digital access and skills to promote equitable growth.

Table 5
The estimation of multidimensional poverty index

Index of multidimensional poverty	Total sample	Adopters	Non-adopters
Head count ratio (H)	0.68 (0.023)	0.519(0.039)	0.88 (0.02)
Intensity of poverty (A)	0.693 (0.017)	0.659 (0.018)	0.743 (0.018)
Adjusted multidimensional head count (M0)	0.471 (0.02)	0.342 (0.014)	0.654 (0.022)

Source: Survey data (2025).

4.2.3 Results for the ESR model

The selection equation illustrates the factors that influence MBDTA, as presented in Table 6, column 2. Considering the reverse causality between MBDTA and multidimensional poverty, we employed ESR approach. The ESR framework corrects for selection bias and offers consistent estimates by estimating factors and outcome variables simultaneously and allowing for correlation between the unobserved factors driving both. The likelihood ratio (LR) test of the independence Eq. (28.22) was statistically significant at the 1% level and shows that the selected data set aligns well with the specified model. This suggests that the ESR model is appropriate for the analysis, in contrast to an exogenous model, where the application of least squares would probably produce biased results.

Factors such as age, age squared, education, and geographical location have significant influence on the MBDTA. Age has a significant negative influence on MBDTA, with older individuals being 20.7% less likely to adopt these technologies. Education has a positive and significant influence on MBDTA. Our results indicate that more educated individuals have a higher probability of being knowledgeable about MBDTs, consistent with Human Capital Theory. The geographical location variable demonstrates that the likelihood of adopting MBDTs was 38.6% higher in urban areas than in rural settings. This highlights the need for greater engagement of individuals in MBDTs for their daily activities in rural areas.

Table 6 in columns 3 and 4 presents the outcome equations that demonstrate the impact of MBDTs on poverty reduction for adopters and non-adopters. For adopters, variables that significantly influence poverty include age, age squared, education, distance to market, and family size. Age negatively and significantly affects poverty, indicating that older individuals have a lower likelihood of being multidimensionally poor. For each additional year of age, individuals were 8% less likely to experience multidimensional poverty. This finding is similar to the research by Compaore et al. (2024). As distances from the market increase for adopters of MBDTs, the impact on poverty becomes positive and

significant. This could be attributed to the inadequate network and internet connectivity for individuals living far from the market centres. This result is consistent with an earlier study by Yang et al. (2021).

The results of family size were positively and significantly influenced multidimensional poverty, indicating an increase in family size increase poverty compared to smaller households for adopters. Each additional family member results in a 12.2 percentage point increase in multidimensional poverty, highlighting the importance of family planning. This result aligns with the studies by Esrael et al. (2025).

In contrast, for non-adopters of MBDTs, the significant variables that influence poverty were gender, education, and geographical location. The coefficient of education was negatively and significantly associated with poverty for adopters and non-adopters. Multidimensional poverty would reduce by 19.6% and 53% for every extra year of education for adopters and non-adopters, respectively. This demonstrates that education is a powerful driver for alleviating poverty. This finding is similar to the study by Wang et al. (2022). The likelihood of poverty deprivation among non-adopters was 98% lower for men than for women, highlighting the importance of enabling women to become adopters of MBDTs. The study by Ueno et al. (2023) supports this finding. The coefficient for geographical location among non-adopters indicates that non-adopters of MBDTs residing in urban areas were 24% more likely to experience higher levels of poverty than their rural counterparts. This finding is supported by Reddick et al. (2020).

The analysis of correlation coefficients for the positive values of ρ_0 and ρ_1 indicates that the multidimensional poverty deprivation scores of adopters and non-adopters are below the average of the multidimensional poverty index. These findings align with the research by Compaore et al. (2024). The significance level of the variance coefficient confirms that those who adopt MBDTs have a comparative advantage over those who do not, ρ_1 (Mtenga et al., 2024). However, ρ_0 and ρ_1 have the same sign, indicating that the unobservable factors influence the outcome in the same direction for both groups, which justifies the use of ESR.

Table 6
Factors influencing MBDTA and its impact on poverty reduction

Variable	Select eq.	Adopters	Non- adopters
Age	-0.207 (0.066) ***	-0.08 (0.037) **	0.328 (0.068)
Agesquared	0.0022 (.0007) ***	-0.00098 (0.00039) **	-0.00002(0.0007)
Gender	0.095 (0.35)	-0.398 (0.244)	-0.98 (0.18) ***
Education	0.253 (0.097) ***	-0.196(0.07) ***	-0.53 (0.09) ***
DSMT	0.0029 (0.0061)	0.0099 (0.0044) **	-0.0024 (0.0048)
Family size	-0.088 (0.072)	0.122 (0.043) ***	0.053 (0.05)
Geography	0.386 (0.097)***	0.049 (0.064)	0.24 (0.079) ***
Social network	1.34 (0.16) ***		
_cons	1.27 (1.42)	1.41(0.74) *	3 (1.54) *
/lns0	0.18 (0.049) ***	sigma0	1.2 (0.06) ***
/lns1	-0.278 (0.073) ***	sigma1	0.76 (0.055) ***
/r0	1.09 (0.21) ***	rho0	0.8 (0.076) ***
/r1	1.14 (0.4) ***	rho1	0.815 (0.13) ***
LR test of indep. eqns.	28.22 ***	Log likelihood	-628.72
Source: Survey data (2025). *, ** and *** mean significant at levels of 0.1, 0.05 and 0.01 respectively. Standard errors in parentheses			

The impact of MBDTA on poverty reduction

Table 7 estimates the ATT of MBDTs on multidimensional poverty. The average values of the number of deprived dimensions for adopters and non-adopters were 1.03 and 2.11, respectively. The ATT value demonstrates that MBDTA negatively and significantly affects multidimensional poverty as priori expectation, indicating that adopters of these technologies face less poverty deprivation compared to their counterfactual. The finding is compatible with the study by Yang et al. (2021).

MBDTA was a crucial tool to increase income and enhance nutrition, greater happiness, and satisfaction, which are essential elements in reducing poverty. The income levels were higher for adopters compared to non-adopters, underscoring the income-increasing potential of MBDTs. As highlighted in the FGD, “Individuals previously had to travel long distances to access job opportunities.” However, mobile phones now provide easy access to income-generating opportunities. This finding is supported by Hübler and Hartje, (2016). Adopters have better access to electricity than non-adopters. “Frequent electricity supply interruptions, particularly in the Ameka and Gombora districts, hinder the effective use of MBDTA for

poverty alleviation”, as noted by the FGD and KII. This finding aligns with the study by Dzator et al. (2023).

Table 7
The impact of MBDTA on poverty alleviation by ATT

Outcome variable	Mean outcome			
	Adopters	Counterfactual	ATT	t-value
Number of deprived dimensions	1.03(0.469)	2.11 (0.75)	-1.084 ***	-26.5
Income	24579.16 (174.7)	19821.4 (237.8)	4757.8***	40.94
Public service	2.177 (0.44)	1.173 (0.54)	1.003***	49.06
Health	0.88 (0.245)	0.56 (0.33)	0.32 (0.24) ***	16
Happiness	4.35 (0.39)	2.46 (0.972)	1.89***	28.05
Satisfaction	4.36 (0.38)	2.37 (0.91)	1.99***	32.79

Source: Survey data (2025). *** mean significant at levels 0.01. Standard errors in parentheses

Adopters of MBDTs consume a significantly more diverse variety of foods compared to non-adopters. The higher nutrition among adopters underscores the crucial role of MBDTA in enhancing nutrition by addressing information asymmetry, consistent with Information Economics Theory. According to one FGD participant, “The variety of foods consumed was significantly lower two decades ago, due to limited mobile phone access.” This aligns with the study by Beuermann et al. (2012). Adopters were happier and more satisfied by accessing internet and mobile money services that save time and cost compared to non-adopters. The FGD discussion highlighted that MBDTA enhances individuals' happiness and satisfaction by providing access to convenient entertainment and smoothing essential services that improve quality of life. The findings are congruent with the result reported by Yang et al. (2021). This demonstrates the applicability of Sen’s Capability Approach, which links poverty to constraints on individuals’ freedoms and opportunities in addition to a lack of income.

Heterogenous effect of MBDTA among various districts

The findings in Table 8 indicate that the impact of MBDTs on poverty reduction varies significantly across different districts in the study area. The results reveal a negative and significant impact of these technologies on multidimensional poverty in the *Gombora*, *Ameka*, *Lemo* and *Hossana* districts. This reveals that the adoption of MBDTs can substantially alleviate multidimensional poverty for individuals residing in these areas. However, the benefits that individuals derive from technologies vary significantly. For instance, the Average Treatment Effect (ATT) values of MBDTA on multidimensional poverty in *Gombora*, *Ameka*, *Lemo*, and *Hossana* were – 0.727, -0.86, -1.27 and – 1.2, respectively. The ATT values for the *Lemo* and *Hossana* districts were higher negative values than those for *Gombora* and *Ameka*. This indicates that the adoption of MBDTs has a less impact on poverty reduction in *Gombora*

and *Ameka* compared to *Lemo* and *Hossana*, underscoring the importance of these technologies in alleviating poverty in the Gombora and Ameka districts. The lower poverty reduction effects of MBDTA in Ameka and Gombora might be attributed to limited infrastructure, lack of digital skills, insufficient policy support, and other socioeconomic factors that hinder households' ability to use these technologies for livelihood activities.

The stronger poverty reduction effects of MBDTA in Hossana and Lemo are attributed due to better digital infrastructure and supportive policies. These findings reinforce the relevance of institutional and governance theories. In addition, given the disparity in MBDTA across districts, this study demonstrates the applicability of the inclusive growth theory in promoting inclusive adoption to alleviate poverty. The findings are consistent with the study conducted by Leng et al. (2020).

Table 8
Heterogeneous effects of MBDTA at different locations

District	Mean	Outcome		
	Adopters	Counterfactual	ATT	t- value
<i>Gombora</i>	1.048	1.7746	-0.727 ***	7.4
<i>Ameka</i>	1.29	2.15	-0.86 ***	12.5
<i>Lemo</i>	1.283	2.55	-1.27 ***	12.74
<i>Hossana</i>	0.82	2.02	-1.2 ***	23.7

Source: Survey data (2025).

5 Conclusions and recommendations

This study examines the impact of MBDTA on poverty reduction in the Hadiya Zone, Ethiopia, using cross-sectional data collected in 2024 from 278 respondents. First, we used Alkire and Foster (2011) methods to estimate multidimensional poverty index. The findings show that adopters of MBDTs were 48% less likely to experience multidimensional poverty compared to non-adopters. The results of an ESR model indicate that age, agesquared, education, and geographical location significantly influence MBDTA. The findings also suggest that age, agesquared, education, distance to market, and family size for adopters and gender, education, and geographical location for non-adopters significantly impact multidimensional poverty. Findings of outcome variables indicate that the adopters of MBDTs were less deprived in number of poverty dimensions such as income, conditions of electricity, nutrition, happiness, and satisfaction compared to the counterfactual. The impact of MBDTA on multidimensional poverty was estimated to vary across different districts. This might be due to disparity in digital infrastructure, supportive policy and socioeconomic conditions. The integration of the Inclusive Growth Framework, Information Economics Theory, Institutional and Governance Theories, and Sen’s Capability Approach strongly supports the poverty reduction effects of MBDTA. The findings are relevant given Ethiopia's

national digital strategy, which emphasizes digital inclusion as an essential element of socio-economic transformation. Furthermore, the findings align with SDG 1 (no poverty), underscoring the crucial role of digital adoption in poverty alleviation.

Policymakers should prioritise reducing the barriers that prevent rural residents from using mobile internet and mobile money, as these tools are crucial to alleviating multidimensional poverty. To this end, expanding 4G and 5G networks in rural areas is essential. Collaborative efforts among the government, Ethio Telecom, and Safaricom can help address the heterogeneous treatment effects associated with these technologies.

Another area that requires government intervention is the expansion of complementary infrastructure, particularly electricity in rural areas, to support the charging of essential mobile devices for daily activities. The positive impact of education on the MBDTA indicates that integrating emerging digital technologies into the educational curriculum is crucial to achieve widespread adoption. Since the incidence and adjusted multidimensional poverty are higher among non-adopters of technology, there is a pressing need for targeted initiatives to empower non-adopters to become adopters of the MBDTs.

This article has the following limitations. First, this study used cross-sectional data to analyse the impact of MBDTA on alleviation of poverty. Further studies should focus on time series analyses, which can provide more comprehensive information on the same variables over time, thereby facilitating better policy decisions. In addition, this study focused on three districts and one town, which limits the generalisability of the findings to the country as a whole. Future studies should target other areas where the MBDTA in poverty reduction could contribute significantly to the existing literature.

Declarations

CRedit roles

Degineh Lagiso Bule: Conceptualisation, formal analysis, software, resources, investigation, methodology, visualisation, project administration, writing-initial draft.

Herbert Ntuli and Colleta Gandidzanwa: Supervision, writing-review and editing, methodology and validation.

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Declarations of conflict of interest

No potential conflict of interest was reported by the author (s).

Ethical approval and consent to participate

The study received ethical approval from the Natural and Agricultural Sciences Ethics Review Committee at the University of Pretoria (approval no. NAS121/2024) on June 25, This research was conducted in accordance with ethical principles for research involving human participants and complied with the research ethics guidelines of the University of Pretoria. In addition, written consent and signatures were obtained from respondents before the interviews commenced.

Availability of data

The data used in this article can be obtained upon request.

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Figures

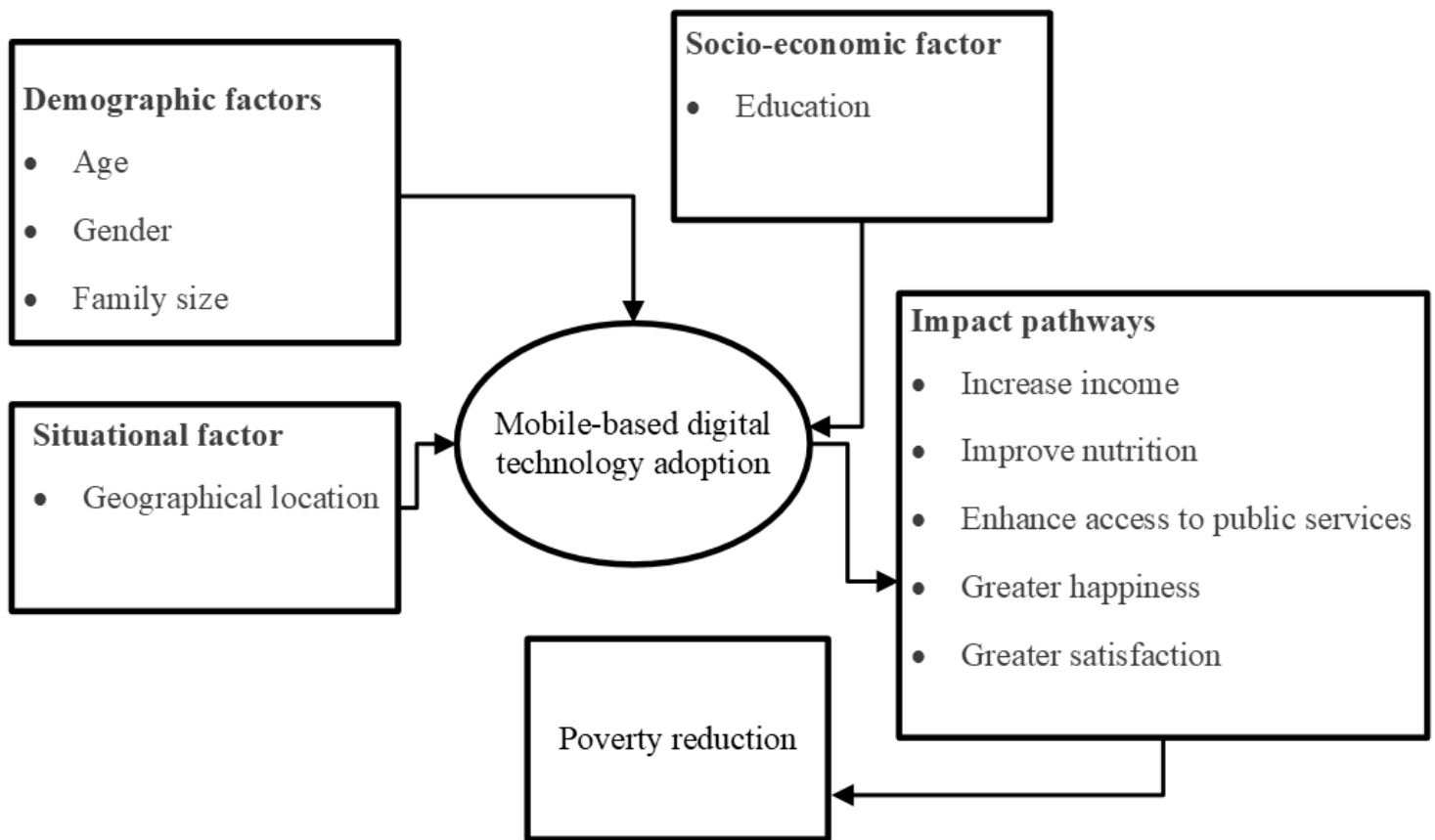


Figure 1

Conceptual framework of the impact of MBDTA on poverty reduction

Source: Own design based on literature (2025)

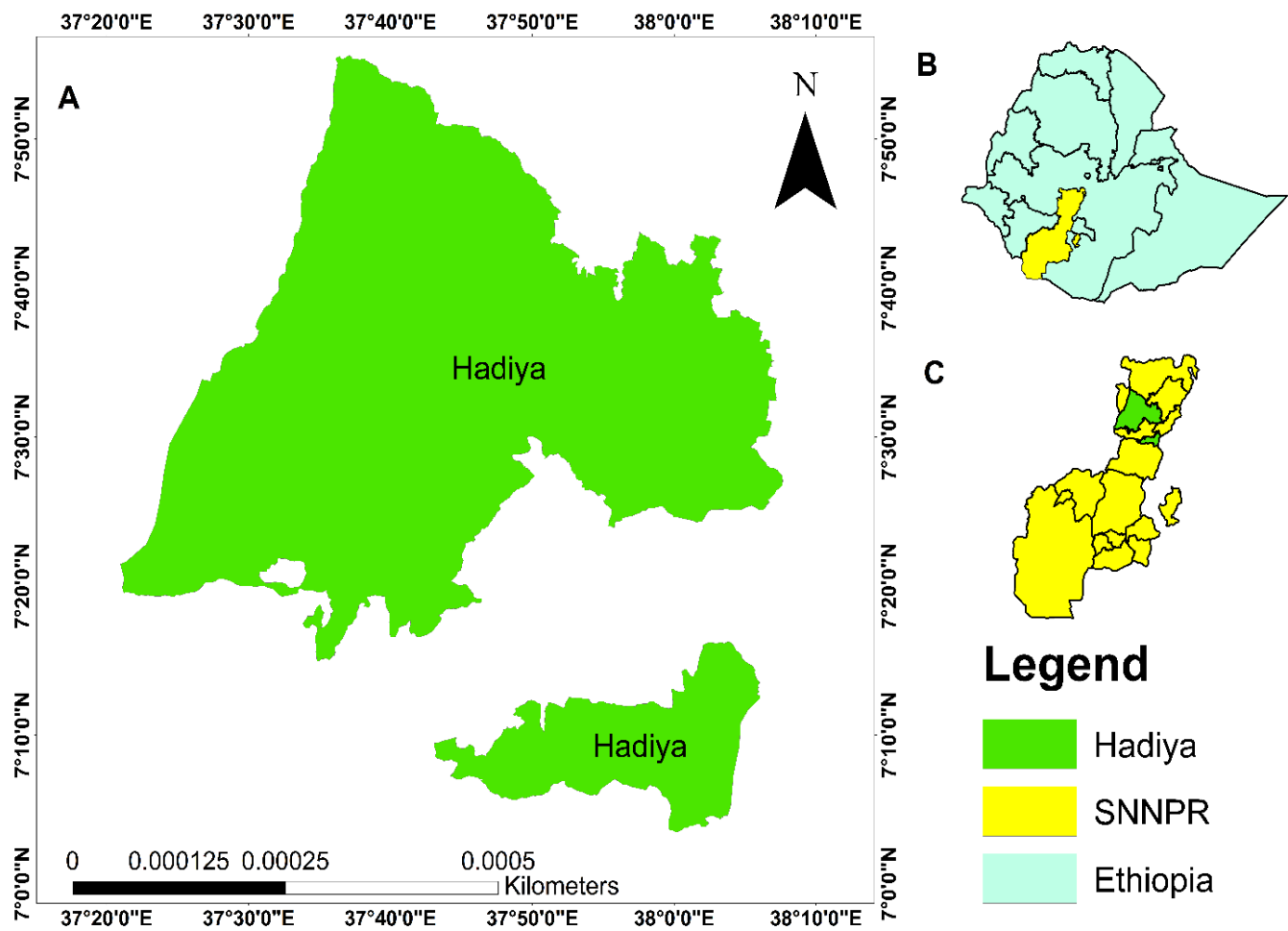


Figure 2

Map of the Hadiya zone