

Factors Affecting the Adoption of Mobile-Based Digital Technologies: Evidence from Ethiopia

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Abstract

Mobile phones and associated services possess substantial potential to improve household livelihoods. However, there is inadequate access to and use of mobile-based technologies, despite their potential to improve livelihoods in the Hadiya zone, Ethiopia. This study aims to analyse the main factors influencing the adoption of mobile-based technology. The analysis employed an ordered logit model on cross-sectional data collected from 278 respondents. The findings indicate that factors such as gender, education, affordability, access to remittances, social networks, awareness, geographical location, trade access, and type of mobile phone have positively and significantly influenced the likelihood of adopting mobile-based digital technology, except age. The implications suggest that mobile-based technology adoption remains under-utilised for essential activities, with adoption particularly lower among women and rural populations. Targeted interventions, including infrastructure improvements, digital connectivity enhancement, awareness campaigns, skill training, income-raising initiatives, and gender-sensitive digital policies, are essential to promote adoption.

Keywords

digital inclusion, Ethiopia, gender, mobile-based digital tools, ordered logit model

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Introduction

The advent of mobile phones has become a key driver of socioeconomic transformation in developing countries (Leng et al., 2020; Vimalkumar et al., 2021). The Sustainable Development Goals (SDGs) acknowledge that information and communication technologies (ICTs) play a significant role in many aspects of modern economic activities, including job creation, government service delivery, financial inclusion, and effective information and efficient communication (Ahmad et al., 2020; Di Tullio & Gómez-Cruz, 2025; GSMA, 2019; UN, 2023). Mobile phones are the most versatile, portable, and widely accessible tools for individuals and businesses, surpassing other forms of ICTs for a variety of tasks (Aker et al., 2016; Alam et al., 2019). In developing nations where infrastructure is less developed, mobile phones and associated services are essential to achieve these goals due to their accessibility and convenience (GSMA, 2019; Mothobi & Grzybowski, 2017). In Ethiopia, mobile penetration has increased over the last two decades and has promising potential to support the livelihoods of rural populations. Mobile-based digital technologies (MBDTs) offer numerous benefits for households, including quick access to information, seamless communication, and the promotion of financial inclusion (Akinyemi & Mushunje, 2020; Baird & Hartter, 2017).

Since 2020, Ethiopia has implemented telecommunication policies with a focus on telecom privatisation, aimed at enhancing digital services (EDS, 2020). There are ongoing efforts in Ethiopia to improve access to mobile phones and their services, including underserved populations, through telecommunications reform and sector privatisation (Shahid et al., 2023). Owing to these efforts, there has been significant progress in mobile-based digital technology adoption (MBDTA) among individuals in the country over the past decades (GSMA, 2019; UN, 2023). Despite this progress, the effective MBDTA remains uneven, particularly in rural and semi-urban areas (Warner et al., 2023). This is attributed to differences in demographic, socioeconomic, technological, and situational factors in Ethiopia compared with other countries (Ferritto, 2024; Shahid et al., 2023; Talwar et al., 2020; Venkatesh et al., 2012).

Existing studies have investigated various aspects of adoption of mobile phones, such as mobile money services, internet use, and ICTs (Domguia & Asongu, 2025; Haile et al., 2019; Jerene & Sharma, 2020; Vimalkumar et al., 2021; Yang et al., 2021). However, many studies were conducted at the national level without further disaggregating the data into specific zones and districts, where there is demographic, socioeconomic, and technological variations (Ali et al., 2024; Banerjee et al., 2022; Ferritto, 2024; Kala, 2023; Li et al., 2023; Ntuli & Muchapondwa, 2017). In addition, much of the existing research predominantly focused on the financial perspectives of mobile services, overlooking the ICTs aspects of mobile phones (Akinyemi & Mushunje, 2020; Malinga & Maiga, 2020; Rana et al., 2020; Teka, 2020). Moreover, the existing literature inadequately addresses the need for a comprehensive analysis that includes both mobile adopters and non-adopters, the types of mobile devices owned, and digital skills. Furthermore, previous research on mobile-based services was mainly concentrated in China, India, Kenya, and Uganda (Leng et al., 2020; Mukong & Nanziri, 2021; Mutuma et al., 2023; Rana et al., 2020), neglecting Ethiopia, where mobile services are progressing for various development efforts.

The Hadiya zone is characterised by a mix of developing urban areas and rural populations, providing a compelling context to explore the MBDTA. The population of the zone heavily relies on mobile phones for communication and sustains its livelihood through diverse crops and livestock production, including essential endemic crops such as *teff* and *enset*. It is also evident that demographic, socioeconomic, technological, and situational factors vary across Ethiopia, and the Hadiya zone is no exception (Ferritto, 2024; Warner et al., 2023). These variations raise research questions about how various factors influence individuals' decisions to adopt or not. Although MBDTs are becoming increasingly important for rural development strategies, there are significant literature gaps on MBDTA in the Hadiya zone. This suggests a lack of understanding of the various factors that influence MBDTA. The lack of research directly related to this topic, both within the country and specifically in the Hadiya zone where this study is conducted, underscores the importance of this research.

To address the mentioned gaps, this study aims to address two questions:

- What demographic and socioeconomic dynamics uniquely shape MBDTA in the Hadiya zone?
- How do local technological ecosystems and situational realities influence MBDTA in the zone?

This study presents three contributions to the existing literature. First, this study examines the production, communication, and transactional aspects of MBDTA, addressing gaps in the existing literature within the specific context of the study area. Second, our findings enrich the existing literature by providing a comprehensive analysis of MBDTA, with an emphasis on the Hadiya zone. To this end, we employed the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), which is widely applicable, allows the integration of organisational factors with consumer variables and enhances the explanatory power of the model (Venkatesh et al., 2012). This analysis offers insights that inform targeted policy interventions aimed at fostering inclusive digital policies and enhancing the effectiveness of mobile tools in development initiatives. Third, the study examines various factors influencing MBDTA using an ordered logit model to understand different levels of adoption, an aspect often neglected in the literature.

Review of the Literature

Mobile-Based Digital Technology Adoption

MBDTA is defined as the uptake and integration of mobile-enabled tools and services, particularly mobile internet and mobile banking, into everyday life, businesses, and public service delivery. In fact, these technologies are crucial to achieving the SDGs for 2030 by providing quick access to information, enhancing communication, and promoting financial inclusion (Malinga & Maiga, 2020; Vimalkumar et al., 2021). Despite its significant role in the transformation of development activities, the benefits derived from

MBDTs are unevenly distributed in various countries. One of the factors contributing to this issue is the digital divide, defined as the gap between individuals, households, and regions that have access to and use ICTs such as mobile phones, mobile internet, and mobile money, and those that do not (Vimalkumar et al., 2021). For instance, much of the research conducted in Africa primarily focuses on Kenya and Uganda (Mukong & Nanziri, 2021; Mutuma et al., 2023), while a country such as Ethiopia exhibits considerable variation in socioeconomic, demographic, technological, and geographical factors that differently influence its individuals (Ferritto, 2024; Talwar et al., 2020). Since Ethiopia has a lower rate of MBDTA compared with many other countries (Warner et al., 2023), conducting an in-depth analysis of several factors in the Hadiya zone of Ethiopia is essential to enhance the understanding of MBDTA for various livelihood activities.

Factors Influencing MBDTA

There are several factors that influence individuals' behavioural intention to adopt MBDTs. The factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions that serve as key indicators of technology adoption (Venkatesh et al., 2012).

According to the studies by Teka (2020) and Ohme (2014), perceived usefulness and perceived ease of use significantly influence the adoption of mobile banking or digital services, indicating that individuals' perceptions of technology as user-friendly, along with their attitudes toward its importance, promote its adoption. Mukong and Nanziri (2021) argue that weak social ties limit the flow of information from friends and family using ICT tools. Regarding facilitating conditions, studies in Australia and Mexico show that socioeconomic, institutional, and political barriers limit rural internet access compared with urban areas (Mora-Rivera & García-Mora, 2021; Park, 2017).

The existing literature shows that younger males, educated individuals, wealthy individuals, employed, and digitally literate individuals are more likely to adopt various MBDTs (Kala, 2023; Leng et al., 2020; Mukong & Nanziri, 2021; Mutuma et al., 2023; Reddick et al., 2020; Shaibu et al., 2018). In addition, the literature indicates that access to remittances and trade, smartphone ownership, urban residency, and proficient digital skills further improve the likelihood of adopting these technologies (Ali et al., 2024; Banerjee et al., 2022; Mutuma et al., 2023; Park, 2017). Mukong and Nanziri (2021) found that mobile money adoption is higher among individuals with a high school education, underscoring the need to enhance educational engagement.

Munyegera and Matsumoto (2016) found that age, education, and gender significantly influence the MBDTA in Uganda. According to Shaibu et al. (2018), the adoption of mobile tools is less prevalent among older individuals compared with younger ones. Li et al. (2023) argue that individuals with limited education often face challenges in accessing digital platforms due to digital illiteracy and the complexity of using these technologies in China.

Ferritto (2024) argues that affordability and digital literacy for mobile-based services are significant challenges hindering technology adoption, particularly among women in

Ethiopia. Similarly, Warner et al. (2023) found that married women in rural Ethiopia are five times less likely to own and use MBDTs. The low adoption of these technologies by women might be attributed to various socioeconomic factors (Ferritto, 2024; Reddick et al., 2020).

Regarding the type of mobile phone owned, a study by Ali et al. (2024) found that smartphone owners have adopted a wider range of advanced MBDTs compared with individuals with basic mobile phones or those without any phone. Banerjee et al. (2022) found a positive relationship between MBDTs and trade, revealing how these technologies facilitate online trade, lower transaction costs, and expand market access.

Based on the preceding literature reviews, which highlights various factors influencing the likelihood of MBDTA, a summary of the hypotheses tested, including the corresponding measurements and expected signs of the relationships between the dependent and explanatory variables, is presented in Table 1.

Conceptual Framework for MBDTA

The Unified Theory of Acceptance and Use of Technology (UTAUT) model is one of the most widely used models to integrate core determinants of technology adoption, which were initially developed by Venkatesh et al. (2003). However, the model was designed for organisational level determinants that overlook consumer-specific factors of technology adoption. To address this issue, the UTAUT2 (extension of UTAUT) was developed, which is a powerful theory compared with other technology adoption theories (Malinga & Maiga, 2020; Tamilmani et al., 2021; Venkatesh et al., 2012). Owing to the potential for integrating various demographic and socioeconomic variables, the UTAUT2 theory is unlike other technology adoption theories (Venkatesh et al., 2012). The model also incorporates the dimensions of all other technology adoption theories or models, enhancing its predictive power over other models (Abrahão et al., 2016). For the study, we considered various variables that influence MBDTA. As illustrated in Figure 1, various factors influence the decision to adopt or refrain from MBDTA. These factors include demographic factors (age, gender, and education), socioeconomic factors (affordability, remittances, social networks, employment, and trade), technological factors (awareness, ease of use, and type of mobile phone), and situational factors (geographical location). The selected variables representing the core components of the UTAUT2 model—performance expectancy, effort expectancy, social influence, and facilitating conditions—correspond to awareness of technology usefulness, ease of use, social networks, and geographical location, respectively. In addition, other mentioned variables have been incorporated to address consumer-specific factors.

Research Methodology

Area Description

This research was conducted in the Hadiya zone, located in the central Ethiopian region. It is located 232 km from Addis Ababa, the capital of Ethiopia, and is the administrative

Table 1. Explanation of the Explanatory Variables Used in This Study.

No.	Variable	Variable Definition	Variable Description	Expected Sign
1	Age	Age of the respondent	Continuous	+
2	Gender	Gender of the respondent	1 = Male, 0 = Female	+/-
3	Education	Education level of respondent	0 = no education, 1 = primary education, 2 = secondary education, 3 = diploma and 4 = degree and above	+
4	Affordability	Cost of digital services	1 = perceived as affordable, 0 = perceived as unaffordable	+
5	Social networks	The influence of peer adoption/online community	0 = no access to social network, 1 = have access to one network, 2 = have access to two networks and 3 = have access to more than two networks	+
6	Remittances	Remittances	1 = received remittances and 0 = no remittances received	+
7	Awareness	Awareness of MBDTs	1 = have awareness and 0 = no awareness	+
8	Employment	Employment	1 = employed, 0 = unemployed	+
9	Geographical location	Geographical location	1 = urban respondent and 0 = rural respondent	+
10	Trade	Trade status	1 = trader, 0 = nontrader	+
11	Ease of use	Perceived user -friendliness of MBDTA	1 = easy to use, 0 = difficulty to use	+
12	Type of mobile owned	Type of mobile owned	1 = own basic phone, 2 = own smartphone	+

(Reddick et al., 2020)
(Shaibu et al., 2018)(Munyegera &
Matsumoto, 2016)
(Kala, 2023)(Mukong & Nanziri,
2021)

(Ali et al., 2024)

(Malinga & Maiga,
2020)

(Park, 2017)

(Mora-Rivera &
García-Mora,
2021)(Banerjee et al.,
2022)(Mutuma et al.,
2023)

(Ali et al., 2024)

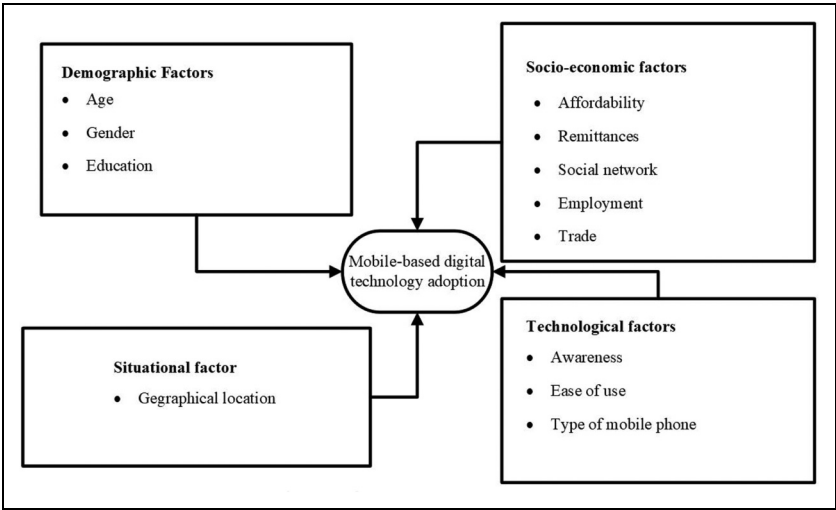


Figure 1. Conceptual framework of the study. Source: Own design based on the reviewed literature (2025).

centre for the Central Ethiopia Region. The zone shares borders with Kembata Tembaro 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 north-east, and the Halaba Zone to the east. Land use in the zone is primarily agricultural, with significant areas allocated for crop cultivation. This includes staple crops such as *enset*, wheat, barley, maize, and *teff*, as well as cash crops such as *coffee* and *khat*. As of the 2021/22 fiscal year, the Hadiya Zone plan department reported that the Hadiya Zone is home to 1,969,866 residents. Among them, 979,595 are male and 990,271 are female. The rural districts of the zone consist of 316 kebeles, covering a total land area of 346,958.5 hectares. Within the zone, 12.9% of the land is classified as low altitude (*Kola*), 68.1% as moderately undulating land (*Woyinadega*), and 19% as high altitude (*Dega*). The annual rainfall distribution ranges between 801 and 1,400 millimeters, while the altitudinal variation spans 800 to 2,970 meters. The livelihood of society in the zone depends on the farm (rearing of livestock and crop production), the off-farm (wage earning from agricultural employment), and the nonfarm jobs (trade, construction work, civil servants, and others) (Figure 2).

Data and Data Sources

The present study used data collected from respondents for the study. Both qualitative and quantitative data were collected from primary and secondary data sources. Primary data were collected directly through face-to-face household surveys administered by trained enumerators using structured questionnaires. The survey captured a wide range of variables, including access to digital devices, the necessary infrastructure for digital

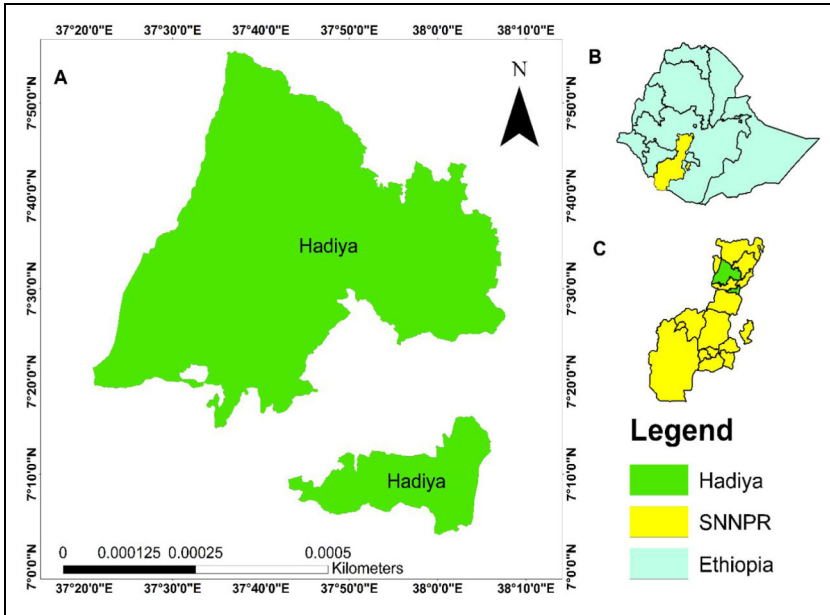


Figure 2. Map of the study area.

activities, household characteristics, access to digital services, and geographical location. Data collected were facilitated using Kobo Toolbox, software installed on tablets which helps to ensure timely data entry and quality of data. In addition to quantitative data, qualitative data were collected through key informant interviews (KII) and focus group discussions (FGD) to strengthen the study by adding depth, context, and triangulation. A total of 12 FGD 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. Furthermore, 12 KII were held with government officials, agricultural extension agents and representatives from the telecom and financial sectors to get in-depth insights into socioeconomic conditions relevant to MBDTA in the study area. Relevant secondary data were sourced from reports, original articles, and reviews.

Sampling Technique and Sample Size

For this study, multistage sampling techniques 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. In the third stage, sample respondents were randomly selected from the list of households obtained from kebeles administrative offices using

simple random sampling relative to their size of the population. Finally, a total of 278 respondents were selected, with the sample size determined based on Yamane's (1967) formula:

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

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

Method of Data Analysis: Specification of an Empirical Model for an Ordered Logit Model

The ordered logit regression was employed to analyse ordinal data. The results can be interpreted using marginal effects, which measure the change in the likelihood of the dependent variable given a change in one explanatory variable while holding other factors constant. The dependent variable (the level of MBDTA) has the following values: 1 for those who use mobile phones with no internet access (low-level adoption); 2 for those who use mobile banking and have limited internet use (medium-level adoption); and 3 for those who use mobile banking, and have extensive internet use (high-level adoption), as adapted from Khiari and Rejeb (2015). Individuals who are daily adopters of the internet are categorised as extensive internet adopters, and individuals who use the internet once a week are limited internet adopters, as per the study by Singleton et al. (2020).

Ordinal ranking is the most appropriate strategy to use in this study, where the dependent variable is given some form of ranking (Lal, 1999). The ordered logit is the best model to analyse ordered nature data. In contrast to the ordered logit model, multinomial logit and probit models neglect the ordinality of the data and lack closed-form likelihood (Kockelman & Kweon, 2002). Ordered regression models provide an easy way to handle categorical variance in variables, making them an excellent tool for examining the link between ordered dependent and explanatory variables.

The following model is specified to analyse factors influencing MBDTA:

$$\begin{aligned} \text{Adoption}_i = & \beta_0 + \beta_1 \text{Age} + \beta_2 \text{Age squared} + \beta_3 \text{Gender} + \beta_4 \text{Education} \\ & + \beta_5 \text{Affordability} + \beta_6 \text{Socialnetwork} + \beta_7 \text{Remittances} \\ & + \beta_8 \text{Awareness} + \beta_9 \text{Employment} + \beta_{10} \text{Location} + \beta_{11} \text{Trade} \\ & + \beta_{12} \text{Easeuse} + \beta_{12} \text{Mobile type} + \varepsilon_i \end{aligned} \quad (2)$$

The degree of collinearity among explanatory variables was measured using a multicollinearity test. Variance inflation factors (VIF) were estimated to evaluate multicollinearity among the explanatory variables. The VIF values for the explanatory variables influencing MBDTA were all below 10, indicating that multicollinearity is not a serious concern in the analysis (Table 5).

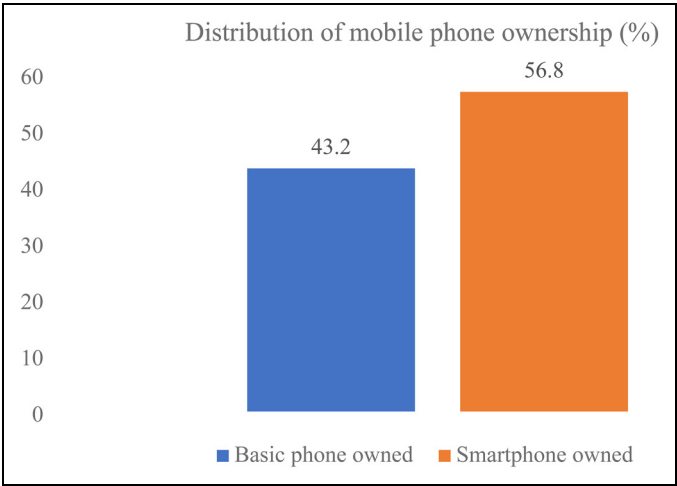


Figure 3. The type of mobile owned. Source: Survey data (2025).

Results and Discussion

This section examines the variables specified in the model through descriptive statistics and econometric estimation. Aspects of the production, communication, and transactions associated with MBDTA are also covered in the descriptive statistics, along with phone types, and digital abilities. In the econometric analysis, the factors that influence MBDTA in the study area were examined using an ordered logit model.

Descriptive Statistics

Types of Phones, and Digital Skills. The results in Figure 3 show that 43.2% of respondents own basic phones, while 56.8% own smartphones. These basic phones restrict adopters from accessing vital services that are only available through internet-enabled mobile devices. This disparity introduces a second level of the digital divide favoring smartphone owners over those with basic mobile phones.

Another factor that impedes MBDTA is the variation in digital skills among adopters of smartphones, which contributes to the third level of the digital divide. Table 3 indicates that only 36 (13%) individuals who own smartphones are adopting MBDTs, such as participating in internet forums (online discussion platforms). This suggests that owning a smartphone does not guarantee optimal usage of MBDTs, which contributes to a digital divide. Individuals with stronger digital skills are better equipped to utilise technology effectively, underscoring the necessity of bridging this gap.

Comparison of Adopters and Non-adopters of MBDTs. Table 2 presents the mean difference between the adopters and non-adopters of MBDTs. The mean age of respondents who use MBDTs is 43 years, while for non-adopters, it is 49 years. This suggests that most

Table 2. Descriptive Statistics for Explanatory Variables.

Variable	Adopters	Non-adopters	Difference	t-Statistics
Age	43.49 (11.21)	49.06 (9.37)	−5.56***	−6.66
Agesquared	1847.4 (1034.5)	2288.9 (826.6)	−441.5***	−4.08
Gender	0.93 (0.252)	0.5 (0.5)	0.43***	11.3
Education	3 (1.1)	1.46 (0.7)	1.54***	14
Affordability	0.953 (0.26)	0.163 (0.372)	0.789***	24.15
Social network	1.41 (0.718)	0.017 (0.13)	1.39***	21.06
Remittances	0.694 (0.461)	0.37 (0.485)	0.323***	6.24
Awareness	0.67 (0.47)	0.28 (0.24)	0.39***	15.4
Trade access	0.223 (0.417)	0.034 (0.183)	1.88***	4.68
Employment	0.234 (0.424)	0.026 (0.16)	0.208***	5.13
Ease of use	0.162 (0.37)	0.034 (0.183)	0.128***	3.54
Geographical location	0.36 (0.033)	0.1935 (0.05)	0.167 **	2.5

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

adopters tend to be younger than nonadopters. The gender statistics reveal a predominance of males among technology adopters compared with females, indicating gender disparity in MBDTA. The results of education indicate that individuals with higher education are more likely to adopt MBDTs than those with lower education. We believe that individuals with at least a secondary education are more inclined to adopt MBDTs compared with those with lower educational attainment. This finding aligns with the study conducted by Mukong and Nanziri (2021).

The results regarding affordability indicate that the cost of digital tools and services is a significant barrier limiting nonadopters from becoming adopters. The distribution of social networks shows that non-adopters have limited connections within the MBDTA community, which may restrict their ability to share experiences related to these technologies (Mukong & Nanziri, 2021). Adopters are more likely to receive remittances than non-adopters, indicating that remittances drive the MBDTA. The adopters have more awareness than nonadopters, highlighting how critical information access is. The likelihood of being non-adopters decreases among those who are employed, perceive the technology as easy to use, and have access to trade. The adoption of MBDTs is higher in urban areas compared with rural areas, suggesting the need to bridge the rural–urban divide through improved infrastructure.

Production, Communication, and Transaction Aspects of MBDTs. Table 3 shows the analysis of the MBDTA on three dimensions, namely production, communication, and transactions in the study area. First, the production aspect of MBDTs is illustrated by the activities such as engagement on short video platforms, and the installation of various mobile applications.

Of the 278 mobile phone owners, 91 (32.73%) reported that they can produce and post videos on short video platforms, particularly on TikTok. This platform hosts a variety of contents, including social and economic activities for adopters in the study area. Regarding the installation of mobile applications, about 108 participants (38.9%) were

Table 3. Production, Communication and Transactional Aspects of MBDTA.

Items	Description	Sample	Percent
Production Aspect			
Short video platforms	User produced and posted short videos	91	32.73
	Haven't produced and posted short videos	187	67.27
Installation of mobile apps	Have ability to install mobile apps	108	38.9
	Those who were unable to install mobile apps	170	61.1
Communication Aspect			
Online call and message	Adopters	121	43.53
	Non-adopters	157	56.47
Internet forums	Adopters	36	12.95
	Non-adopters	242	87.05
Social network	Individuals lacked access to social network	15	5.4
	Individuals have access to one network	158	56.83
	Individuals have access to two networks	82	29.5
	Individuals have access to more than two networks	23	8.27
Transaction Aspect			
Mobile banking	Adopters	141	50.72
	Non-adopters	137	49.28

Source: Survey data (2025).

able to install various mobile applications for different purposes. The most widely used mobile applications include WhatsApp, Imo, Telegram, Facebook, annual calendars, and banking applications.

An analysis of communication dimensions such as online text messaging, voice calls, internet forums, and social networks reveals several key insights. Regarding text messaging and online calling, 121 participants (43.53%) reported that they made calls and sent messages using online platforms. Although this mode of communication requires minimal digital skills, quite a significant proportion of respondents (56.47%) struggled to access these tools more effectively, probably due to the limited access to the internet in rural areas. The results of participation in internet forums show that only 36 out of 278 mobile phone owners (12.95%) actively engaged in these platforms. This indicates that most respondents are unfamiliar with online forum discussions, which are a relatively new form of online discussion (Li et al., 2023).

Among the sample of individuals who owned mobile phones, 15 participants (5.4%) reported that they were unaware of issues related to MBDTs. Although few respondents fall into this category, lack of awareness remains a key driver of the digital divide (Malinga & Maiga, 2020). In contrast, a significant proportion of the respondents (94.6%) were aware of one (56.83%), two (29.5%) or more (8.27%) sources of information regarding MBDTs. An increase in awareness can enhance the likelihood of MBDTA.

Table 4. Drivers of MBDTA Based on Ordered Logit Model.

Sample		278		
LR chi2(18)		382.34		
Prob > chi2		0.0000		
Pseudo R2		0.586		
Log likelihood		−134.98		
Level of MBDTA		Ordered logit	Marginal Effects	
Coef.		Std. Err.	dy/dx	Std. Err.
Age	−0.197**	0.101	−0.0064*	0.00328
Age squared	0.00173	0.0011	0.00063*	0.000363
Gender (Men = 1)	1.25**	0.633	0.058**	0.028
Education				
Primary	2.15	1.45	0.02*	0.011
Secondary	3.24**	1.48	0.05***	0.0188
Diploma	4.75***	1.617	0.135***	0.034
≥ Degree	7.04***	1.72	0.36***	0.07
Affordability	5.3***	1.04	0.255***	0.055
Social network				
One network	0.985	0.986	0.038	0.033
Two networks	2.74***	1.046	0.131***	0.0387
> Two networks	2.72**	1.155	0.13***	0.049
Remittances	0.964**	0.417	0.046**	0.0206
Awareness	0.9088**	0.44	0.044**	0.0208
Employment	0.303	0.635	0.0146	0.0305
Geographical location	0.384**	0.178	0.0185**	0.0083
Trade	1.18***	0.433	0.0567***	0.0195
Ease of use	0.3077	0.444	0.015	0.0215
Type of mobile	1.785***	0.426	0.086***	0.0215

Source: Survey data (2025).
Note. *, **, and ***mean significant at levels of 0.1, 0.05, and 0.01, respectively. The values assigned to women, individuals without education, and individuals without social networks are 0, 1, and 0, respectively. These variables were used as the base outcomes.

The last dimension of MBDTA is the transactional aspect (mobile banking). According to the survey results, 141 respondents, representing 51% of the total sample, indicated that they actively use mobile banking applications to make financial transactions. The remaining 49% of respondents reported not using mobile banking services, indicating that the adoption of this technology needs to be improved.

Econometric Analysis

Table 4 presents the ordered logit analysis that examines the factors influencing the extent of MBDTA among respondents. The likelihood ratio, pseudo R², and log-likelihood values indicate that the ordered logit model provides a better fit for the analysis. The analysis considered a range of explanatory variables, including age, gender, education,

Table 5. Variance Inflating Factor (VIF) for Explanatory Variables Used for the Analysis.

Variable	VIF	1/VIF
Education	3.11	0.32
Employment	2.57	0.39
Social network	1.62	0.62
Awareness	1.52	0.656
Type of mobile	1.50	0.67
Geographical location	1.49	0.67
Age	1.40	0.71
Affordability	1.20	0.83
Remittances	1.19	0.84
Trade	1.12	0.89
Gender	1.07	0.93
Ease of use	1.03	0.97
Mean VIF	1.57	

affordability, social networks, access to remittances, digital awareness, employment, geographical location, trade, ease of use, and type of mobile phone owned. These factors were hypothesized to significantly influence the level of MBDTA. Of the 12 explanatory variables analysed, 10 showed a statistically significant influence on the level of adopting MBDTs. However, employment status and perceived ease of use have no significant relationship with MBDTA in this context, which was unexpected. As expected, all statistically significant variables had a positive effect on adoption except for age, which had a negative effect.

The results presented in Table 6 use quintile 1 (non-adopters) as the base outcome. According to the findings, factors such as being male, younger age, possessing strong social ties, receiving remittances, awareness of technology, owning smartphones, being a trader, and residing in urban areas are associated with a lower likelihood of being categorised as non-adopters or low adopters of MBDTs.

The results for age show that as age increases, the level of MBDTA decreases. The marginal effect of age, -0.0064 , indicates that with each additional year, the likelihood of being in the high adoption category increases by 0.64%, holding other factors constant. All marginal effects in this study are interpreted under the assumption of holding other factors constant. Compared with older generations, younger individuals exhibit noticeably greater levels of familiarity and engagement with mobile-based digital technologies. Intergenerational knowledge transfer, digital mentorship, and the promotion of user-friendly mobile applications can potentially bridge the adoption gap between older and younger individuals (Hashimi, 2021). This result aligns with previous research that has demonstrated the age-related digital divide (Hänninen & Tiihonen, 2025; Reddick et al., 2020; Shaibu et al., 2018).

The results for the gender variable show a positive and significant association with the level of MBDTA, indicating that men were more engaged in higher levels of MBDTA. Men were 5.8% more likely than women to exhibit a high level of MBDTA. As noted by

Table 6. Marginal Effects for the Ordered Logit Model (Quintile 1–3).

Average Marginal Effects Model VCE		Number of Obs. = 278 OIM	
Delta Method			
Pr(Level of MBDTA ==1), Pr(Level of MBDTA ==2), Pr(Level of MBDTA ==3), Quintile 1		predict(pr outcome(1)) predict(pr outcome(2)) predict(pr outcome(3)) Quintile 3	
dy/dx		dy/dx	
Age	0.00383 (.002)*	0.0079 (0.0034)**	-0.0064* (0.00328)
Age squared	-0.000377 (0.000219)*	-0.00078 (0.00044)*	0.00063* (0.000363)
Gender (Men = 1)	-0.082 (0.0366)**	0.046 (0.023)**	0.058 (0.028)**
Education			
Primary	-0.132 (0.423)***	0.19 (0.108)*	0.02 (0.011)*
Secondary	-0.24 (0.056)**	0.284 (0.114)**	0.05 (0.0188)***
Diploma	-0.395 (0.093)***	0.371 (0.13)***	0.135 (0.034)***
≥ Degree	-0.593 (0.087)***	0.357 (0.115)***	0.36 (0.07)***
Affordability	-0.385 (0.09)***	0.204 (0.0526)***	0.255 (0.055)***
Social network			
One network	-0.0766 (0.068)	0.056 (0.057)	0.038 (0.033)
Two networks	-0.24 (0.0816)***	0.147 (0.0653)**	0.131 (0.0387)***
> Two networks	-0.238 (0.094)**	0.146 (0.068)**	0.13 (0.049)***
Remittances	-0.07 (0.03)**	0.037 (0.0164)**	0.046 (0.0206)**
Awareness	-0.066 (0.032)**	0.035 (0.0186)*	0.044 (0.0208)**
Employment	-0.022 (0.046)	0.0116 (0.024)	0.0146 (0.0305)
Geographical location	-0.028 (0.013)**	0.0148 (0.0077)*	0.0185 (0.0083)**
Trade	-0.0856 (0.0327)***	0.045 (0.0207)**	0.0567 (0.0195)***
Ease of use	-0.022 (0.032)	0.0118 (0.0168)	0.015 (0.0215)
Type of mobile	-0.13 (0.0277)***	0.0686 (0.0174)***	0.086 (0.0215)***

Note. *, ** and *** mean significant at levels of 0.1, 0.05, and 0.01, respectively.
VCE = variance-covariance estimator; OIM = observed information matrix.

KII, “Women lag behind men in MBDTA primarily due to a lack of economic autonomy.” This highlights the gender-based disparity in the uptake of MBDTA, indicating a need for interventions that enhance women’s engagement with technology. This finding aligns with the study conducted by Ferritto (2024).

Education is a key predictor influencing the level of MBDTA. Individuals with a higher level of education were 36% more likely to be in the high adoption category, suggesting that education is a key predictor of adoption. It reveals that education is a crucial factor to access and benefit from mobile tools. As a FGD participant noted, “Due to my limited education and the fact that mobile applications are in English, it is difficult for me to use mobile internet and mobile money easily.” This finding corroborates the results by Munyegeera and Matsumoto (2016).

In terms of affordability, our results indicate that individuals with higher incomes were 25.5% more likely to adopt MBDTs than those with lower incomes. As highlighted in the FGD, “The costs of data plans and frequent power outages for charging devices hinder the consistent use of mobile phones for managing finances and online communication.” This finding suggests that income is a crucial factor for accessing and benefiting from digital products and services. This finding aligns with studies that highlight the direct relationship between income and MBDTA (Kala, 2023). As expected, social networks significantly influence MBDTA. This implies that increased social interaction enhances the likelihood of adopting such technology. One participant in the FGD stated, “Thanks to the patient guidance of friends, I can navigate mobile internet and now confidently transfer and receive money.” This finding corroborates the results of Mukong and Nanziri (2021).

Individuals who received remittances were more likely to adopt MBDTs compared with those who did not, highlighting the significant role of remittances in driving adoption. This result aligns with the findings of Ali et al. (2024). Awareness is another important driver of MBDTA. Our results show that respondents who have a greater awareness of MBDTs are more likely to adopt them. This result implies that limited awareness is associated with lower adoption and is consistent with the study by Malinga and Maiga (2020).

The finding of the geographical location variable indicates that MBDTA is higher in urban areas than in rural areas. This highlights the importance of improving network coverage and addressing socioeconomic challenges in rural areas. Similar findings show regional disparity influences the adoption (Ferritto, 2024; Mora-Rivera & García-Mora, 2021; Park, 2017). The analysis indicates that participation in trade increases the likelihood of MBDTA. Individuals engaged in trade were 5.67% more likely to demonstrate a high level of MBDTA compared with those who are not involved in trade. This finding is consistent with research conducted by Banerjee et al. (2022). Lastly, the type of mobile device owned significantly influences the extent of MBDTA. Smartphone owners were 8.6% more likely to adopt a broader range of digital services than those with basic phones. This highlights the enabling role of smartphones in facilitating access to online communication and information. This finding is consistent with the study by Ali et al. (2024).

On the other hand, employment status and perceived ease of use did not show a statistically significant relationship with MBDTA. The insignificance of the employment

variable might be due to the prevalence of remittances, which results in no significant difference between employed and unemployed individuals. Another insignificant variable, ease of use, might be attributed to users being more motivated by benefits (awareness of perceived usefulness) and peer influence than by how easy the technology is to use. This is supported by Jerene and Sharma (2020), who emphasise that perceived usefulness is a more important predictor of adoption than perceived ease of use in Ethiopia.

It is also important to acknowledge the exclusion of frequently cited variables in the literature that influence the adoption of mobile tools. Variables, such as mobile network coverage and digital literacy, are widely recognised determinants of adoption. The geographical location variable partially captures network coverage, which is often inadequate in rural areas compared with urban areas. Education and awareness of perceived usefulness are used as proxies to capture the digital literacy of the sample respondents.

Conclusions and Recommendations

Conclusions

This study examines MBDTA in Hadiya Zone, Ethiopia, using cross-sectional data from 278 respondents collected in 2024. An ordered logit model was employed to analyse the data. The findings indicate that demographic variables (age, gender, and education), socioeconomic variables (affordability, social network, trade, and remittances), technological factors (awareness and type of mobile owned), and situational factors (geographical location) significantly influence individuals' adoption of mobile services. MBDTA is more prevalent among younger individuals, those with higher education, and males, underscoring a persistent digital divide along generational, gender, and educational lines. Remittance recipients and individuals with higher income were more likely to use mobile services than individuals who do not receive remittances and have lower income. Urban residents have a higher rate of adoption compared with rural counterparts. The role of social interaction and awareness has been emphasized as key factors in driving adoption through information sharing and community engagement. Individuals engaged in trade and smartphone owners are more likely to adopt various MBDTs than non-traders and users of basic mobile phones. Factors such as geographical location, awareness, social networks, and affordability are crucial drivers of MBDTA. These findings affirm the relevance of the adapted UTAUT2 framework in capturing complex and context-specific drivers of MBDTA. The findings emphasise how the adoption of mobile tools could enhance financial inclusion; however, disparities persist in adoption, driven by several socioeconomic factors similar to those in Ethiopia. Furthermore, Alam et al. (2019) show that mobile phone adoption is higher among individuals who are more educated and younger, which parallels the Ethiopian context. The findings align with the national digital strategy and the SDGs, particularly SDG 9 (industry, innovation, and infrastructure), which supports the advancement of MBDTA. By integrating global insights into local context, the findings not only inform Ethiopian digital strategies but also enrich the broader field of MBDTA for nations comparable to Ethiopia by emphasising the need for localised studies to enhance digital transformation.

Recommendations

Based on the findings of this study, the following recommendations were forwarded.

To bridge digital disparities in the study area, especially among women, older adults, and rural communities, age and gender-sensitive digital literacy programs are essential. The regional government should integrate emerging digital technologies into primary education to foster long-term engagement. Expanding 4G and 5G coverage, particularly in Ameka and Gombora, can reduce rural–urban gaps in MBDTA. Affordability of smartphones and data plans should be improved for underserved groups, while mobile money services should be scaled to enhance rural remittance flows. Community-based initiatives leveraging social networks can boost awareness and skills in mobile services. Supporting small traders through training and incentives will stimulate innovation and market access. Finally, addressing structural gender barriers through targeted training, device provision, and credit access is vital to advancing women’s participation in the digital economy.

To accelerate digital adoption in rural areas of developing nations in the future, emerging technologies such as artificial intelligence (AI) tools and mobile innovation hubs can serve as engines of learning and service delivery. Localising these tools can democratise adoption, particularly for women and rural populations. While this study emphasises the importance of expanding MBDTA in underserved areas, it highlights potential risks such as exposure to harmful content, reduced social interaction, and screen addiction, which are negative consequences of adoption if not managed appropriately. It also acknowledges that the expansion of AI, particularly in Africa, raises the concern of labour market disruptions unless proactive measures need to be taken for job transition strategies.

It is important to acknowledge the limitations of this article. This study utilised cross-sectional data to analyse factors that affect MBDTA. Future research should focus on time series analyses, which can provide more comprehensive information on the same variables over time, thereby facilitating better policy decisions. Another limitation of this study is that it focused on three districts and one town, which limits the generalisability of the findings throughout the nation. Future studies should be conducted in other areas where various factors influence the usage of mobile technologies, as this could significantly contribute to the existing literature.

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Ethical Considerations and Informed Consent Statements

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, 2024. In addition, respondents gave written consent and signatures before starting interviews.

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Data Availability Statement

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

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