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What drives digital finance use in rural Africa? Insights from Ethiopia

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ABSTRACT

Despite the growing role of digital finance particularly mobile money in advancing financial inclusion, its use remains limited in many rural parts of Africa. This study examines the drivers of digital finance use in rural Ethiopia, focusing on the adoption and usage intensity of CBE Birr and Telebirr in the Kembata Tambaro Zone. Using the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), data from 399 respondents were analysed through a double-hurdle model combining binary logit and zero-inflated negative binomial regression. Results show that education, mobile ownership, social influence, trust, perceived ease of use, perceived usefulness, and internet access positively drive adoption, while distance to financial institutions or agents negatively affects it. Usage intensity rises with formal employment, distance to financial institutions, and internet access, while unemployment reduces transaction frequency. Moreover, education, occupation, trust, perceived ease of use and usefulness lower the likelihood of zero transactions. The study confirms that both individual-level and structural factors significantly shape the adoption and intensity of digital finance use in rural Ethiopia. The study emphasizes the need for digital literacy, broader internet access, and context-sensitive service design, while contributing to the literature methodologically by addressing both adoption and usage intensity.

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Digital finance; mobile money; factors; adoption and intensity; zero inflated negative binomial; Ethiopia

1. Introduction

Digital banking has changed the financial sector by delivering innovative products that improve customer experience, accessibility, and operational efficiency (Magomaeva and Galazova 2021). Among these innovations, mobile money has emerged as an effective tool for reducing financial exclusion and promoting financial inclusion, particularly in developing countries (Demirguc-Kunt et al. 2018). According to Demirgüç-Kunt et al. (2022), 33% of adults in sub-Saharan Africa possess a mobile money account, compared to a global average of 10%. Although this widespread adoption has greatly benefited the region's economic development, mobile money adoption differs highly across countries.

Financial inclusion in Ethiopia is poor compared to other East African countries. In 2022, less than half of the adults in Ethiopia were banked or had mobile money, compared to nearly 80% in Kenya, 77% in Rwanda, and 66% in Uganda (Demirgüç-Kunt et al. 2022). Mobile money-based financial inclusion is still in its infancy in Ethiopia due to the largely rural population and low technological literacy. In response to these challenges, the National Bank of Ethiopia (NBE) released the mobile money market to private investors in 2020, which led to the quick adoption of platforms such as Telebirr (NBE 2021). Furthermore, the CBE Birr mobile money service has been introduced by the Commercial Bank of Ethiopia, which has been significant in facilitating greater access to digital financial services and promoting the broader nationwide adoption of mobile money platforms (NBE 2023). Maintaining user involvement despite these innovations is still challenging, especially in rural areas where socioeconomic inequality and mistrust of technology are still prevalent. Adoption is also hindered by challenges such as social norms that prevent it, a lack of mobile phone access, poor perceived significance, and a lack of digital skills (GSMA 2023).

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Globally, several studies have explored factors affecting the adoption of digital finance, focusing on diverse topics across various countries. Saidu et al. (2023) in Nigeria and Yan et al. (2023) in Bangladesh investigated factors influencing the adoption of mobile money services. Akinyemi and Mushunje (2020) conducted research on the determinants of mobile money technology adoption in rural areas of Africa. Nonvide and Alinsato (2023) studied what factors affect the mobile money adoption process: evidence from smallholder households in Cote d'Ivoire. Ghosh and Hom (2022) highlighted the determinants of digital finance in India.

Moyo et al. (2022) explored factors affecting the adoption and usage of mobile money services by artisan gold miners in the case of Umzingwane District in Zimbabwe. Wibella, Fahmi, and Saptono (2018) focused on the factors affecting consumer acceptance of digital financial inclusion. These studies, examined as a whole, demonstrate a comprehensive understanding of the factors affecting the adoption of digital finance in different countries worldwide.

The factors influencing the adoption of mobile banking have also been the subject of some research conducted in Ethiopia. Kejela and Porath (2021) investigated the factors influencing end-users' attitudes and the impact of attitudes on the adoption of mobile banking. Dandena, Abera, and Mengesha (2020) investigated the factors influencing the adoption of mobile banking in the context of United Bank Addis Ababa City. Goshu (2019) investigated the determinants of mobile banking adoption at the Commercial Bank of Ethiopia in Bako District. Beyene (2020) studied the adoption and challenges of mobile banking systems in Ethiopia, focusing on the Cooperative Bank of Oromiya. Abebe and Lessa (2022) investigated the factors that influence Ethiopian retailers' acceptance of mobile payments (CBE Birr and M-birr).

Except for Abebe and Lessa (2022), most of the research has been conducted on bank-led platforms, like mobile banking, with little attention paid to mobile money providers like CBE Birr and Telebirr. Abebe and Lessa (2022) looked at the factors that influence the adoption of mobile payments, particularly CBE Birr and M-Birr, but they only looked at merchant adoption, ignoring the viewpoint of the customer, and didn't address the Tele Birr mobile money service.

The Kembata Tambaro Zone in southern Ethiopia is a rural area facing financial inclusion challenges. Despite ongoing efforts by the government and financial institutions to promote digital banking, the adoption of mobile money services remains limited. In response to these gaps, this study investigates the drivers of both the adoption and intensity of use of digital finance, specifically non-bank-led mobile money platforms such as CBE Birr and Telebirr, within this rural context. This study makes a distinctive contribution to the existing literature by examining both the adoption and the intensity of use of non-bank-led mobile money services, specifically platforms such as CBE Birr and Telebirr, within the rural Ethiopian context. Unlike the majority of prior studies that have primarily employed the Technology Acceptance Model (TAM) as their sole theoretical foundation, the present study adopts the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2). This choice is motivated by UTAUT2's enhanced explanatory power, broader applicability in consumer contexts, and its ability to incorporate additional constructs such as hedonic motivation, price value, and habit that are particularly relevant to understanding digital finance adoption. Moreover, whereas existing studies have largely focused on factors affecting adoption decisions, the present study addresses a notable gap by investigating the intensity of mobile money usage. To this end, a zero-inflated negative binomial regression model was employed, which is an innovative methodological approach well-suited to account for overdispersion and the prevalence of excess zeros in transaction data. This analytical strategy not only captures nuanced patterns of usage but also contributes to advancing the methodological rigour within the digital finance literature.

2. Literature review: adoption and use of digital finance

2.1. Concepts of digital finance

Digital finance refers to the utilization of digital channels such as mobile phones, cards, computers, tablets, and similar devices for carrying out financial activities. It encompasses essential functions such as saving money, accessing credit and insurance, and conducting transactions. Digital finance enables various capabilities, including cash-in and cash-out services, fund transfers, cross-border payments, and more (Jeremiah and Paul 2013). Mobile money refers to a financial service that enables people to use their mobile devices to conduct financial transactions, send money, and make payments. Customers who use mobile money can only transact with mobile network carriers; they do not need to have a bank account with a financial institution (Aker and Mbiti 2010). Tele Birr (Amharic: ቴሌብር) is a mobile money service developed by Ethiopia's state-owned internet and telecommunications company (NBE 2021).

2.2. Theories of technology innovation

Understanding the factors that influence the adoption of digital finance necessitates a comprehensive theoretical foundation that encompasses both technological attributes and individual behavioural intentions. Accordingly, this study synthesizes key insights from two well-established theoretical models that have been widely applied in the domains of technology acceptance and behavioural science. These include the Unified Theory of Acceptance and Use of Technology (UTAUT), and Extended Unified Theory of Acceptance and Use of Technology (UTAUT2).

UTAUT, developed by Venkatesh et al. (2003), integrates core elements from earlier technology acceptance models and focuses on determinants such as performance expectancy, effort expectancy, social influence, and facilitating conditions. Although empirically robust, UTAUT was originally designed for organizational settings and does not fully address consumer-specific factors.

UTAUT2, the extended version proposed by Venkatesh, Thong, and Xu (2012), enhances the original model by incorporating hedonic motivation, price value, and habit, making it more applicable to consumer contexts. This study adopts UTAUT2 given its strong alignment with key variables such as sex, age, education level, occupation, mobile phone ownership, social influence, trust, awareness, perceived ease of use, perceived usefulness, internet access, and distance to financial institutions. Core constructs of the model performance expectancy, effort expectancy, social influence, and facilitating conditions closely correspond to these variables, while trust and awareness are integrated to address context-specific barriers related to digital finance. By applying UTAUT2, the study offers a robust theoretical lens to explain both the decision to adopt digital finance and the intensity of its use among rural populations in Ethiopia (Figure 1).

2.3. Factors influencing the adoption of digital finance

Technology features and user attitudes have been identified as key factors influencing the adoption of digital banking. Perceived ease of use, usefulness, relative advantage, and compatibility all significantly influenced

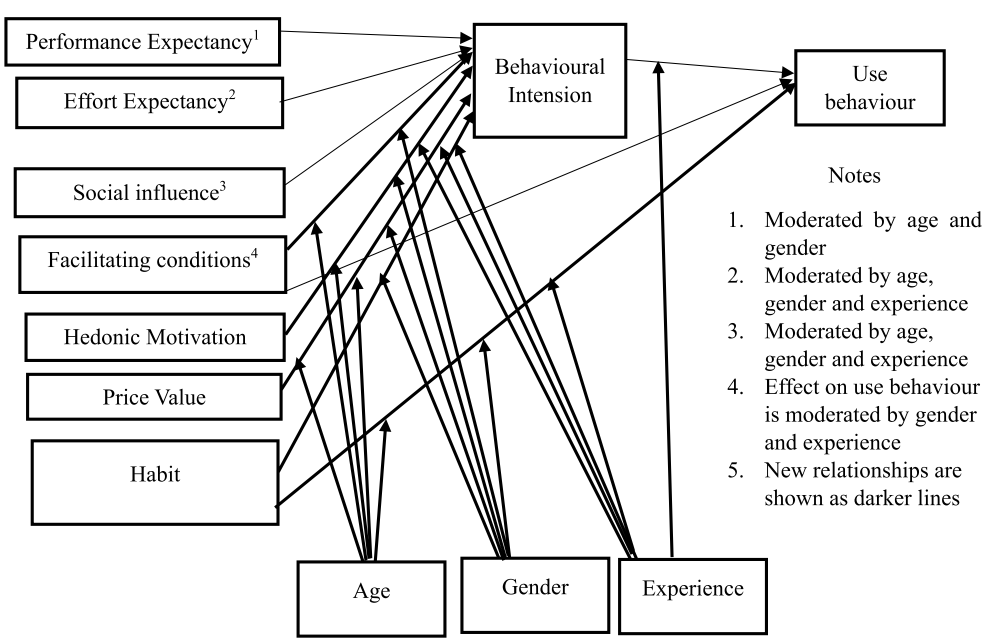

Figure 1. Extended Unified Theory of Acceptance and Use of Technology (UTAUT2). Source: (Venkatesh, Thong, and Xu 2012).

consumer opinions towards mobile payment adoption in Ethiopia (Abebe and Lessa 2022). The adoption of mobile financial services was also found to be significantly affected by trust and technological readiness (Dass and Pal 2011). According to other studies, Saidu et al. (2023) and Yan et al. (2023), mobile money services in Bangladesh and Nigeria were significantly affected by perceived value, perceived trust, and simplicity of use, respectively. N'dri and Kakinaka (2020) presented empirical evidence that mobile phone ownership leads to increasing mobile money adoption.

Age, gender, and education were significant demographic variables that influenced mobile money adoption in Côte d'Ivoire (Nonvide and Alinsato 2023). Ahmed (2016) stated that younger people dominate internet banking. Ghosh and Hom (2022) revealed that being male, wealthy, and educated increased the probability of adopting digital financial services. Moyo et al. (2022) found that education improved mobile money adoption in Zimbabwe. Onyia and Tagg (2011) found that demographic variables, including education level and occupation, influenced attitudes and intentions to use internet banking services.

Oshora et al. (2021) identified the factors that affect the adoption of digital banking, such as inadequate documentation, lack of financial institutions, and low internet and cell phone penetration. Moyo et al. (2022) stated that registration fees, poor connectivity, and perceived transaction costs all made using mobile money more difficult. Melubo and Musau (2020) found that women entrepreneurs face various challenges, including limited literacy, internet access, and computer skills, which were significant barriers to online banking. Kelly and Palaniappan (2023) identified perceived risks and costs as major barriers.

Social influence was a major factor in the adoption of digital financial services (Banerjee et al. 2013; Naito and Yamamoto 2022; Zhang, Lin, and Li 2012). Social networks enhance the sharing of information, which increases adoption rates (Murendo et al. 2018). Moyo et al. (2022) argue that social influence has a negative effect on mobile money adoption and usage. According to Dandena, Abera, and Mengesha (2020), technological and organizational factors, as well as consumer experiences and voluntary use, have a substantial positive effect on mobile banking adoption. Similarly, Goshu (2019) found a correlation between awareness, trust, ease of use, and higher adoption rates, emphasizing the importance of psychological readiness and behavioural aspects.

Wibella, Fahmi, and Saptono (2018) revealed the positive effect of ease of use and credibility on digital financial services in Indonesia, whereas Goshu (2019) identified ease of use and trust as significant factors in Ethiopia. According to Naito and Yamamoto (2022), research conducted in Sub-Saharan Africa shows that network coverage is crucial for increasing the adoption of digital financial services. Kelly and Palaniappan (2023) concluded that Ghanaian customers' decisions to continue using mobile money services were influenced by the perceived risk, perceived cost, perceived usefulness, perceived ease of use, and social influence.

2.4. Mobile money adoption status in Ethiopia

Mobile money usage in Ethiopia still remains limited. Only 5% of people 15 years old and over had a mobile money account in the year 2022, reports the World Bank. To the contrary, adoption rates were higher in Tanzania and Kenya, two neighbouring countries, at 45% and 70%, respectively (Demirgüç-Kunt et al. 2021). It is challenging for Ethiopia to adopt cashless payment systems, especially in rural areas and among young people without a bank account (Mothobi and Grzybowski 2017). For example, cash was used to pay 99 percent of Ethiopia's power bills in 2017. This percentage was much lower than the Sub-Saharan African average of 59% and was 27% in Tanzania, 12% in Kenya, and other nearby nations. Furthermore, only 0.2% of Ethiopian wage earners got payments via mobile phones, compared to 37% in Kenya, 24% in Tanzania, and 19% throughout Sub-Saharan Africa (Demirguc-Kunt et al. 2018).

2.5. The conceptual framework of the study

The conceptual framework of this study (Figure 2) synthesizes key empirical insights and is grounded in the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2). It organizes the factors influencing digital finance adoption into four categories: demographic, socioeconomic, institutional, and psychological. Demographic factors such as age, gender, education, and occupation shape individuals' access to and capacity for adopting digital finance, influencing cognitive perceptions and behavioural readiness. Socioeconomic factors, including mobile phone ownership, trust in digital financial systems, and

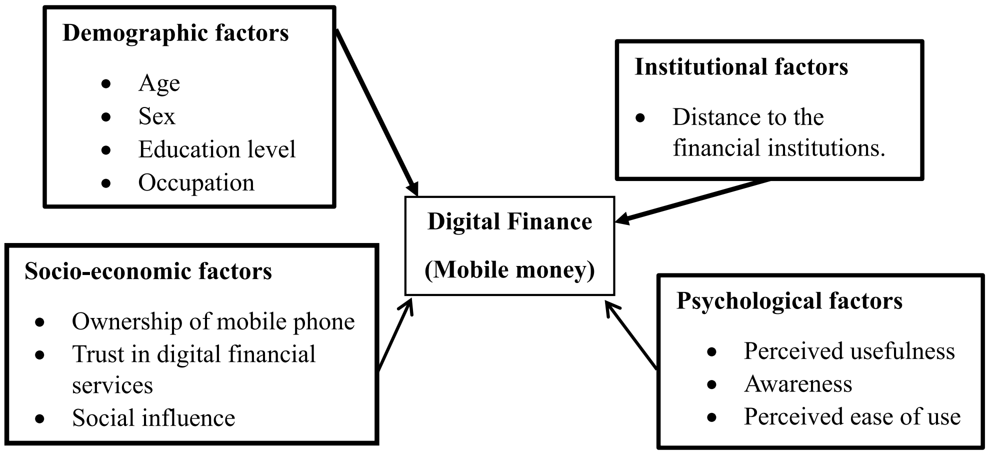

Figure 2. Conceptual framework of the study. Source: Author's computation from review of the literature (2025).

social influence, reflect enablers and social dynamics affecting user behaviour. Institutional factors account for infrastructural conditions like proximity to financial institutions and internet access, which shape the feasibility of digital finance usage. Psychological factors, such as perceived usefulness, ease of use, and awareness, directly influencing the intention to adopt digital financial services. Together, these dimensions provide a comprehensive framework capturing the ability and motivation of individuals to adopt mobile money services, serving as a basis for empirical analysis in the rural Ethiopian context.

3. Methodology of the study

3.1. Description of the study area

Kembata Tambaro is a zone in the Southern Nations, Nationalities, and Peoples' Region of Ethiopia. The zone is bordered on the south by Wolayita, on the southwest by Dawro, on the northwest by Hadiya, on the north by Gurage, on the east by the Alaba special woreda, and on the southeast by an exclave of the Hadiya Zone (CSA 2007).

Based on the 2007 census conducted by the Central Statistical Agency (CSA), this zone has a total population of 1,080,837, of whom 536,676 are men and 544,161 are women. The total adult (18+) population in Kembata Tambaro is 153,850, of whom 75,380 are men and 78,470 are women. With an area of 1,355.89 square kilometres, Kembata Tambaro has a population density of 502.13. While 97,797, or 14.36%, are urban inhabitants, a further 35 individuals are pastoralists. A total of 122,580 households were counted in this zone, which results in an average of 5.55 persons per household and 118,077 housing units (CSA 2007).

Kembata Tambaro Zone was purposively selected for this study due to its distinctive socio-economic characteristics relevant to digital finance adoption. The Zone is characterized by a high adult population, the presence of marginalized and financially excluded groups, substantial remittance inflows, and limited access to formal banking services compared to other Zones in Ethiopia. Furthermore, the average landholding per rural household in the Zone is 0.6 hectares, significantly below the national average of 1.01 hectares and the Southern Nations, Nationalities, and Peoples' Region average of 0.89 hectares. Additionally, only 10.7% of the population is engaged in non-farm employment, which is lower than both the national average (25%) and the regional average (32%) (CSA 2007). These conditions make the Kembata Tambaro Zone a pertinent setting for investigating the factors influencing both the adoption and intensity of digital financial services. Insights from this context can inform policy development aimed at enhancing financial inclusion and improving livelihoods through digital finance in underbanked rural areas.

Although the demographic and socio-economic data presented above are based on the 2007 census conducted by the Central Statistical Agency (CSA), they remain the most comprehensive and officially recognized figures available for the Kembata Tambaro Zone. As no updated official census data has been released to replace the CSA (2007) figures, this information continues to serve as the primary source for describing the study area.

3.2. Research design, sampling techniques, and data sources

This study employed a cross-sectional research design, which entailed obtaining data at a particular time using both qualitative and quantitative methods. A multistage simple random sampling procedure was used to select participants. The first stage involved selecting three districts randomly from the eight districts in the Kembata Tambaro Zone. The second stage involved randomly selecting three Kebeles (formal administrative entities in Ethiopia) from each district. Finally, individual respondents aged 18 years and older were selected using probability proportional to size (PPS) based on the civilian population in each Kebele.

To determine representativeness, the Yamane (1967) formula was used to determine the sample size, applying a 95% confidence level and a 5% margin of error, as expressed below:

$$n = \frac{N}{1 + N(e)^2} = \frac{153850}{1 + 153850(0.05)^2} = 399$$

n = required sample size

N = the total number of the population aged ≥18 years

E = the error term

To show proportionality to sample size by using Bowley's (1926) formula: –

$$Ni = n\,\frac{Ni}{N}$$

Where n represents sample size, Ni represents population size of the i^{th} Kebele, and

N represents the population size. Following data collection, respondents were divided into 105 adopters and 294 non-adopters of digital finance (mobile money) based on their self-reported responses.

Primary data were collected through structured questionnaires, nine focus group discussions (one per Kebele, with 8–12 participants each), and nine key informant interviews with stakeholders such as financial institution representatives, government officials, and community leaders. Secondary data were sourced from academic literature and institutional reports to support and triangulate findings.

3.3. Method of data analysis

The research employed a combination of qualitative and quantitative analytical methods to enhance the understanding of the data at hand.

3.3.1. Specification of econometric models

This study employs the double hurdle model to analyse both the adoption and intensity of mobile money usage. The model is particularly suited for situations where the dependent variable has two components: a binary outcome (adoption vs. non-adoption) and a count outcome (mobile money transaction frequency). It allows for separate examination of factors influencing adoption decisions (first hurdle) and usage intensity (second hurdle).

The double hurdle model is advantageous as it provides unbiased estimation of the continuous dependent variable in the second stage, even when data accumulate at specific values (Burke 2009). This approach enables independent analysis of adoption through a binary logistic regression model in the first stage and intensity of use through a zero-inflated negative binomial (ZINB) regression model in the second stage. This two-stage method provides a detailed understanding of both the adoption process and the intensity of usage. Below is the specification for each of the hurdles:

3.3.1.1. First hurdle: binary logistic regression model. The first hurdle in this study addresses the binary adoption decision, determining the likelihood of adopting digital finance (a binary outcome: 0 for non-adopters, 1 for adopters) based on relevant predictors. While various methods exist for analysing binary outcomes, a binary logit model was chosen over discriminant and linear probability models. Although the linear probability model (LPM) is computationally simple, it has a significant limitation, as the estimated probabilities can fall outside the valid 0–1 range, as noted by Amemiya (1981) and Gujarati (2003). In contrast, the binary logit model ensures probabilities are constrained between 0 and

1. Additionally, the binary logit model better accommodates the non-linear relationship between the dependent and explanatory variables. In studies involving qualitative choices, researchers typically choose between logit and probit models. While both models share statistical similarities, the logit model was preferred for its computational simplicity and the interpretability of its results, as emphasized by Amemiya (1981) and Hosmer and Lemshow (1998). The logistic distribution (logit) is particularly advantageous in analyzing dichotomous outcomes due to its flexibility and ease of use.

Thus, a binary logistic regression model was employed to examine the factors influencing digital finance adoption among residents, with the logit regression equation used to predict the probability of adoption.

The logit regression equation for this study is expressed as

$$P(Y) = \frac{exp^{(b0+\beta 1x1+\beta 2x2+.....\beta nxn)}}{1 + exp^{(b0+\beta 1x1+\beta 2x2+...\beta nxn)}} \quad (1)$$

Where P(Y) is the probability of Y occurring, e is the natural logarithm base (e ≈ 2.71828 …), b_0 is the intercept at the y-axis, βn is the regression slope coefficient of Xn, and Xn is a predictor or independent variable that predicts the likelihood of Y.

As indicated above, the logit model for this study is expressed as

$$P(MM) = \frac{exp^{(b0+\beta 1SEX+\beta 2AGE+\beta 3EDL+\beta 4OCC+\beta 5OWM+\beta 6PRU+\beta 7AW+\beta 8TDF+\beta 9PREU+\beta 10DFI+\beta 11SI+\beta 12AI}}{1 + exp^{(b0+\beta 1SEX+\beta 2AGE+\beta 3EDL+\beta 4OCC+\beta 5OWM+\beta 6PRU+\beta 7AW+\beta 8TDF+\beta 9PREU+\beta 10DFI+\beta 11SI+\beta 12AI}} \quad (2)$$

3.3.1.2. Second hurdle: Zero-inflated negative binomial regression model. To assess the intensity of mobile money adoption, a zero-inflated negative binomial (ZINB) regression model was utilized. The volume of mobile money transactions served as a proxy for adoption intensity due to the lack of a direct measure. Count data models, such as the ZINB, are commonly applied in such analyses (Cameron and Trivedi 2005).

Ordinary Least Squares (OLS) regression is unsuitable for count variables, as they often exhibit non-normal distributions with significant skewness and a predominance of low values. While Poisson regression is frequently used for count data, it assumes that the mean and variance are equal, a condition that often does not hold in practice, leading to the limitations of the Poisson model (Cameron and Trivedi 2005; Favero and Belfiore 2019; Zeviani et al. 2014). When the variance exceeds the mean, overdispersion occurs. To address this, a negative binomial regression model is applied, incorporating a dispersion parameter that accounts for unexplained variance between cases (Cameron and Trivedi 2013; Hennigan 2021; Paxton et al. 2011).

Zero-inflated models, like the ZINB, are suitable for count variables with an excess of zeros. These models assume two distinct processes: one for generating zero outcomes and another for the count process. In the case of mobile money transactions, the first process pertains to non-participants (reporting zero transactions), and the second captures transaction volumes among adopters. The ZINB model integrates a binary logit model for the zero-inflation process and a negative binomial model for the count process.

i. Zero-inflation component (logit model): This component models the probability that the observed outcome is zero, as opposed to a positive count (i.e. it models non-participation or inactivity). This component applies to both adopters and non-adopters, focusing on the likelihood of reporting zero transactions, either due to non-adoption or inactivity among adopters.

The zero-inflation component (logit model) is defined as

$$p(yi = 0) = \frac{1}{1 + \exp(-\eta \mathrm{i})} = \pi \mathrm{i} \quad (3)$$

Where yi is the observed count for participant I, πi is the probability of an excess zero outcome (non-participation), and ηi is a linear function of the explanatory variables (predictors for the zero outcome).

$$\eta \mathrm{i} = \beta 0 + \beta 1X1 + \beta 2X2i + \ldots \beta nXni \quad (4)$$

Where:

- Xni represents the predictors.

The zero-inflation component (logit model) equation for this study is expressed as

$$\eta i = \beta 0 + \beta 1SEX + \beta 2AGE + \beta 3EDL + \beta 4OCC + \beta 5OWM + \beta 6PRU + \beta 7AW + \beta 8TDF + \beta 9PREU + \beta 10DFI + \beta 11SI + \beta 12AI \quad (5)$$

Table 1. Summary of variables.

Category of variables	Variables Code	Description	Type	Measurement	References	Expected sign
Dependent variable	DF	Digital finance (Mobile money)	Dummy	1 = adopter 0 = non-adopter	–	
Outcome Variables	MMT	Mobile money transactions	Continuous	Frequency of transactions per month	–	
Demographic factors	SEXR	Sex of the respondent	Dummy	1 = Male 0 = Female	Ghosh and Hom (2022), Nonvide & Alinsato,(2023), Moyo et al. (2022)	
	AGER	Age of respondent	Continuous	Year	Ahmed (2016), Nonvide and Alinsato (2023), Moyo et al. (2022)	+
	EDLR	Education level of respondent	Continuous	Year of schooling	Ghosh and Hom (2022), Nonvide and Alinsato (2023), Onyia and Tagg (2011), Akinyemi and Mushunje (2020), Melubo and Musau (2020), Moyo et al. (2022)	+
	OCCR	Occupation of respondent	Categorical	Types of occupation 1. Farmer, 2. Government/ NGO employee, 3. Self-employed 4. Student 5. Unemployed	Onyia and Tagg (2011)	+
Socio-economic factors	OMP	Ownership of mobile phone	Dummy	1 if owned mobile phone, 0 otherwise	Murendo et al. (2018), Akinyemi and Mushunje (2020), N'dri and Kakinaka (2020)	+
	SI	Social Influence	Ordinal	Likert scale: 1. Not at all, 2. Slightly, 3. Moderately, 4. Very much, 5. Extremely	Banerjee et al. (2013), Zhang, Lin, and Li (2012), Ahmed (2016), Dass and Pal (2011), Kelly and Palaniappan (2023), Yan et al. (2023), Kiconco, Rooks, and Snijders (2020), Moyo et al. (2022)	+/−
	TFD	Trust in digital financial services	Ordinal	Likert scale: 1. Completely trust 2. Trust, 3. Neutral, 4. Distrust 5. Completely distrust	Abebe and Lessa (2022), Dass and Pal (2011), Saidu et al. (2023), Yan et al. (2023), Goshu (2019)	−
Psychological factors	PREU	Perceived ease of use	Ordinal	Likert scale: 1. Very easy, 2. Easy, 3. Neutral, 4. Difficult, 5. Very difficult	Kelly and Palaniappan (2023), Wibella, Fahmi, and Saptono (2018), Abdinoor and Mbamba (2017), Abebe and Lessa (2022), Goshu (2019), Saidu et al. (2023), Beyene (2020).	+
	PRU	Perceived usefulness	Ordinal	Likert scale: 1. Strongly disagree, 2. disagree, 3. Neutral, 4. agree, 5. Strongly disagree	Abdinoor and Mbamba (2017), Abebe and Lessa (2022), Saidu et al. (2023), Kelly and Palaniappan (2023), Beyene (2020)	+
	AW	Awareness	Dummy	1 = Yes 0 = No	Abdinoor and Mbamba (2017), Abebe and Lessa (2022)	+
Institutional factor	DFI	Distance to the financial institutions	Continuous	Km	Bachas et al. (2021), Grzybowski et al. (2023)	+/−
	AI	Access to internet	Dummy	1 = Yes 0 = No	Oshora et al. (2021), Mothobi and Kebotsamang (2024), Melubo and Musau (2020), Moyo et al. (2022), Naito and Yamamoto (2022)	+/−

ii. **Count component (negative binomial model)**: The count component of the zero-inflated negative binomial (ZINB) model is based on a negative binomial distribution, which is well-suited for handling count data exhibiting overdispersion, where the variance exceeds the mean. This component models the frequency of transactions among individuals who engage in mobile money transactions, either as active adopters of the service or due to some form of non-zero participation. The count component specifically represents non-zero outcomes and is commonly characterized by the negative binomial distribution, which effectively captures the over dispersed nature of such transaction data.

The count component (negative binomial model) is given by

$$p(yi = k) = \frac{\Gamma(\mathrm{k} + \alpha)}{k!\Gamma(\alpha)} = \left(\frac{\mu_i}{\mu_i + \alpha}\right)^k \left(\frac{\alpha}{\mu_i + \alpha}\right)^\alpha \tag{6}$$

where Yi represents the count outcome (i.e. the number of mobile money transactions) for individual i, and k denotes the observed count value. The mean of the distribution, μi, is modelled as a log-linear function of the explanatory variables: $\mu_{i=\exp\ (\gamma o + \gamma 1 Z1i + \gamma 2 Z2i + \cdots + \gamma n Zni)}$

Here, Z1i, Z2i … , Zni denote the covariates associated with individual i, and γ0, γ1γ0, γ1 … , γn are the corresponding coefficients. The parameter $\alpha > 0$ is the dispersion parameter, which allows for overdispersion in the count data. The gamma function is denoted by Γ (·).

The full likelihood function combining zero-inflation and count processes is expressed as

$$L(\beta, \gamma, \alpha; y) = \prod_{i-1}^{n} \left[\pi i^{1(yi=0)}(1 - \pi i)^{1(yi>0)} \cdot \frac{\Gamma(yi + \alpha)}{yi!\Gamma(\alpha)} \left(\frac{\mu_i}{\mu_i + \alpha}\right)^{yi} \left(\frac{\alpha}{\mu_i + \alpha}\right)^{\alpha}\right] \tag{7}$$

Where 1(·) is an indicator function that equals 1 if the condition is true and 0 otherwise.

- μi and πi are the predictors for the count and zero outcomes, respectively, and α is the dispersion parameter (Table 1).

4. Results and discussion

This section presents the results obtained using econometric models and descriptive statistics. This is followed by the overall characteristics of the sample respondents and the descriptive statistics for continuous, dummy, and categorical variables. The last two sections show the empirical findings from the econometric analysis carried out for the study.

4.1. Characteristics of sample respondents

Table 2 presents the overall characteristics of the sample respondents, revealing a substantial disparity between adopters and non-adopters of digital finance. A majority of respondents (74%) had not adopted mobile money services, while a smaller proportion (26%) had. Among both groups, husbands represented the largest share, comprising 87.6% of adopters and 92.5% of non-adopters. The share of wives among adopters was notably lower (4.8%) compared to 3.4% among non-adopters. Adoption among daughters (4.8%) and sons (2.9%) was also minimal, with 2% of each remaining non-adopter. Lack of trust emerged as the most cited reason for non-adoption (55.78%), followed by difficulties in using mobile accounts (19.73%) and limited knowledge of digital finance services (15.9%). Other barriers included not meeting minimum registration requirements (3.74%), a preference for keeping cash at home (2.72%), and challenges related to physical distance from financial institutions (2.04%). Among the 105 individuals who adopted mobile money, there was a marked preference for Tele Birr (88.6%), with a small minority using CBE Birr (11.4%). Key transactions performed via mobile money included airtime purchases (65.7%), money transfers (55.2%), and payment of utility bills such as electricity and water (39%). In addition, mobile money was used for purchasing farm inputs (29.5%) and receiving remittances (29.5%).

Table 2. The overall characteristics of sample respondents.

Variables	Category	Digital finance adoption status: Adopter (105) Frequency	Adopter (105) Percentage	Non-adopter (294) Frequency	Non-adopter (294) Percentage
Adoption status of digital finance	–	105	26%	294	74%
Position of the respondents	Husband	92	87.6%	272	92.5%
	Wife	5	4.8%	10	3.4%
	Daughter	5	4.8%	6	2%
	Son	3	2.9%	6	2%
The main reasons for not adopting mobile money for non-adopter	Lack of awareness	–	–	47	16%
	I do not meet the minimum requirements	–	–	11	3.7%
	I do not trust mobile money	–	–	164	55.8%
	Difficulty when using mobile money	–	–	58	19.7%
	Distance to financial institutions	–	–	6	2%
	I keep my money at home	–		8	2.7%
Types of mobile money accounts adopted in the study area.	Tele Birr	93	88.6%	–	–
	CBE Birr	12	11.4%	–	–
Types of transactions that respondents perform on mobile money.	Bought airtime	69	65.7%	–	–
	Sent money	58	55.2%	–	–
	Received remittance	31	29.5%	–	–
	Paid water and electricity bill	41	39.0%	–	–
	Bought farm inputs	37	35.2%	–	–

4.2. Results of the descriptive statistics for continuous, dummy, and categorical variables

The data presented in Table 3 shows the descriptive statistics for continuous, dummy, and categorical variables. On average, adopters were younger than non-adopters, with a mean age of about 36 years, in contrast to 38 years for non-adopters. When it comes to education, adopters have a higher level of education, averaging 7.42 years of schooling, while non-adopters average only 3.54 years. In terms of distance to financial institutions, adopters live on average 2.90 km from mobile money agents or financial institutions, whereas non-adopters were located farther away, averaging 3.64 km. As for social influence, adopters indicated experiencing greater social influence (mean = 3.28) than non-adopters (mean = 2.48). Additionally,

Table 3. Results of the descriptive statistics.

Variables	Digital finance adoption status: Adopter (n = 105) Mean	Non-adopter (n = 294) Mean	Total (n = 399) Mean
Age	36	38	37
Education	7.42	3.54	4.56
Distance to FI	2.90	3.64	3.44
Social influence	3.28	2.48	2.69
Trust	3.40	2.71	2.89
Perceived ease of use	3.42	2.36	2.64
Perceived usefulness	3.33	2.68	2.85

Variables	Category	Digital finance adoption status: Adopter Percentage	Non-adopter Percentage
Sex	Male	52.38%	61.56%
	Female	44.62%	38.44%
Occupation	Farmer	22.86%	58.16%
	Business owner	15.24%	1.36%
	Government/NGO employee	29.52%	6.80%
	Self-employed	19.05%	4.08%
	Student	10.48%	8.16%
	Unemployed	2.86%	21.43%
Ownership of mobile phone	Yes	88.57%	66.67%
	No	11.43%	33.33%
Awareness	Yes	74.29%	59.52%
	No	25.71%	40.48%
Access to internet	Yes	88.57%	23.81%
	No	11.43%	76.19%

adopters show a stronger trust in digital financial services, scoring a mean of 3.40 compared to 2.71 for non-adopters. Regarding ease of use, adopters found digital financial services to be more user-friendly, with an average score of 3.42, while non-adopters scored only 2.36. Lastly, adopters viewed digital financial services as more advantageous, with a mean usefulness score of 3.33 compared to 2.68 for non-adopters.

In terms of gender, a higher percentage of non-adopters was male (61.56%) in contrast to adopters (52.38%), while a greater share of adopters was female (44.62%) compared to non-adopters (38.44%). Regarding employment, non-adopters mostly worked as farmers (58.16%), while adopters had a more varied occupational background, including roles as government/NGO employees (29.52%), self-employed individuals (19.05%), and business owners (15.24%). Furthermore, the rate of unemployment was significantly greater among non-adopters (21.43%) than among adopters (2.86%). Regarding mobile phone ownership, 88.57% of adopters own a mobile phone, whereas 66.67% of non-adopters reported owning a mobile phone. In terms of awareness, a larger proportion of adopters (74.29%) were aware of digital finance services compared to non-adopters (59.52%). When it comes to internet access, most adopters (88.57%) have internet connectivity, while only 23.81% of non-adopters have access.

4.3. Factors affecting adoption of digital finance (mobile money): Evidence from binary logistic regression model

Table 4 shows the findings of a binary logistic regression analysis. The model demonstrates strong statistical significance, as evidenced by the likelihood ratio Chi-square test ($\chi^2 = 255.64$, $p < 0.0001$), which confirms that at least one predictor significantly influences mobile money adoption. The pseudo-R^2 value of 0.5558 implies that the independent variables incorporated in the model explain roughly 55.58% of the variation in mobile money adoption, suggesting a robust model fit. The log-likelihood value (−102.1376) indicates how well the model fits the data, with higher absolute values suggesting a better fit.

Empirical evidence from this study (Table 4) revealed a relationship between various factors and the adoption of mobile money services. Education level was a significant predictor of mobile money adoption ($p < 0.01$). Specifically, the marginal effect shows that for each additional year of education, the probability of adopting mobile money increases by 3.53%, holding other variables constant. Phone ownership was a statistically significant positive effect on mobile money adoption ($p < 0.01$). This indicates that individuals who own a mobile phone are 8.84% more likely to adopt mobile money compared to non-owners, holding other variables constant. The marginal effect of social influence is estimated at 0.0644 ($p < 0.001$), indicating that a one-unit increase in social influence is associated with a 6.44% higher probability of adopting mobile money, holding other variables constant. Trust has a positive and statistically significant effect on mobile money adoption ($p < 0.001$). The marginal effects estimate that a one-unit increase in trust increases the probability of adoption by 5.71%, holding other variables constant. Perceived ease of use has a positive and statistically significant effect on mobile money adoption ($p < 0.001$). The marginal effect of 0.0671

Table 4. Results of the binary logistic regression.

DFS	Marginal effect	Std. Err.	z
Age	−0.00079	0.0236	−0.40
Sex	0.0244	0.3796	0.83
Education level	0.0353***	0.0734	6.17
Occupation	0.0079	0.0987	1.03
Ownership of mobile phone	0.0884**	0.4672	2.43
Social influence	0.0644***	0.1869	4.42
Trust	0.0571***	0.1717	4.27
Perceived ease of use	0.0671***	0.1880	4.58
Perceived usefulness	0.0602***	0.1787	4.33
Awareness	0.0481	0.3947	1.57
Distance to financial institutions	−0.0152**	0.0731	−2.67
Internet access	0.1172**	0.5104	2.95
cons	−0.0007	2.0202	−7.52
LR $Chi^2(12)$	255.64	Pseudo R^2	0.5558
Prob > Chi^2	0.0000	Number of obs	399
Log-likelihood	−102.1376		

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

indicates that a one-unit increase in perceived ease of use increases the probability of adoption by 6.71%, holding other variables constant. Perceived usefulness has a positive and statistically significant impact on the probability of adopting mobile money ($p < 0.001$). Specifically, the marginal effect of 0.0602 indicates that a higher perception of usefulness increases the probability of adoption by 6.02%, holding other variables constant. Internet access significantly influences adoption ($p < 0.01$), with higher access to the internet associated with an 11.72% increase in the probability of adopting mobile money, holding other variables constant. The distance to financial institutions or mobile money agents negatively affected adoption; for each additional kilometre, the probability of adopting mobile money services decreases by 1.52%, holding other variables constant.

4.4. Factors influencing the intensity of digital finance (mobile money) use: evidence from a zero-inflated negative binomial model

To account for overdispersion and excess zeros in mobile transaction data, a zero-inflated negative binomial (ZINB) model was applied. The model effectively handled the structure of the data, which included 294 zero and 105 non-zero observations, with a significant dispersion parameter ($\alpha = 8.60$, $p < 0.001$). It demonstrated a good fit, with a log-likelihood of −267.439 and a likelihood ratio chi-square of 55.84 ($p < 0.001$).

The count model (negative binomial) incorporated variables hypothesized to affect the frequency of mobile transactions, including age, sex, education level, occupation, mobile phone ownership, social influence, trust in digital finance, perceived ease of use, perceived usefulness, awareness, distance to financial institutions, and internet access. In contrast, the inflation model (logit), which estimates the probability of zero transactions, included a subset of variables: education, occupation, mobile phone ownership, trust, perceived ease of use, perceived usefulness, and internet access. Variables excluded from the inflation model were omitted due to their weak significance in preliminary analyses.

4.4.1. Factors influencing the frequency of mobile money transactions: evidence from the count component of the zero-inflated negative binomial model

In the count model (negative binomial) presented in Table 5, some key factors were found to significantly influence the frequency of mobile transactions. Occupational status significantly affects the frequency of

Table 5. Results of the zero-inflated negative binomial regression.

	Count model (Negative binomial)			Inflation model (Logit)		
Mobile transactions	Marginal effect	Std. Err.	z	Marginal effect	Std. Err.	z
Age	0.0003	0.006	0.06	–	–	–
Sex						
Female	0.163	0.120	1.56	–	–	–
Education level	0.040	0.0303	−1.44	−0.037***	0.108	−5.32
Occupation						
Business owner	0.336	0.200	1.61	−0.257**	1.445	−2.21
Government/NGO employee	1.212**	0.173	2.51	−0.259***	0.723	−4.45
Self-employed	0.796	0.210	−0.41	−0.397***	1.061	−4.30
Student	0.1030	0.285	−1.41	−0.176***	0.869	−2.68
Unemployed	−1.019**	0.561	−2.09	−0.028	1.134	−0.38
Ownership of mobile phone	0.289	0.206	0.91	−0.061	0.635	−1.48
Social influence	0.086	0.058	1.71	–	–	–
Trust	0.197	0.048	1.68	−0.060***	0.256	−3.61
Perceived ease of use	0.152	0.057	0.38	−0.063***	0.278	−3.51
Perceived usefulness	0.264	0.060	1.89	−0.078***	0.292	−4.15
Awareness	0.033	0.140	0.28	–	–	–
Distance to financial institutions	0.081***	0.026	3.57	–	–	–
Internet access	0.581**	0.211	2.25	−0.082	0.776	−1.64
_cons	0.629	0.629	−0.37	16.438	2.501	6.57
/lnalpha				−16.26***	1169.777	−0.01
Alpha				8.60	0.000	
Number of obs = 399	Inflation model = logit					
Nonzero obs = 105	Log-likelihood = −267.439					
Zero obs = 294	LR chi2(16) = 55.84			Prob > chi2 = 0.0000		

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

mobile transactions. Specifically, individuals employed in government or NGO roles show a marginal effect of 1.212, indicating a 121.2% higher rate of mobile transaction usage compared to farmers, the reference group. This suggests that formal sector employees are more likely to engage in mobile financial services, likely due to regular income flows, greater financial literacy, and higher exposure to digital technologies. In contrast, being unemployed is associated with a significant reduction in transaction frequency, with a marginal effect of −1.019, reflecting a 101.9% decrease in usage. This implies that unemployed individuals are considerably less active in mobile financial transactions, potentially due to limited disposable income and lower financial engagement. These findings are consistent with Maradung (2013), who reported higher adoption rates of mobile money services among employed individuals seeking convenient access to financial tools and services.

Distance to financial institutions has a statistically significant and positive effect on the frequency of mobile transactions, with a marginal effect of 0.081. This indicates that for each additional kilometre between a respondent's residence and the nearest financial institution or mobile money agent, the expected number of mobile transactions increases by approximately 8.1%, holding other variables constant. This result suggests that individuals living farther from formal financial service points are more likely to rely on mobile platforms as a substitute for in-person transactions. The finding aligns with De L' and Superieur (2021), who observed higher mobile banking usage among women and individuals residing at intermediate distances from bank branches. However, it contrasts with Asravor, Boakye, and Essuman (2022), who reported that increased distance from mobile money agents was associated with reduced usage intensity, highlighting that the relationship may vary by context and service accessibility.

Internet access has a positive and statistically significant effect on the frequency of mobile transactions, with a marginal effect of 0.581. This indicates that individuals with internet access conduct, on average, 58.1% more mobile transactions than those without, holding other factors constant. This result underscores the critical role of digital connectivity in enabling mobile financial activity. Reliable internet access facilitates real-time interaction with mobile finance platforms, improves user experience, and reduces technical barriers such as failed transactions or delays.

4.4.2. Factors affecting the probability of reporting zero transactions: evidence from the inflation (logit) component of the zero-inflated negative binomial model

The inflation (logit) component of the zero-inflated negative binomial (ZINB) model presented in Table 5 examines the factors influencing the probability of reporting zero mobile money transactions, whether due to non-adoption of mobile money or inactivity among adopters who have the service but do not engage in transactions.

Education plays a significant role in reducing zero transactions. Specifically, each additional year of schooling is associated with a 3.73% decrease in the probability of reporting zero transactions. This suggests that individuals with higher education are more likely to engage with mobile money services, either by adopting the service or actively using it, likely due to greater digital literacy, enhanced access to information, and a better understanding of the functionality and benefits of digital finance platforms.

Occupational status significantly affects the probability of zero transactions. Compared to farmers (the reference group), business owners are 25.73% less likely to report zero transactions, indicating the practical benefits of mobile money for business operations. Government and NGO employees exhibit a 25.97% lower probability of zero transactions, which may be due to their regular interaction with formal financial systems and digital tools. Self-employed individuals show the strongest effect, being 39.71% less likely to report zero transactions, likely because of their need for flexible transaction methods. Students are also 17.67% less likely to report zero transactions, potentially due to their greater familiarity with digital tools and higher comfort with technology-based financial services.

Psychological factors also play a significant role in influencing the probability of mobile transactions. A one-unit increase in trust in digital financial services is associated with a 6.00% reduction in the probability of reporting zero transactions, suggesting that greater confidence in the security and reliability of mobile platforms encourages user engagement. Similarly, perceived ease of use has a significant negative effect, with each unit increase resulting in a 6.35% decrease in the likelihood of reporting zero transactions. This indicates that when users perceive mobile financial services as simple and user-friendly, they are more inclined to not report zero transactions. Additionally, perceived usefulness contributes meaningfully to engagement in mobile money services, as a one-unit increase corresponds to a 7.86% reduction in the probability of zero transactions. This underscores the importance of demonstrating the practical value and benefits of mobile financial services in promoting user uptake.

4.5. Discussion

The study emphasizes the significance of education in mobile money adoption. Participants with higher education levels showed confidence and independence in managing transactions, whereas those with less education struggled to use platforms and check transactions, leading to mistrust. Key informants also stated that educated people are more inclined to use mobile money due to a better understanding of the terms and conditions. This finding is consistent with the studies of Ghosh and Hom (2022), Nonvide and Alinsato (2023), Onyia and Tagg (2011), Akinyemi and Mushunje (2020), Melubo and Musau (2020), and Moyo et al. (2022).

The adoption of mobile money was found to be positively associated with phone ownership. The focus group discussion confirmed that phone ownership significantly facilitates mobile money adoption. Participants with mobile phones highlighted ease of registration, transaction convenience, and enhanced trust due to direct access and timely notifications. In contrast, non-owners reported challenges such as dependency on others' devices, concerns about privacy, and difficulty following transactions. This finding is also in line with Murendo et al. (2018), Akinyemi and Mushunje (2020), N'dri and Kakinaka (2020).

Social influence was a major factor in the adoption of mobile money. Community leaders, families, and peer networks all had a big impact on adoption decisions. Participants consistently shared that the decisions to use mobile money were strongly shaped by social influence. One participant noted, '*I started using mobile money because my friends were already using it, and they kept telling me how easy it is to send and receive money.*' This finding is in line with the studies of Banerjee et al. (2013), Zhang, Lin, and Li (2012), Ahmed (2016), Dass and Pal (2011), Kelly and Palaniappan (2023), Yan et al. (2023), and Kiconco, Rooks, and Snijders (2020). However, the findings of this study oppose the study of Moyo et al. (2022).

Trust was an important factor in mobile money adoption. The focus group discussion confirmed that trust plays a crucial role in mobile money adoption. Participants emphasized that confidence in the security and reliability of mobile money services significantly influenced their decision to adopt. This finding is in line with the studies conducted by Abebe and Lessa (2022), Dass and Pal (2011), Saidu et al. (2023), Yan et al. (2023), and Goshu (2019).

Ease of use significantly influenced mobile money adoption. The focus group discussion highlighted that perceived ease of use is a key factor in mobile money adoption. Participants stressed that they are more likely to use mobile money services when the apps are simple and intuitive. One participant stated, '*I prefer mobile money because it's easy to use; I can quickly send money or check my balance without any bother*.' This finding is in line with Kelly and Palaniappan (2023), Wibella, Fahmi, and Saptono (2018), Abdinoor and Mbamba (2017), Abebe and Lessa (2022), Goshu (2019), Saidu et al. (2023), and Beyene (2020).

Perceived usefulness significantly affected mobile money adoption. Moreover, the focus group discussion confirmed that perceived usefulness is a key driver of mobile money adoption. Participants emphasized that they are more likely to adopt mobile money when they see clear benefits such as convenience, cost savings, and improved financial management. One participant shared, '*I use mobile money because it saves me time and money compared to going to the bank*.' This study's finding is consistent with the findings of Abdinoor and Mbamba (2017), Abebe and Lessa (2022), Saidu et al. (2023), Kelly and Palaniappan (2023), and Beyene (2020).

Internet access was a significant factor in mobile money adoption. The focus group discussion assured internet access as a determinant of mobile money adoption. Participants underlined that reliable internet connectivity facilitates smooth transactions and enhances confidence in using mobile money services. Most of the participants noted, '*Without good internet access, it's difficult to complete transactions or even check balances, which discourages usage*'. This study is in line with the studies conducted by Oshora et al. (2021), Mothobi and Kebotsamang (2024), Melubo and Musau (2020), Moyo et al. (2022), and Naito and Yamamoto (2022).

The finding indicates that road distance significantly and negatively affects the likelihood of adopting mobile money adoption. The focus group discussion revealed that road distance to financial institutions affects mobile money adoption. Participants noted that those living farther from banks or agents face challenges in accessing essential support services, such as registration and troubleshooting, which discourages adoption. Participants stated, '*For people living in remote areas, the long distance to financial institutions makes it hard to use mobile money consistently*.' This study is in line with the study conducted by Bachas et al. (2021). While it is opposed to the study conducted by Grzybowski et al. (2023).

5. Conclusions

This study concludes, based on the application of binary logistic regression and zero-inflated negative binomial (ZINB) models, that education, mobile phone ownership, trust in digital finance, and internet access are significant determinants of mobile money adoption in rural Ethiopia. The binary logistic regression results indicate that these factors substantially increase the likelihood of adopting digital financial services. In addition to demographic characteristics, the findings demonstrate that social influence, perceived ease of use, and perceived usefulness also play a critical role in shaping adoption decisions, thereby affirming the relevance of the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) as the study's theoretical framework. The ZINB model provides further insights into the intensity of digital finance usage. Specifically, the count component (negative binomial) reveals that formal employment, distance to financial institutions, and internet access significantly increase the frequency of mobile money transactions among adopters. Concurrently, the inflation component (logit) shows that education, formal employment, trust in digital finance, perceived ease of use, and perceived usefulness significantly reduce the likelihood of non-participation or reporting zero transactions. Among these, internet access emerges as a strong and consistent determinant across both adoption and usage phases, likely due to the critical role of stable connectivity in enabling continuous engagement with digital platforms. Formal employment also demonstrates a consistent effect across both components of the ZINB model, contributing to increased transaction frequency and a reduced probability of zero transactions. Interestingly, some factors exhibit opposite effects across models. For example, greater distance from financial institutions negatively influences the likelihood of adoption, likely due to reduced physical access to agents or support services, yet positively affects usage frequency among adopters, as users substitute physical visits with digital transactions. Finally, the study concludes that some factors, specifically age, sex, occupation, and awareness, do not exhibit statistically significant effects on mobile money adoption within the study area. This lack of significance may reflect a relatively uniform exposure to mobile technology across demographic groups or the limited effectiveness of generic awareness campaigns that fail to address underlying structural constraints.

6. Policy prescription

The findings of this study offer several important policy prescriptions for enhancing mobile money adoption and usage in rural Ethiopia. First, investments in digital and financial literacy programmes are essential, particularly for individuals with limited formal education, to foster confidence and digital engagement. Expanding reliable and affordable internet infrastructure is also critical, as internet access consistently supports both adoption and frequent usage. Given the importance of trust, ease of use, and perceived usefulness, policymakers and service providers should prioritize user-friendly, transparent, and secure digital finance platforms. Moreover, promoting formal employment can indirectly enhance digital finance adoption, as stable income and exposure to formal systems facilitate regular usage. Awareness campaigns should move beyond general messaging and focus on localized, targeted outreach that addresses specific structural barriers. Finally, geographically differentiated strategies are needed, such as expanding agent networks and improving onboarding services in remote areas, to account for the complex role of distance in both discouraging adoption and encouraging frequent digital use.

7. Limitation of the study and future research agenda

This study does not thoroughly analyze the role of financial institutions or service providers; instead, it focuses on user-related factors (demand side) in the adoption of mobile money. Particularly, it concentrates on mobile money services such as CBE Birr and Tele Birr. Future studies may investigate supply-side elements, such as the role of financial institutions, and include a wider variety of mobile money services, such as Hello Cash, M-Pesa, and other similar platforms.

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Ethics approval

Ethical approval was obtained on June 03, 2024, from the Faculty of Natural and Agricultural Sciences ethics committee of the University of Pretoria (Protocol.number-NAS247/2023). Informed written consent was obtained from all study participants.

Data availability statement

The datasets collected and analysed to support the findings of this study are openly available at https://doi.org/10.6084/m9.figshare.28351121.v1

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