DETERMINANTS OF MOBILE MONEY ADOPTION IN UGANDA: EVIDENCE FROM UNHS 2023/24

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S21B34/016

A DISSERTATION SUBMITTED TO THE SCHOOL OF BUSINESS IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF A DEGREE OF BACHELOR OF SCIENCE IN ECONOMICS AND STATISTICS OF UGANDA CHRISTIAN UNIVERSITY

May, 2026

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DECLARATION

I, **GENRWOTH DANIEL RAPHAEL**, hereby certify that this dissertation is my original work and has been submitted in partial fulfilment of the requirements for the award of the Bachelor of Science in Economics and Statistics degree at Uganda Christian University. It has not been submitted to any other academic institution for any award. Where the work of others has been used, it has been duly acknowledged through proper citations and clear references.

Signature: daniel raphael .... Date: 22/05/2026

APPROVAL

This is to certify that the research report by **GENRWOTH DANIEL RAPHAEL**, Registration Number **S21B34/016**, entitled *"Determinants of Mobile Money Adoption in Uganda: Evidence from UNHS 2023/24"*, was carried out under my supervision and is hereby approved for submission to the School of Business in partial fulfilment of the requirements for the award of the Bachelor of Science in Economics and Statistics degree of Uganda Christian University.

Signature:.. **Date:**...22/05/2026...

DR. SEBAGGALA RICHARD

DEDICATION

This study is dedicated to the millions of Ugandan adults who remain excluded from mobile money services, the farmer in Karamoja, the market woman in Bundibugyo, the young graduate in Mbarara, whose daily economic lives are shaped by digital barriers that policy has the power to dismantle. May this work contribute, in however small a measure, to the evidence that guides a more inclusive digital economy for every Ugandan household.

ACKNOWLEDGEMENTS

First and above all, praise and thanks go to God, whose grace made this work possible.

To my supervisor, sincere gratitude is owed for the patience, intellectual rigour, and generous guidance that shaped this dissertation from its earliest draft to its final form. The tough questions asked along the way made this a better piece of work.

To the Uganda Bureau of Statistics (UBOS), acknowledgement is due for making the Uganda National Household Survey 2023/24 dataset available for academic research. Without that data, this study would not exist.

To my family, friends, and classmates, thank you for the encouragement, the honest feedback, and the late-night conversations that kept the momentum going. This journey was lighter because of you.

TABLE OF CONTENTS

DECLARATION i

APPROVAL ii

DEDICATION iii

ACKNOWLEDGEMENTS iv

TABLE OF CONTENTS v

LIST OF TABLES ix

LIST OF ABBREVIATIONS x

ABSTRACT xi

CHAPTER ONE 1

INTRODUCTION 1

- 1.0 Introduction 1
- 1.1 Background of the Study 1
- 1.2 Statement of the Problem 2
- 1.3 Purpose of the Study 3
- 1.4 Specific Objectives of the Study 3
- 1.5 Research Questions 3
- 1.6 Justification of the Study 4
- 1.7 Scope of the Study 4
  - 1.7.1 Content Scope 5
  - 1.7.2 Population Scope 5
  - 1.7.3 Geographical Scope 5
  - 1.7.4 Time Scope 5
- 1.9 Operational Definition of Key Terms 5
- 1.10 Conceptual Framework 6

CHAPTER TWO 8

LITERATURE REVIEW ... 8
2.0 Introduction ... 8
2.1 Theoretical Framework ... 8
2.1.1 Human Capital Theory (Becker, 1964) ... 8
2.1.2 Economic Constraints Theory ... 8
2.1.3 Technology Acceptance Model (Davis, 1989) ... 9
2.1.4 Demographic and Geographic Factors ... 9
2.2 Historical Context of Mobile Money in Uganda ... 10
2.3 Human Capital and Mobile Money Adoption ... 10
2.4 Economic Resources and Technology Access ... 11
2.4.1 Household Wealth ... 12
2.4.2 Mobile Phone Ownership ... 12
2.5 Demographic and Geographic Factors ... 13
2.5.1 Age ... 13
2.5.2 Sex ... 13
2.5.3 Rural Residence ... 13
2.5.4 Subgroup Variation in Adoption Determinants ... 14
2.6 Research Gap ... 14
CHAPTER THREE ... 16
RESEARCH METHODOLOGY ... 16
3.0 Introduction ... 16
3.1 Research Design ... 16
3.2 Data Source and Sample ... 16
3.2.1 Sampling Design ... 17
3.2.2 Sample Size and Response Rate ... 17
3.2.3 Refugee Sample ... 17

3.3 Variable Definition and Measurement 18
3.3.1 Dependent Variable 18
3.3.2 Independent Variables 18
3.4 Econometric Model Specification 19
3.4.1 Rationale for the Logit Model 19
3.4.2 The Logit Model 19
3.4.3 Full Regression Equation 20
3.4.4 Marginal Effects 20
3.5 Model Validation 20
3.6 Estimation Strategy 21
3.7 Ethical Considerations 21
3.8 Methodological Limitations 22
CHAPTER FOUR 23
ANALYSIS, INTERPRETATION AND DISCUSSION OF FINDINGS 23
4.0 Introduction 23
4.1 Descriptive Statistics 23
4.2 Multicollinearity Diagnostics 25
4.3 Main Logit Results and Average Marginal Effects 25
4.4 Predicted Probability Analysis 27
4.5 Subgroup Analysis 27
4.6 Robustness Check 29
4.7 Summary of Findings 29
CHAPTER FIVE 30
DISCUSSIONS, CONCLUSIONS, AND RECOMMENDATIONS 30
5.0 Introduction 30
5.1 Discussion of Findings 30

5.1.1 Objective 1: Education and Mobile Money Adoption 30

5.1.2 Objective 2: Wealth, Phone Ownership, and Mobile Money Adoption................. 31

5.1.3 Objective 3: Demographic, Geographic Factors, and Subgroup Variation 32

5.2 Conclusions 33

5.3 Recommendations for Policy and Practice 34

5.3.1 Recommendations to the Bank of Uganda and Uganda Communications Commission 34

5.3.2 Recommendations to MTN Uganda and Airtel Uganda 34

5.3.3 Recommendations to the Ministry of Education and Sports............................. 34

5.3.4 Recommendations to Development Partners... 34

5.4 Limitations of the Study.. 35

5.5 Areas for Further Research 35

REFERENCES 36

LIST OF TABLES

Table 1.1: Expected Signs of Determinants and Theoretical Basis

Table 2.1: Theory-to-Variable Mapping

Table 3.1: Dependent Variable Definition

Table 3.2: Independent Variables Definition and Measurement

Table 3.3: Model Validation and Diagnostic Tests

Table 4.1: Descriptive Statistics by Mobile Money Adoption Status

Table 4.2: Mobile Money Adoption Rates by Subgroup

Table 4.3: Average Marginal Effects on Mobile Money Adoption, Full Sample (n=3,704)

Table 4.4: Average Marginal Effects by Subgroup

LIST OF ABBREVIATIONS

Abbreviation	Full Form
AUC-ROC	Area Under the Receiver Operating Characteristic Curve
AME	Average Marginal Effects
BoU	Bank of Uganda
EA	Enumeration Area
GDP	Gross Domestic Product
GSMA	Global System for Mobile Communications Association
IMF	International Monetary Fund
MTN	Mobile Telephone Networks
OLS	Ordinary Least Squares
OTC	Over-the-Counter
PPS	Probability Proportional to Size
SDG	Sustainable Development Goal
TAM	Technology Acceptance Model
UBOS	Uganda Bureau of Statistics
UGX	Uganda Shilling
UNHS	Uganda National Household Survey
VIF	Variance Inflation Factor

ABSTRACT

This study analysed the determinants of mobile money adoption among Ugandan adults using data from the Uganda National Household Survey (UNHS) 2023/24. The analytical sample included 3,704 adults aged 16 years and above. A survey-weighted logit model with average marginal effects was estimated to examine the influence of education, household wealth, mobile phone ownership, age, sex, rural residence, and sub-region.

Mobile phone ownership emerged as the strongest predictor, raising the probability of adoption by 47.5 percentage points. Completing secondary education or higher increased adoption probability by 13.3 percentage points, while primary education increased it by 8.1 percentage points. Each step up the wealth quintile was associated with a 3.9 percentage point increase. Women were 10.8 percentage points less likely to adopt than men, with a larger gap in rural and poorer households. Rural residence was not statistically significant after controlling for other factors.

The findings indicate that phone access, education, economic resources, and gender remain the key barriers to mobile money adoption in Uganda's mature market. The study recommends policies targeting handset affordability, digital literacy, and gender-sensitive interventions to promote greater financial inclusion.

Keywords: Mobile money, financial inclusion, determinants, logit model, Uganda

CHAPTER ONE

INTRODUCTION

1.0 Introduction

This chapter presents the background of the study, statement of the problem, purpose of the study, specific objectives, research questions, justification, scope, limitations, operational definitions of key terms, and the conceptual framework that guided the analysis.

1.1 Background of the Study

Mobile money is one of the most transformative financial innovations in Sub-Saharan Africa. Unlike traditional banking, mobile money allows users to store, send, and receive money using a basic mobile phone without requiring a formal bank account. According to the GSMA (2024), there were over 1.75 billion registered mobile money accounts worldwide, with Sub-Saharan Africa accounting for nearly half of all transactions. In this region, mobile money became a critical tool for financial inclusion, enabling previously unbanked populations to participate in the formal economy. The growth of mobile money was particularly rapid in East Africa, where countries such as Kenya, Tanzania, and Uganda pioneered its adoption (Jack & Suri, 2011; Munyegera & Matsumoto, 2016).

Uganda is widely recognised as a pioneer in mobile money adoption. Since the service was launched in 2009 by MTN Uganda, followed by Airtel Uganda, the country experienced exponential growth. The number of registered mobile money agents grew from a few thousand in 2010 to over 250,000 by 2023 (Bank of Uganda, 2023). This agent network was far denser than the branch network of commercial banks, especially in rural areas. As of 2023, Uganda had approximately 1,200 commercial bank branches, meaning mobile money agents outnumbered bank branches by a ratio of more than 200 to 1 (Bank of Uganda, 2023). Consequently, mobile money became the primary means of digital payments, remittances, and savings for millions of Ugandans.

According to the Uganda Bureau of Statistics (UBOS, 2024), 54 percent of Ugandan adults had an active mobile money account in 2023/24. This represented a substantial increase from 35 percent in 2016/17 and just 8 percent in 2011/12, demonstrating rapid diffusion over a decade. Mobile money usage was highest in urban areas (65 percent of adults) but was also significant in rural areas (47 percent of adults). The total value of mobile money transactions in Uganda reached approximately UGX 150 trillion in 2023, equivalent to nearly 80 percent of the country's GDP (Bank of Uganda, 2023).

However, these national averages concealed persistent disparities. Adoption rates among adults with no formal education stood at only 31 percent, compared to 87 percent for those with post-secondary education (UBOS, 2024). Only 34 percent of adults in the poorest wealth quintile used mobile money, compared to 78 percent in the richest quintile. Women also lagged behind men: 48 percent of women used mobile money versus 61 percent of men. Regionally, adoption ranged from a low of 19 percent in Karamoja to a high of 76 percent in Kampala. These gaps indicated that approximately 12 million Ugandan adults remained excluded from mobile money services.

The Government of Uganda and the Bank of Uganda actively promoted mobile money as a pathway to financial inclusion. Regulatory changesincluding the National Payment Systems Act (2020) and the introduction of interoperability between different mobile money networks lowered transaction costs and increased convenience. The Financial Inclusion Strategy (2017–2022) set a target of reducing the proportion of financially excluded adults to 20 percent by 2022, with mobile money identified as a key driver (Bank of Uganda, 2017). Despite these advances, nearly half of Ugandan adults did not use mobile money.

This study focused on the individual-level determinants of mobile money adoption among Ugandan adults. Specifically, it examined how education, wealth, mobile phone ownership, age, sex, rural residence, and sub-region affected the probability that an adult adopted mobile money. The findings provided evidence for policymakers and mobile network operators to target digital literacy programmes, network expansion, and product design toward excluded populations.

1.2 Statement of the Problem

Globally, mobile money was recognised as a critical tool for advancing financial inclusion and reducing poverty (GSMA, 2024; World Bank, 2023). As Uganda's mobile money market matured reaching 54 percent adult adoption, near-universal interoperability, and over 250,000 agents by 2023/24 a theoretically important question emerged that existing studies had not addressed: whether the determinants of adoption had shifted structurally as the market evolved.

Early studies of mobile money adoption in Uganda used data from periods of low and rapidly rising adoption: Munyegera and Matsumoto (2016) used 2009/10 data when only 8 percent of adults were users, and Kasirye (2018) drew on 2012/13 to 2016/17 data covering the 8–35 percent adoption range. In these early-stage market settings, education and wealth were strong predictors because basic access phone ownership, registration documents, and awarenesswere significant barriers. However, as mobile money became mainstream and barriers of access softened, it was plausible that the relative importance of determinants shifted: trust, digital literacy, and agent proximity may have become more binding constraints than raw economic or educational access.

No study had examined this question using the most recent UNHS 2023/24 data, which captured Uganda's mature mobile money market for the first time. Consequently, policymakers lacked current, nationally representative evidence on which household characteristics were most strongly associated with non-adoption in the present context, making it difficult to design precisely targeted financial inclusion interventions. This study addressed that gap by estimating the determinants of mobile money adoption using the UNHS 2023/24 data and reporting average marginal effects that directly answered policy-relevant questions about which barriers remained binding in a mature market.

1.3 Purpose of the Study

The study aimed to analyse the individual-level determinants of mobile money adoption among Ugandan adults using data from the Uganda National Household Survey 2023/24.

1.4 Specific Objectives of the Study

The study was guided by the following specific objectives:

i. To estimate the marginal effects of education level on the probability of mobile money adoption among Ugandan adults.
ii. To assess the effects of household wealth quintile and mobile phone ownership on the probability of mobile money adoption.
iii. To examine how age, sex, and rural residence influenced mobile money adoption, and to compare determinants across urban/rural and wealth subgroups.

1.5 Research Questions

The following research questions guided the study:

i. How did education level affect the probability of mobile money adoption among Ugandan adults?
ii. How did household wealth and mobile phone ownership affect the probability of mobile money adoption?
iii. How did demographic and geographic characteristics influence mobile money adoption, and did these effects vary across urban/rural and wealth subgroups?

1.6 Justification of the Study

This study contributed to knowledge and practice in four key respects.

To policymakers specifically the Bank of Uganda, the Uganda Communications Commission, and the Ministry of Finance, Planning and Economic Development the findings provided current, nationally representative evidence on which household characteristics were associated with lower adoption in a mature mobile money market. This informed more precisely targeted financial inclusion interventions, including digital literacy programmes and network expansion strategies in underserved sub-regions.

To mobile network operators such as MTN Uganda and Airtel Uganda, the findings identified which household segments remained non-adopters in 2023/24, informing customer acquisition strategies and product design decisions aimed at closing the remaining 46 percent non-adoption gap.

To academia, the study updated the mobile money adoption literature for Uganda using the most recent nationally representative data, providing a methodological benchmark for studying mature digital financial markets. It applied established economic theories human capital, economic constraints, technology access, and demographic factors to the specific context of a mature Sub-Saharan African mobile money market, contributing to comparative evidence across the region.

To development partners including the World Bank, GSMA, and UNCDF, the study offered evidence for the design of financial inclusion programmes targeting specific household characteristics, contributing to Sustainable Development Goal 1 (no poverty) and Goal 8 (decent work and economic growth) by identifying barriers that prevented the most vulnerable households from benefiting from digital financial services.

1.7 Scope of the Study

1.7.1 Content Scope

The study examined mobile money adoption as the dependent variable and analysed its relationship with education level (primary and secondary completion), household wealth quintile, mobile phone ownership, age, sex, rural residence, and sub-region. Adoption of other digital financial services including online banking and agency banking was not examined.

1.7.2 Population Scope

The study targeted adults aged 16 years and above who were usual members of sampled households. The UNHS defined usual members as those who had lived in the household for at least six of the past twelve months. Institutional populations (prisons, army barracks, hospitals, schools) were excluded from the UNHS sample. The unit of analysis was the individual adult respondent, not the household.

1.7.3 Geographical Scope

The study covered all 135 districts and 11 cities of Uganda as represented in the UNHS 2023/24 sample. The survey was nationally representative and included both urban and rural areas, as well as refugee settlements and host communities, though the refugee oversample was excluded from the main analysis to maintain representativeness of the Ugandan household population.

1.7.4 Time Scope

The study used cross-sectional data collected between March 2023 and February 2024. No longitudinal or time-series analysis was attempted. Findings reflected the state of mobile money adoption in Uganda during that specific survey period.

1.9 Operational Definition of Key Terms

- **Mobile money adoption**: An adult was classified as a mobile money adopter if they reported having an active, registered mobile money account at the time of the UNHS 2023/24 interview (Section 9A). This excluded over-the-counter (OTC) usage where a person sent or received money through an agent without owning an account.
- **Respondent's sex**: The sex of the individual adult respondent (female = 1, male = 0), as recorded in the UNHS household roster (Section 2). This variable captured gender effects

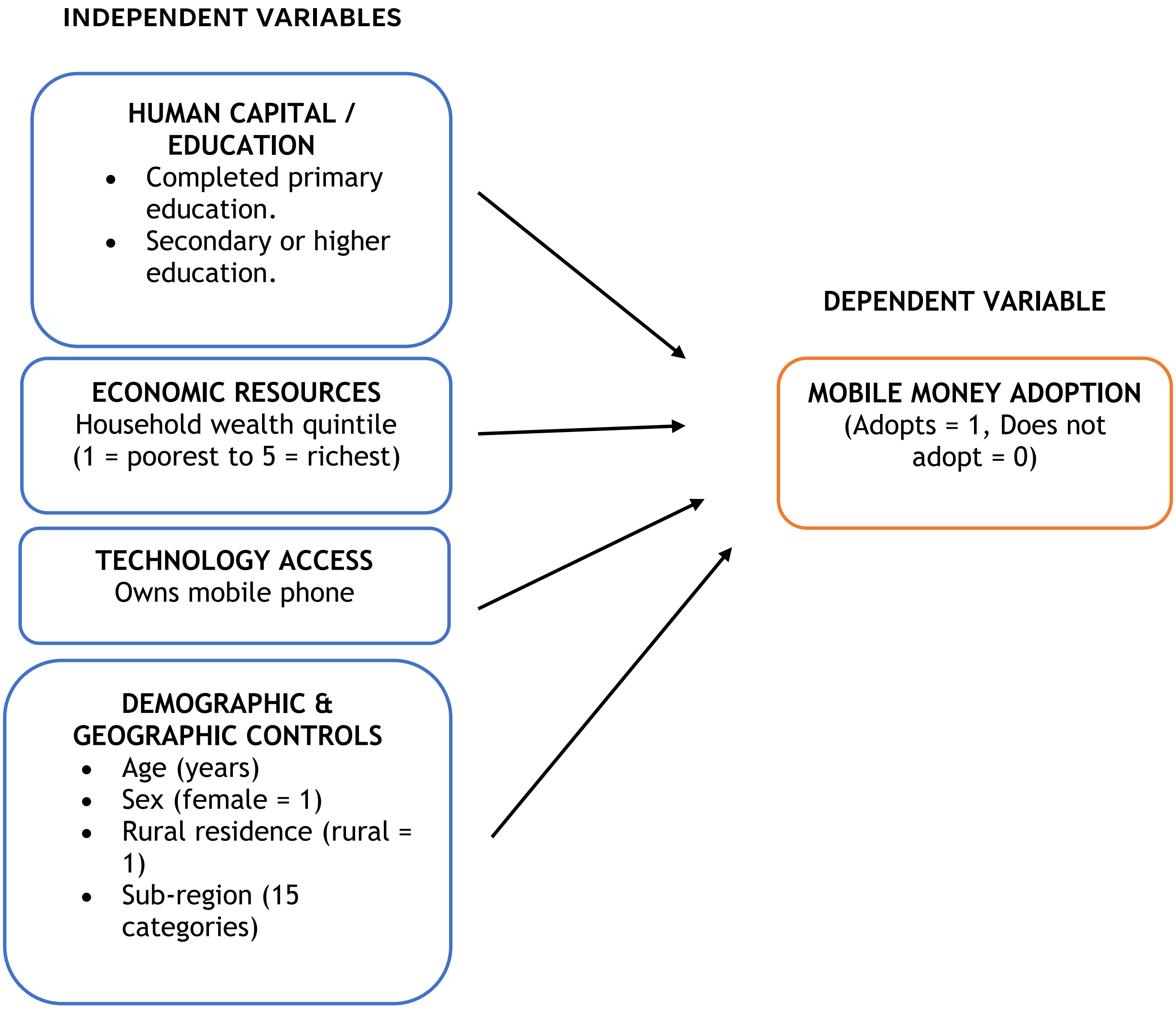
on individual adoption behaviour directly, rather than using the sex of the household head as a proxy.

- **Wealth quintile**: A variable derived by UBOS that ranked households by consumption expenditure per adult equivalent, divided into five equal groups. Quintile 1 represented the poorest 20 percent of households; quintile 5 represented the richest 20 percent.
- **Rural residence**: As defined by UBOS based on the 2014 National Population and Housing Census classification of Enumeration Areas. Rural areas were characterised by lower population density, fewer paved roads, and limited access to services compared to urban areas.

1.10 Conceptual Framework

Figure 1.1 presents the conceptual framework linking education, wealth, mobile phone ownership, and demographic and geographic factors to individual mobile money adoption. The framework posited that adoption was directly influenced by four categories of factors: human capital (education), economic resources (household wealth), technology access (mobile phone ownership), and demographic and geographic characteristics (age, sex, rural residence, sub-region). These relationships were grounded in the theoretical lenses discussed in Chapter 2.

Figure 1.1: Conceptual Framework


INDEPENDENT VARIABLES
HUMAN CAPITAL / EDUCATION
Completed primary education.
Secondary or higher education.
ECONOMIC RESOURCES
Household wealth quintile (1 = poorest to 5 = richest)
TECHNOLOGY ACCESS
Owns mobile phone
DEMOGRAPHIC & GEOGRAPHIC CONTROLS
Age (years)
Sex (female = 1)
Rural residence (rural = 1)
Sub-region (15 categories)
DEPENDENT VARIABLE
MOBILE MONEY ADOPTION
(Adopts = 1, Does not adopt = 0)

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter reviewed the theoretical and empirical literature that underpinned the three study objectives. Section 2.1 presented the theoretical framework, explicitly linking four economic theories to the study variables. Section 2.2 provided the historical context of mobile money in Uganda. Sections 2.3, 2.4, and 2.5 reviewed empirical evidence organised around each of the three specific objectives, education (Objective 1), wealth and phone ownership (Objective 2), and demographic and geographic factors (Objective 3). Section 2.6 identified the research gap derived from the review, and Section 2.7 summarised the chapter.

2.1 Theoretical Framework

A study of mobile money adoption determinants required explicit theoretical grounding to justify variable selection and predict the direction of relationships. Rather than beginning with a list of variables, this study began with a theoretical question: what determined whether an adult individual adopted a digital financial technology? Four theoretical lenses guided the answer.

2.1.1 Human Capital Theory (Becker, 1964)

Human Capital Theory, developed by Becker (1964), posited that education and skills increased an individual's ability to process information, understand new technologies, and make informed economic decisions. Applied to mobile money adoption, more educated individuals were better positioned to navigate registration processes, understand transaction costs and fee structures, read promotional materials, and perceive the long-term benefits of holding a digital financial account. The theory predicted a positive relationship between education and technology adoption, with the effect increasing at higher levels of education — secondary and post-secondary education conferred greater information-processing capacity than primary education alone. This theory directly motivated the inclusion of two education variables: completion of primary education, and completion of secondary or higher education, allowing the model to capture non-linear effects across education thresholds.

2.1.2 Economic Constraints Theory

Economic constraints theory held that the adoption of any financial service required the ability to afford associated costs, including the purchase of a mobile phone, transaction fees, data, and airtime. Households with greater economic resources faced fewer binding constraints to adoption. In Uganda's context, even small transaction fees, typically between UGX 500 and UGX 2,000, could represent a significant share of daily income for households in the lowest wealth quintiles. Economic constraints theory thus predicted a positive gradient between household wealth and mobile money adoption probability, with each step up the wealth distribution associated with a higher likelihood of adoption. The UNHS wealth quintile, derived from consumption expenditure per adult equivalent, captured this economic access dimension directly.

2.1.3 Technology Acceptance Model (Davis, 1989)

The Technology Acceptance Model (TAM), developed by Davis (1989), proposed that technology adoption was driven by two key constructs: perceived usefulness (the degree to which a person believed that using a technology would enhance their performance) and perceived ease of use (the degree to which a person believed that using a technology would require minimal effort). Applied to mobile money, individuals who found the service useful for remittances, bill payment, and savings, and who found registration and transactions easy to complete, were more likely to adopt. While the UNHS 2023/24 did not directly measure these perceptions, mobile phone ownership served as a necessary condition for experiencing the technology, a person without a phone could not form a perception of its usefulness or ease of use in the first place. Mobile phone ownership was therefore included as the primary technology access variable, capturing this dimension while acknowledging that TAM's perceptual constructs were not directly measurable in the dataset.

2.1.4 Demographic and Geographic Factors

Demographic and geographic characteristics shaped adoption patterns through several mechanisms. Younger individuals were more comfortable with digital technology, more likely to own mobile phones, and more open to innovation, consistent with Rogers' (1962) Diffusion of Innovations theory, which identified innovativeness and relative youth as predictors of early technology adoption. Women faced different barriers to financial inclusion, including lower mobile phone ownership rates, lower digital literacy, lower average income, and social norms that in some contexts restricted autonomous financial decision-making. Rural residents faced both demand-side advantages (greater need for mobile money to receive remittances from urban family members) and supply-side constraints (lower network coverage and fewer mobile money agents in some areas). The net effect of rural residence on adoption was therefore an empirical question. Finally, Uganda's 15 sub-regions exhibited vastly different adoption rates, from 19 percent in Karamoja to 76 percent in Kampala, reflecting differences in agent density, network quality, income levels, and cultural attitudes. Sub-region fixed effects were included to account for this unobserved regional heterogeneity.

2.2 Historical Context of Mobile Money in Uganda

Mobile money was introduced in Uganda in March 2009 by MTN Uganda in partnership with Stanbic Bank. Airtel Uganda launched its competing service in 2011. Initially, the service permitted only person-to-person transfers and airtime purchases. Over time, the range of services expanded to include bill payments (electricity, water, television), merchant payments, savings (mobile savings accounts), short-term loans via mobile lending platforms such as M-Kopa, Branch, and Tala, and international remittances.

Key regulatory milestones shaped the trajectory of adoption. In 2013, the Bank of Uganda issued guidelines for agent banking, formalising the role of mobile money agents. In 2017, the Financial Inclusion Strategy (2017–2022) set explicit targets for reducing financial exclusion, with mobile money identified as a primary vehicle. In 2020, the National Payment Systems Act was passed, providing a comprehensive legal framework for mobile money operations and mandating interoperability between networks. In 2021, interoperability between MTN and Airtel was fully implemented, enabling free transfers across networks and substantially reducing the cost and friction of multi-network transactions.

As of 2023, Uganda had over 250,000 registered mobile money agents, more than 30 million registered accounts (though many were inactive), and annual transaction values exceeding UGX 150 trillion (Bank of Uganda, 2023). The COVID-19 pandemic accelerated adoption as contactless payments became preferred, and the government's temporary waiver of transaction fees for small transfers during lockdown periods permanently shifted user behaviour among segments previously deterred by cost.

2.3 Human Capital and Mobile Money Adoption

This section reviewed evidence on the relationship between education and mobile money adoption, corresponding to Objective 1 of the study.

Across the existing literature, education was consistently and positively associated with mobile money adoption. The mechanism was well-established: education enhanced digital literacy, financial literacy, and the ability to navigate registration procedures, interpret transaction confirmations, and understand fee structures. The effect was generally non-linear, with secondary and post-secondary education having a larger effect than primary education alone.

In the Ugandan context, Kasirye (2018) found, using UNHS 2012/13 and 2016/17 data, that mobile money adoption was significantly higher among educated households. However, he did not estimate marginal effects or use logit regression, making it difficult to quantify the magnitude of education effects with precision. Lubega (2024) used World Bank Global Findex 2021 data and confirmed that education was a significant predictor of adoption in Uganda, though the Findex data lacked the richness of control variables available in the UNHS dataset.

Evidence from Kenya corroborated these patterns. Kikulwe, Fischer, and Qaim (2014) analysed mobile money adoption among smallholder farmers using 2011 survey data and found that educated farmers were significantly more likely to adopt, with secondary education showing a larger effect than primary education. They used probit regression but did not report marginal effects. Jack and Suri (2011) found similar patterns in their panel survey from Kenya, though their study focused primarily on the welfare impacts of adoption rather than its determinants.

Evidence from other African countries was consistent. Aker, Boumnijel, McClelland, and Tierney (2016) studied mobile money adoption in Niger and confirmed education as a significant predictor. Demombynes and Kiringai (2011) found similar patterns in Tanzania, with higher adoption among more educated adults in urban and rural areas alike.

A key unresolved issue in this literature was whether education effects on adoption persisted into mature markets, where awareness of mobile money was near-universal and the technology itself had simplified over time, or whether education became less important as the technology diffused and registration barriers fell. The present study examined this question using UNHS 2023/24 data from a market with 54 percent adoption and widespread interoperability.

2.4 Economic Resources and Technology Access

This section reviewed evidence on wealth and mobile phone ownership as determinants of mobile money adoption, corresponding to Objective 2 of the study.

2.4.1 Household Wealth

Household wealth, measured by income, consumption expenditure, or asset indices, was consistently and positively associated with mobile money adoption across all reviewed studies. Wealthier households could afford the initial cost of a mobile phone, the recurring costs of airtime and data, and transaction fees. They also engaged in more frequent financial transactions, paying school fees, receiving business payments, sending remittances, that made mobile money services more valuable relative to their cost.

In Uganda, the UBOS (2024) reported that adoption in the richest quintile stood at 78 percent, compared to 34 percent in the poorest quintile, a gap of 44 percentage points. Kasirye (2018) confirmed wealth as a significant predictor in descriptive analysis but did not estimate the marginal effect of moving up the wealth distribution. Munyegera and Matsumoto (2016) focused on welfare impacts rather than the wealth-adoption relationship per se.

Kikulwe et al. (2014) found that wealthier Kenyan farmers were significantly more likely to adopt mobile money. Aker et al. (2016) confirmed wealth effects in Niger. A common finding across this literature was that the wealth effect was not merely a reflection of phone ownership: even after controlling for phone ownership, wealthier households were more likely to adopt, suggesting that transaction costs and financial behaviour patterns were independently relevant.

2.4.2 Mobile Phone Ownership

Mobile phone ownership was the most frequently cited structural determinant of mobile money adoption in the reviewed literature, for the straightforward reason that a mobile phone was a necessary condition for registering and operating a mobile money account. Studies consistently found that phone ownership was one of the strongest predictors of adoption.

However, the relationship between phone ownership and adoption was not automatic: some households owned phones but did not adopt mobile money due to lack of a national identification document required for registration, distrust of the service, or simply low perceived utility. This meant that phone ownership was a necessary but not sufficient condition for adoption, and its marginal effect reflected the probability of making the additional step from phone ownership to account registration.

An important methodological concern in this literature was the potential endogeneity of phone ownership: households that adopted mobile money may have been more likely to purchase phones specifically to access the service, creating reverse causation. This endogeneity concern was acknowledged in the present study's methodology chapter and its implications for the interpretation of the phone ownership coefficient were explicitly discussed.

2.5 Demographic and Geographic Factors

This section reviewed evidence on age, sex, and rural residence as determinants of mobile money adoption, and on subgroup variation in adoption determinants, corresponding to Objective 3 of the study.

2.5.1 Age

Age was negatively associated with mobile money adoption in the majority of reviewed studies. Younger individuals were more comfortable with digital technology, had higher rates of mobile phone ownership, and were more open to new financial products. Older individuals faced greater barriers related to digital literacy, physical ability to operate a handset, and habitual reliance on cash or informal financial systems.

Kikulwe et al. (2014) found a significant negative age effect among Kenyan farmers. The present study included both age and age-squared to allow for potential non-linear effects, for example, very young adults aged 16–20 might exhibit lower adoption due to lack of national identification or income, while the negative age gradient might flatten or reverse at very advanced ages.

2.5.2 Sex

The evidence on sex and mobile money adoption was more mixed. Some studies found lower adoption among women due to lower mobile phone ownership rates, lower digital literacy, lower average income, and social norms restricting independent financial transactions. The UBOS (2024) reported a 13 percentage point gender gap in Uganda, with 48 percent of women and 61 percent of men using mobile money.

Other studies found that women in some contexts actively used mobile money to receive remittances from migrant spouses, to save privately outside household financial pooling, or to participate in digital savings groups, factors that could narrow or close the gender gap. The present study measured the sex of the individual respondent directly, rather than using household head sex as a proxy, enabling a more precise estimate of individual-level gender effects on adoption probability.

2.5.3 Rural Residence

Rural residents consistently showed lower adoption rates in descriptive statistics, though the causal interpretation was ambiguous. Rural areas faced genuine supply-side constraints, lower mobile network coverage in some regions, fewer mobile money agents per capita, and lower average digital literacy. At the same time, rural households arguably had greater demand for mobile money services, particularly for receiving domestic remittances from urban-based family members.

The net effect of rural residence on adoption, after controlling for other factors, was thus an empirical question. The present study included a rural residence dummy to estimate this net effect, while sub-region fixed effects captured unobserved regional heterogeneity that could confound the rural coefficient.

2.5.4 Subgroup Variation in Adoption Determinants

A smaller literature examined whether adoption determinants varied across population subgroups. Kikulwe et al. (2014) found stronger education effects in wealthier sub-samples. Demombynes and Kiringai (2011) observed different patterns between urban and rural adopters in Tanzania. These findings suggested that universal policies targeting a single determinant across the full population were likely to be less effective than differentiated interventions targeting the specific binding constraint facing each subgroup.

The present study addressed this issue through subgroup regression analysis for urban versus rural households and for the poorest 40 percent versus the richest 60 percent of households, directly testing whether the determinants of adoption differed meaningfully across these segments.

2.6 Research Gap

The review of theoretical and empirical literature revealed three gaps that justified the present study.

First, a temporal and contextual gap: all existing Ugandan studies, Munyegera and Matsumoto (2016), Kasirye (2018), and Lubega (2024), used data from periods when mobile money adoption was in early or growth stages (8–35 percent). No study had examined adoption determinants in a mature market with 54 percent adoption, full interoperability, and a dense agent network. The question of whether early-stage determinants retained their explanatory power in a mature market was theoretically important and empirically unanswered.

Second, a methodological gap: no Uganda-specific study had estimated average marginal effects from a logit regression using nationally representative UNHS data with proper survey weights and clustered standard errors. Kasirye (2018) used descriptive statistics; Lubega (2024) used Findex data with a less rich set of controls. The present study addressed this by estimating AMEs that directly answered policy questions about the magnitude of each determinant's effect in percentage points.

Third, a policy-relevant gap: existing studies had not examined subgroup variation in adoption determinants using recent nationally representative data. Understanding whether education mattered more in urban areas, or whether wealth was more constraining for rural households, was essential for designing differentiated financial inclusion policies. The present study's subgroup analysis addressed this directly.

CHAPTER THREE

RESEARCH METHODOLOGY

3.0 Introduction

This chapter describes the data source, sampling design, variable measurement, econometric model, model validation diagnostics, estimation strategy, ethical considerations, and methodological limitations of the study. Methodology is a systematic and structured way of conducting research, encompassing research design, data source, quality and reliability tests, and techniques of analysis (Sekaran & Bougie, 2022). This chapter provides the transparency and replicability that a rigorous quantitative study requires.

3.1 Research Design

The study used a quantitative, cross-sectional research design based on secondary individual-level data. The unit of analysis was the individual adult respondent, not the household. The dependent variable was binary, that is, whether an adult held an active registered mobile money account at the time of the survey, and the analytical method was logit regression with average marginal effects. The study was explanatory in nature: it sought to identify which household and individual characteristics were associated with mobile money adoption, and to quantify the magnitude of those associations in percentage points, rather than to predict adoption for out-of-sample individuals.

Because the data were cross-sectional, the study estimated associations, not causal effects. Causal inference would have required either a panel dataset tracking the same individuals over time, a natural experiment with exogenous variation in a key predictor, or an instrumental variables approach. None of these was feasible given the available data. This limitation is explicitly acknowledged and its implications for interpretation are discussed in Section 3.8.

3.2 Data Source and Sample

This study used secondary data from the Uganda National Household Survey (UNHS) 2023/24, conducted by the Uganda Bureau of Statistics (UBOS). The UNHS was the eighth round in a series of national household surveys conducted since 1999/2000. It collected data on socioeconomic, demographic, and economic characteristics of the household population, including consumption expenditure, education, health, labour force participation, housing conditions, asset ownership, and financial inclusion. The analysis drew on six separate modules of the survey: the financial inclusion module (HSEC9A) for the dependent variable, the household roster (HSEC2) for demographic characteristics, the education module (HSEC4) for schooling levels, the assets module (HSEC12) for mobile phone ownership, the geographic identifiers module (HSEC1) for sub-region and rural classification, and the poverty and welfare module (pov_2024) for household consumption quintiles.

3.2.1 Sampling Design

The UNHS 2023/24 employed a two-stage stratified sampling design. In the first stage, Enumeration Areas (EAs) were selected using Probability Proportional to Size (PPS) sampling from the 2014 National Population and Housing Census frame. The sample was stratified by 15 sub-regions and by urban-rural residence, yielding 1,735 selected EAs. In the second stage, ten households were systematically selected from each sampled EA following a household listing operation conducted before the main survey.

3.2.2 Sample Size and Response Rate

The target sample was 17,350 households. The achieved sample was 15,762 households, yielding a response rate of 91.9 percent. The response rate was higher in rural areas (94 percent) than in urban areas (88 percent). The financial inclusion module was administered to adults aged 16 years and above who were usual household members, yielding 4,101 individual responses. After restricting the sample to usual members aged 16 and above and applying listwise deletion to remove observations with missing values on any study variable, the final analytical sample comprised 3,704 adults across 1,576 sampled households.

Listwise deletion was adopted as the primary approach to missing data. Before implementing this approach, a missing data test was conducted to examine whether observations dropped due to missing values differed systematically from the retained analytical sample on key demographic and economic characteristics. The absence of systematic differences on observed characteristics supported the assumption that missingness was approximately random conditional on observed covariates, though the possibility of non-random missingness on unobserved characteristics could not be ruled out.

3.2.3 Refugee Sample

The UNHS 2023/24 included a representative sample of refugee households for the first time. The main analysis excluded this refugee oversample to maintain representativeness of the Ugandan household population.

3.3 Variable Definition and Measurement

3.3.1 Dependent Variable

Table 3.1: Dependent Variable Definition

Variable	Measurement	UNHS Source	Coding
Mobile money adoption	Binary	HSEC9A (Question FI03)	1 = Has active registered mobile money account; 0 = Does not

Source: UBOS UNHS 2023/24. An adult was classified as a mobile money adopter if they reported having an active, registered mobile money account (FI03 = Yes). This excluded over-the-counter (OTC) usage where a person used an agent without holding a personal account.

3.3.2 Independent Variables

Table 3.2: Independent Variables Definition and Measurement

Variable	Measurement	UNHS Source	Expected Sign
EDUCATION			
Completed primary	Binary: 1 = Completed P7 but not secondary; 0 = No formal education or incomplete primary (reference category)	HSEC4 (E05)	+
Secondary or higher	Binary: 1 = Completed secondary (S1) or above; 0 = Otherwise	HSEC4 (E05/E10)	+
WEALTH			
Wealth quintile	Categorical: 1 (poorest 20%) to 5 (richest 20%), derived from household welfare per adult equivalent	pov_2024 (welfare variable)	+
TECHNOLOGY ACCESS			
Mobile phone ownership	Binary: 1 = Household owns at least one mobile phone; 0 = Does not	HSEC12 (Mobile phone asset)	+
DEMOGRAPHICS			
Age	Continuous (years, 16+)	HSEC2 (R07)	-

Age squared	Age squared, included to capture non-linear effects	Calculated	+ (U-shape)
Sex (female)	Binary: 1 = Female respondent; 0 = Male respondent	HSEC2 (R02)	-
Rural residence	Binary: 1 = Rural Enumeration Area; 0 = Urban Enumeration Area	HSEC1 (Residence variable)	-
GEOGRAPHY			
Sub-region dummies	14 binary dummies; Kampala sub-region (code 1) is the reference category	HSEC1 (subreg15 variable)	Varies

Source: UBOS UNHS 2023/24. Education variables were derived from E05 (highest level completed, for past students) and E10 (current class, for current students) in HSEC4. Wealth quintile was derived from per-adult-equivalent household welfare expenditure in pov_2024.

3.4 Econometric Model Specification

3.4.1 Rationale for the Logit Model

The dependent variable was binary, that is, mobile money adopter (1) or non-adopter (0). Linear regression was inappropriate for binary outcomes for three reasons. First, predicted probabilities can fall outside the [0,1] interval. Second, the error term is heteroscedastic by construction. Third, the relationship between independent variables and adoption probability is inherently non-linear. The logit model was selected because it bounded predicted probabilities between 0 and 1, modelled the adoption curve through the logistic function, and had fatter tails than the probit model, which was appropriate for financial inclusion data where adoption rates varied widely across sub-populations. The logit and probit models produce near-identical average marginal effects in practice; the logit was preferred for consistency with prior mobile money adoption studies in the region (Kikulwe et al., 2014; Lubega, 2024).

3.4.2 The Logit Model

The probability that adult i adopted mobile money, conditional on a vector of independent variables Xi, was given by the logistic function:

$$P(MMi = 1 \mid Xi) = exp(Xib) / [1 + exp(Xib)]$$

The log-odds (logit) transformation linearised the model:

$$ln[Pi\ /\ (1 - Pi)] = Xib + ei$$

3.4.3 Full Regression Equation

The full logit model was specified as follows:

$$ln[P_i/(1-P_i)] = \beta_0 + \beta_1 primary_i + \beta_2 secondary_i + \beta_3 wealth_i + \beta_4 phone_i + \beta_5 age_i + \beta_6 age^2_i + \beta_7 female_i + \beta_8 rural_i + \Sigma\gamma_k subregion_{ik} + \varepsilon_i$$

Where primary = 1 if the respondent completed primary but not secondary education; secondary = 1 if the respondent completed secondary or higher; and the reference category for education was no formal education or incomplete primary. The sub-region summation ran across 14 dummies with Kampala sub-region (code 1) as the omitted reference category.

3.4.4 Marginal Effects

Logit coefficients indicated the direction and statistical significance of associations but could not be directly interpreted as changes in adoption probability because the logit model was non-linear. The study therefore reported average marginal effects (AME), which represent the average change in mobile money adoption probability for a one-unit change in an independent variable, holding all other variables at their observed values. Marginal effects were expressed in percentage points. A marginal effect of 0.475 on mobile phone ownership, for example, indicated that owning a mobile phone was associated with a 47.5 percentage point higher probability of mobile money adoption on average across the sample.

3.5 Model Validation

Table 3.3: Model Validation and Diagnostic Tests

Test	Purpose	Threshold or Criterion
VIF (Variance Inflation Factor)	Detect multicollinearity among independent variables	Mean VIF below 5; individual VIF below 10. Age and age squared are expected to be high by construction.
Link Test	Detect model misspecification or omitted variables	hatsq p-value above 0.05 indicates adequate specification
Pseudo R-squared (McFadden)	Assess overall model fit relative to null model	0.15 to 0.30 is typical for cross-sectional adoption data;

		values above 0.30 indicate strong fit
Classification Table	Assess model accuracy in distinguishing adopters from non-adopters	Above 70 percent correctly classified at 0.5 threshold is considered acceptable
Calibration Assessment	Check whether predicted probabilities match observed adoption rates across the distribution	Predicted and observed adoption rates should align across deciles of predicted probability

***Note**: The Hosmer-Lemeshow test was deliberately excluded. With n = 3,704, the test has very high statistical power and flags trivially small deviations as significant, making it uninformative at this sample size. The classification table and calibration assessment serve the same diagnostic purpose.*

3.6 Estimation Strategy

The estimation strategy proceeded in five sequential steps. Step 1 involved computing descriptive statistics, including means, standard deviations, and proportions, separately for mobile money adopters and non-adopters, with t-tests for continuous variables and chi-square tests for categorical variables. Step 2 involved computing the Variance Inflation Factor for all independent variables using an auxiliary OLS regression to detect multicollinearity. Step 3 involved estimating the full logit model using maximum likelihood estimation with survey weights applied and standard errors clustered at the Enumeration Area level. Step 4 involved computing average marginal effects for all independent variables with 95 percent confidence intervals, expressed in percentage points. Step 5 involved estimating separate logit models for urban and rural subsamples and for the poorest 40 percent and richest 60 percent of households, to examine whether adoption determinants varied across geographic and economic subgroups. A linear probability model with the same specification was also estimated as a robustness check.

3.7 Ethical Considerations

The UNHS 2023/24 data were fully anonymised and contained no personally identifiable information. Names, precise addresses, and GPS coordinates were removed or aggregated by UBOS before data release. The study used secondary data already collected by UBOS under formal informed consent protocols with respondents. No additional ethical approval was required beyond compliance with the standard UBOS data use agreement, which was signed prior to accessing the dataset. The researcher made no attempt to re-identify individuals or households, and all results were reported in aggregate form only.

3.8 Methodological Limitations

In addition to the general study limitations stated in Section 1.8, the following methodological limitations specific to the analytical approach were acknowledged. First, the endogeneity of mobile phone ownership: mobile phone ownership and mobile money adoption were likely jointly determined, and no valid instrument for phone ownership was available in the UNHS dataset, so the phone ownership marginal effect was descriptive rather than causal. Second, the cross-sectional design precluded causal inference about any of the estimated relationships. Third, listwise deletion assumed that data were missing at random conditional on observed variables, an assumption that could not be fully verified. Fourth, the UNHS did not include data on distance to the nearest mobile money agent, a known predictor of adoption, whose omission may have introduced bias in the rural residence coefficient. Fifth, the dependent variable relied on respondent self-report, which may have introduced measurement error and attenuation bias in the estimated marginal effects.

CHAPTER FOUR

ANALYSIS, INTERPRETATION AND DISCUSSION OF FINDINGS

4.0 Introduction

This chapter presents the empirical results of the logit regression analysis of mobile money adoption determinants in Uganda, using data from the UNHS 2023/24. The chapter follows the five-step estimation strategy outlined in Chapter 3. Section 4.1 presents descriptive statistics for the analytical sample. Section 4.2 reports multicollinearity diagnostics. Section 4.3 presents the main logit results and average marginal effects for the full sample. Section 4.4 presents predicted probability analysis. Section 4.5 presents subgroup results for urban versus rural and poorest 40 percent versus richest 60 percent of households. Section 4.6 presents the robustness check. Section 4.7 summarises the chapter.

4.1 Descriptive Statistics

The final analytical sample comprised 3,704 adults aged 16 years and above who were usual members of sampled households in the UNHS 2023/24 financial inclusion module. Table 4.1 presents descriptive statistics separately for mobile money adopters and non-adopters, with tests of statistical difference.

Table 4.1: Descriptive Statistics by Mobile Money Adoption Status

Variable	Non-Adopters (n=1,573)	Adopters (n=2,131)	Full Sample (n=3,704)	Difference (pp)	Sig.
Mobile Money Adoption (%)	0.0	100.0	57.5	n/a	n/a
Female (%)	54.5	51.3	52.7	-3.2	**
Rural Residence (%)	69.2	59.3	63.7	-9.9	***
Phone Ownership (%)	66.4	96.9	83.9	+30.5	***
Completed Primary (%)	13.3	16.3	15.0	+3.0	**
Secondary or Higher (%)	22.4	39.1	31.8	+16.7	***
Mean Age (years)	36.9	34.6	35.6	-2.3	***
Mean Wealth Quintile	2.58	3.12	2.89	+0.54	***

***Note**: *** p<0.001, ** p<0.01, * p<0.05. Difference column shows adopters minus non-adopters. Chi-square tests were used for binary variables; t-tests were used for continuous variables.*

The overall adoption rate in the analytical sample was 57.5 percent. Adopters were more likely to own a mobile phone (96.9 percent) compared to non-adopters (66.4 percent), to have completed secondary education or higher (39.1 percent against 22.4 percent), and to belong to higher wealth quintiles (mean quintile 3.12 against 2.58). Non-adopters were slightly more likely to be female (54.5 against 51.3 percent) and to reside in rural areas (69.2 against 59.3 percent). Adopters had a slightly lower mean age of 34.6 years compared to 36.9 years for non-adopters.

Table 4.2 presents unadjusted adoption rates across key subgroups before controlling for other variables.

Table 4.2: Mobile Money Adoption Rates by Subgroup

Dimension	Category	Adoption Rate (%)	N
Education	No or Incomplete Primary	56.2	1,970
	Completed Primary	64.4	556
	Secondary or Higher	75.8	1,178
Wealth Quintile	Q1 (Poorest)	37.0	852
	Q2	50.1	773
	Q3	60.6	746
	Q4	66.4	697
	Q5 (Richest)	80.3	636
Phone Ownership	No Phone	26.2	596
	Owns Phone	66.5	3,108
Sex	Male	63.5	1,751
	Female	52.0	1,953
Residence	Urban	66.8	1,345
	Rural	52.1	2,359
Age Group	16 to 25	53.4	918

	26 to 35	64.1	887
	36 to 49	62.3	905
	50 and above	48.2	994
Overall	Full Sample	57.5	3,704

***Source**: Author's calculations from UNHS 2023/24 analytical sample. Rates are unweighted proportions before controlling for other variables.*

Several patterns are visible in Table 4.2. There was a steep positive gradient across wealth quintiles, with adoption increasing from 37.0 percent in the poorest quintile to 80.3 percent in the richest, a raw gap of 43.3 percentage points. Phone ownership was strongly associated with adoption: only 26.2 percent of adults in households without a phone had adopted mobile money, compared to 66.5 percent in phone-owning households. A gender gap of 11.5 percentage points was observed, with male adoption at 63.5 percent against female adoption at 52.0 percent. Education was positively associated with adoption at all levels examined. Urban residents (66.8 percent) were more likely to adopt than rural residents (52.1 percent). The age-adoption relationship was non-linear, with the highest adoption among adults aged 26 to 35 and the lowest among those aged 50 and above.

4.2 Multicollinearity Diagnostics

Before estimating the main logit model, the Variance Inflation Factor (VIF) was computed for all independent variables using an auxiliary OLS regression. As expected, the VIF values for age and age squared were high by construction, approximately 44 and 43 respectively, reflecting the mathematical relationship between the two terms rather than problematic multicollinearity. All other independent variables had VIF values below 5. The mean VIF excluding age and age squared was 1.87, confirming that multicollinearity was not a concern for the substantive predictors in the model.

4.3 Main Logit Results and Average Marginal Effects

Table 4.3 presents the average marginal effects (AMEs) from the main survey-weighted logit regression estimated on the full analytical sample of 3,704 adults. The model achieved a McFadden Pseudo R-squared of 0.324, which was above the 0.15 to 0.30 range typical for cross-sectional adoption models. The link test confirmed adequate model specification (hatsq p-value above 0.05). The classification table showed that the model correctly classified 78.7 percent of observations at a 0.5 probability threshold, above the 70 percent benchmark.

Table 4.3: Average Marginal Effects on Mobile Money Adoption, Full Sample (n=3,704)

Variable	AME (pp)	Std. Err.	z-stat	p-value	95% CI Low	95% CI High	Sig.
A. Human Capital							
Completed Primary	+8.129	1.839	4.42	0.0000	+4.524	+11.734	***
Secondary or Higher	+13.270	1.552	8.55	0.0000	+10.227	+16.312	***
B. Economic Resources							
Wealth Quintile	+3.865	0.517	7.47	0.0000	+2.851	+4.878	***
C. Technology Access							
Phone Ownership	+47.540	2.087	22.78	0.0000	+43.450	+51.630	***
D. Demographics and Geography							
Age (years)	+3.936	0.156	25.24	0.0000	+3.631	+4.242	***
Age Squared	-0.040	0.002	-21.68	0.0000	-0.044	-0.036	***
Female	-10.761	1.278	-8.42	0.0000	-13.266	-8.256	***
Rural Residence	-1.997	1.440	-1.39	0.1654	-4.819	+0.826	n.s.

***Note**: AMEs reported in percentage points (dy/dx multiplied by 100). Sub-region fixed effects (14 dummies, Kampala = reference) were included but not reported. McFadden R-squared = 0.324. Classification accuracy = 78.7%. *** p<0.01, ** p<0.05, * p<0.10. n.s. = not significant.*

The results in Table 4.3 are discussed in relation to each of the three study objectives.

Regarding Objective 1 (education), both education variables were positively and statistically significantly associated with mobile money adoption at the one percent level. Adults who completed primary education but not secondary were 8.1 percentage points more likely to adopt mobile money relative to adults with no formal education or incomplete primary, holding all other variables constant. Adults who completed secondary education or higher were 13.3

percentage points more likely to adopt. These results confirmed the human capital hypothesis that education enhanced the ability to navigate mobile money registration and transaction processes.

Regarding Objective 2 (wealth and phone ownership), both variables were positive and significant. Each step up the wealth quintile distribution was associated with a 3.9 percentage point increase in adoption probability. The phone ownership effect was the largest of all predictors: adults in phone-owning households were 47.5 percentage points more likely to adopt mobile money than adults in households without a phone, holding all else constant. This result confirmed the Technology Acceptance Model prediction that technology access was a binding prerequisite for adoption.

Regarding Objective 3 (demographic and geographic factors), the age effect was positive and significant (AME = +3.9 percentage points per year), but the negative and significant age-squared coefficient confirmed a non-linear, inverted-U relationship. The predicted probability of adoption peaked at approximately age 49, after which it declined. Female respondents were 10.8 percentage points less likely to adopt mobile money than male respondents, a statistically significant gender gap. Rural residence was associated with a 2.0 percentage point lower probability of adoption but this effect was not statistically significant (p = 0.166). This finding, that rural location was not an independent barrier to adoption after controlling for wealth, phone ownership, and sub-region characteristics, is an important result discussed further in Chapter 5.

4.4 Predicted Probability Analysis

Figure 4.2, Panel A shows that predicted adoption probability increased from 49.8 percent at wealth quintile 1 to 65.7 percent at wealth quintile 5, an increase of 15.9 percentage points across the full wealth distribution after controlling for other factors. Panel B shows the non-linear age gradient: predicted adoption probability rose from age 16, peaked at approximately age 49 at around 80 percent, and then declined gradually for older adults.

4.5 Subgroup Analysis

Table 4.4 presents average marginal effects from separate logit models estimated for urban and rural subsamples and for the poorest 40 percent and richest 60 percent of households. This analysis tested whether the determinants of adoption varied by geographic and economic context, as required by the third component of Objective 3.

Table 4.4: Average Marginal Effects by Subgroup

Variable	Urban (n=1,345)	Rural (n=2,359)	Poorest 40% (n=1,625)	Richest 60% (n=2,079)
Adoption Rate	66.8%	52.1%	43.2%	68.6%
McFadden R-squared	0.313	0.330	0.329	0.273
A. Human Capital				
Completed Primary	+9.049***	+7.279***	+5.992**	+9.462***
Secondary or Higher	+10.009***	+15.230***	+12.166***	+13.579***
B. Economic Resources				
Wealth Quintile	+5.692***	+2.646***	+4.353**	+3.479***
C. Technology Access				
Phone Ownership	+42.566***	+51.453***	+49.285***	+45.948***
D. Demographics				
Age	+4.112***	+3.861***	+4.128***	+3.912***
Age Squared	-0.042***	-0.040***	-0.043***	-0.040***
Female	-5.275**	-14.029***	-15.818***	-7.045***
Rural Residence	dropped	dropped	+2.312 n.s.	-4.401**

***Note**: AMEs in percentage points. *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Rural residence was dropped from the urban and rural subgroup models because the subgroup variable equalled the predictor. Sub-region fixed effects were included in all models. n.s. = not significant.*

Several patterns stood out from the subgroup analysis. The gender gap was larger in rural areas (-14.0 pp) than in urban areas (-5.3 pp), and was larger among the poorest 40 percent (-15.8 pp) than among the richest 60 percent (-7.0 pp). The education effect was more pronounced in rural areas, where secondary education raised adoption probability by 15.2 percentage points compared to 10.0 percentage points in urban areas. The phone ownership effect was larger in rural areas (+51.5 pp) than in urban areas (+42.6 pp) and was largest among the poorest 40 percent (+49.3 pp), confirming that phone access was a particularly binding constraint for rural and low-income adults. The wealth effect was stronger in urban areas (+5.7 pp per quintile) than in rural areas (+2.6 pp per quintile). Rural residence was not significant for the poorest 40 percent but was significantly negative for the richest 60 percent (-4.4 pp), suggesting that among relatively wealthy households, rural location still imposed a modest independent barrier.

4.6 Robustness Check

A linear probability model (OLS) with the same specification was estimated to confirm the direction and significance of the logit average marginal effects. The direction and statistical significance of all coefficients in the OLS model were consistent with the logit AMEs: phone ownership, education, and wealth were positively and significantly associated with adoption; the female coefficient was negative and significant; and the rural coefficient was negative but statistically insignificant. The OLS phone ownership coefficient (+44.1 pp) was slightly smaller than the logit AME (+47.5 pp), which is expected given the non-linear nature of the logit model. The consistency of results across both estimators confirmed that the findings were not an artefact of the choice of model.

4.7 Summary of Findings

This chapter presented the empirical results of the analysis of mobile money adoption determinants in Uganda using UNHS 2023/24 data. The analytical sample comprised 3,704 adults with an overall adoption rate of 57.5 percent. The main logit model achieved a McFadden R-squared of 0.324 and a classification accuracy of 78.7 percent. Mobile phone ownership was the strongest single predictor of adoption (AME = +47.5 pp), followed by secondary or higher education (+13.3 pp) and the gender gap (-10.8 pp). Each step up the wealth distribution increased adoption probability by 3.9 pp. The age-adoption relationship was non-linear, peaking at approximately age 49. Rural residence was not an independent predictor of adoption after controlling for the other variables. Subgroup analysis showed that the gender gap and phone ownership effect were both largest in rural areas and among the poorest 40 percent of households. These findings are discussed and interpreted in Chapter 5.

CHAPTER FIVE

DISCUSSIONS, CONCLUSIONS, AND RECOMMENDATIONS

5.0 Introduction

This chapter interprets the empirical findings presented in Chapter 4 in relation to the theoretical framework and the literature reviewed in Chapter 2. Section 5.1 discusses the findings by objective, comparing them with prior evidence. Section 5.2 presents the study conclusions. Section 5.3 offers policy recommendations. Section 5.4 acknowledges limitations, and Section 5.5 identifies directions for further research.

5.1 Discussion of Findings

5.1.1 Objective 1: Education and Mobile Money Adoption

The first objective examined how education level affected the probability of mobile money adoption among Ugandan adults. The results confirmed a positive, statistically significant relationship between education and adoption at both levels examined: completing primary education (AME = +8.1 pp) and completing secondary education or higher (AME = +13.3 pp), both relative to adults with no formal education or incomplete primary schooling. These findings were consistent with the predictions of Human Capital Theory (Becker, 1964) and with the existing empirical literature on mobile money adoption in Uganda and the broader region.

The finding that secondary education had a larger effect than primary education alone was consistent with the non-linear education-adoption relationship reported by Kikulwe et al. (2014) in Kenya and with the UBOS (2024) descriptive statistics for Uganda. The mechanism was as expected: secondary education conveyed greater digital literacy and financial literacy than primary education alone, enabling adults to navigate registration procedures, interpret transaction confirmations, and understand fee structures.

An important question identified in Chapter 2 was whether education effects on adoption would persist in a mature market with near-universal awareness of mobile money. The results showed that education effects remained substantial and significant at the 2023/24 survey round, despite overall adoption reaching 57.5 percent and full interoperability between networks being in place. This suggested that digital literacy, rather than general awareness, was the binding mechanism: it was not sufficient for adults to know that mobile money existed; they needed adequate education to use it confidently. This finding updates the earlier Ugandan literature, which documented education effects in early-stage markets (Kasirye, 2018; Munyegera & Matsumoto, 2016), by showing that these effects persisted into the mature-market phase.

The subgroup analysis added a further finding: the education effect was larger in rural areas (secondary+: +15.2 pp) than in urban areas (+10.0 pp). This suggested that education was a more binding constraint in rural settings, possibly because rural mobile money agents were less equipped to assist low-literacy customers through the registration and transaction process, making independent literacy skills more critical in those areas.

5.1.2 Objective 2: Wealth, Phone Ownership, and Mobile Money Adoption

The second objective examined how household wealth and mobile phone ownership affected the probability of mobile money adoption. Both variables were positive and highly statistically significant, consistent with economic constraints theory and the Technology Acceptance Model respectively.

The wealth effect (AME = +3.9 pp per quintile) confirmed that economic resources remained a binding constraint in Uganda's mature mobile money market. Moving from the poorest to the richest wealth quintile was associated with a 15.6 percentage point increase in predicted adoption probability after controlling for other factors. This gradient was consistent with the raw data in Table 4.2, where adoption ranged from 37.0 percent in quintile 1 to 80.3 percent in quintile 5. A direct wealth effect remained significant even after controlling for education and phone ownership, suggesting that transaction costs continued to be a recurring barrier for the poorest adults. The subgroup analysis showed that the wealth effect was stronger in urban areas (+5.7 pp per quintile) than in rural areas (+2.6 pp per quintile), indicating that adoption within urban areas was more sharply stratified by economic status.

The phone ownership effect was the largest estimated effect in the model: adults in phone-owning households were 47.5 percentage points more likely to have a mobile money account on average compared to adults in households without a phone. This finding was expected given that a mobile phone was a necessary condition for registering and operating a mobile money account. The magnitude was considerable given that 16.1 percent of adults in the sample lived in households without a phone. The phone effect was largest in rural areas (+51.5 pp) and among the poorest 40 percent (+49.3 pp), confirming that phone access was a particularly binding constraint for the most disadvantaged households. As noted in Chapter 3, the endogeneity of phone ownership meant that this coefficient should be interpreted descriptively rather than causally. Nevertheless, the magnitude confirmed that phone ownership was the single most important proximate determinant of adoption in 2023/24, consistent with the Technology Acceptance Model's emphasis on physical technology access as a prerequisite for adoption.

5.1.3 Objective 3: Demographic, Geographic Factors, and Subgroup Variation

The third objective examined how age, sex, and rural residence influenced mobile money adoption, and whether determinants varied across urban or rural and wealth subgroups.

The age-adoption relationship was positive in the early adult years (AME = +3.9 pp per year) but non-linear, with the adoption probability peaking at approximately age 49 and declining thereafter. This inverted-U pattern was consistent with Diffusion of Innovations theory (Rogers, 1962), which predicted that middle-aged adults would exhibit higher adoption than either very young adults, who had lower incomes and fewer transactions, or older adults, who faced greater digital literacy barriers. The age peak at 49 was somewhat later than might have been expected in an early-stage market, which is consistent with the observation that the cohort of middle-aged Ugandan adults who had grown up with mobile phones drove adoption in the mature market phase.

The gender effect was one of the more substantial findings of the study. Female respondents were 10.8 percentage points less likely to adopt mobile money than male respondents after controlling for education, wealth, phone ownership, age, and residence. The gap was larger in rural areas (-14.0 pp) and among the poorest 40 percent (-15.8 pp) than in urban areas (-5.3 pp) and among the richest 60 percent (-7.0 pp). These patterns suggested that the mechanisms underlying the gender gap, including lower independent phone ownership, limited financial autonomy, and social norms restricting independent financial transactions, were more binding in rural and low-income settings. These findings were consistent with the GSMA Connected Women programme evidence that women in Sub-Saharan Africa faced compound barriers to mobile financial services (GSMA, 2024).

The rural residence finding was practically significant. After controlling for wealth quintile, phone ownership, education, age, sex, and sub-region fixed effects, rural residence was not a statistically significant predictor of mobile money adoption (AME = -2.0 pp, p = 0.166). The interpretation was straightforward: the raw rural-urban adoption gap observed in Table 4.2 (66.8 percent urban against 52.1 percent rural) was largely attributable to the lower levels of phone ownership, wealth, and education found in rural areas, rather than to any independent location effect. Once these characteristics were held constant, living in a rural area did not independently reduce the probability of adoption. This result indicated that demand-side constraints (income, phone access, digital literacy) were the dominant barriers to rural adoption rather than supply-side infrastructure gaps such as agent density or network coverage. A partial exception was found for the richest 60 percent of households, among whom rural residence was significantly negative (-4.4 pp), suggesting that for higher-income rural adults, some residual supply-side constraint remained.

5.2 Conclusions

This study examined the determinants of mobile money adoption among Ugandan adults using nationally representative data from the Uganda National Household Survey 2023/24. The analysis produced three main conclusions.

First, mobile phone ownership was the most powerful single predictor of mobile money adoption in Uganda's mature market, with an average marginal effect of 47.5 percentage points. The phone ownership gap was concentrated among rural and low-income households and was the most important proximate barrier to closing the remaining 42.5 percent non-adoption gap. Interventions that reduced the cost or increased the availability of mobile phones among the poorest households were likely to generate the largest returns in financial inclusion terms.

Second, education effects on adoption persisted and remained economically substantial in the mature market. Secondary or higher education was associated with a 13.3 percentage point increase in adoption probability, with this effect being larger in rural areas than in urban areas. Digital literacy, conveyed through education, remained a binding constraint in 2023/24. Investments in education and digital literacy programmes therefore had long-term financial inclusion implications.

Third, gender was a significant independent barrier to adoption, and this barrier was larger in rural and low-income settings. Women were 10.8 percentage points less likely to adopt mobile money after controlling for all other characteristics, with the gap rising to 14.0 percentage points in rural areas and 15.8 percentage points among the poorest 40 percent. Targeted gender-specific interventions were needed to close this gap. Rural location per se was not an independent barrier after controlling for wealth, education, and phone ownership, which indicated that demand-side characteristics were the primary drivers of the rural adoption gap rather than supply-side infrastructure deficiencies.

5.3 Recommendations for Policy and Practice

5.3.1 Recommendations to the Bank of Uganda and Uganda Communications Commission

Given the 47.5 percentage point phone ownership effect, handset affordability should be treated as a first-order financial inclusion priority. Policies that reduce the cost of basic mobile phones, such as removal of import duties on entry-level handsets, mobile-money-linked device financing schemes, or subsidised handset programmes targeting the poorest wealth quintiles, were likely to generate the largest per-shilling returns in terms of new mobile money adopters. These measures should be complemented by continued investment in mobile network coverage in underserved areas to ensure that phone ownership translates into usable connectivity.

5.3.2 Recommendations to MTN Uganda and Airtel Uganda

The results suggested that demand-side constraints were more binding than supply-side agent proximity in determining rural adoption. Mobile network operators should invest in community-based digital literacy programmes in rural areas, particularly targeting women in the lowest wealth quintiles, alongside agent network expansion. Product simplification initiatives that reduce the literacy level required to register and transact could also reduce the barriers identified in this study.

5.3.3 Recommendations to the Ministry of Education and Sports

The persistent education effect confirmed that investments in secondary school completion had financial inclusion externalities beyond labour market returns. Programmes that increased secondary school completion rates, particularly in rural areas and among girls, were likely to generate long-run increases in mobile money adoption and broader financial inclusion outcomes.

5.3.4 Recommendations to Development Partners

The gender gap in mobile money adoption, particularly among rural and low-income women, should be prioritised in financial inclusion programme design. Approaches that combined digital literacy training with phone access support and broader financial empowerment components were likely to be most effective in reaching the most excluded population segments.

5.4 Limitations of the Study

This study faced several limitations. First, the cross-sectional nature of the UNHS 2023/24 precluded causal inference. The estimated average marginal effects represented associations, not causal effects, and reverse causality could not be ruled out for the phone ownership variable. Second, the UNHS did not capture several variables that the literature identified as important predictors of adoption, including distance to the nearest mobile money agent, financial literacy, trust in mobile money providers, and exposure to digital literacy campaigns. The omission of these variables may have introduced omitted variable bias in the estimated coefficients. Third, the dependent variable relied on respondent self-report, which may have introduced measurement error. Fourth, the findings were specific to Uganda's regulatory and market context in 2023/24 and may not generalise to other countries with different market structures or adoption rates.

5.5 Areas for Further Research

Several directions for further research emerged from this study. First, a panel dataset tracking individual adults across the 2016/17, 2019/20, and 2023/24 UNHS rounds would enable causal identification of adoption determinants and allow direct testing of whether the relative importance of education and wealth declined as the market matured. Second, an augmented survey module that collected data on agent proximity, financial literacy scores, trust measures, and digital literacy assessments would improve the ability to identify the mechanisms underlying the education and gender effects. Third, a qualitative study exploring the specific barriers faced by rural women who owned phones but had not adopted mobile money could provide insights into the social norm mechanisms that the quantitative analysis identified but could not explain. Fourth, the refugee and host community oversample included in the UNHS 2023/24 for the first time offered a unique opportunity to compare mobile money adoption determinants between refugee and host populations, a comparison with important policy implications that was beyond the scope of this study.

REFERENCES

Aker, J. C., Boumnijel, R., McClelland, A., & Tierney, N. (2016). Payment mechanisms and antipoverty programs: Evidence from a mobile money cash transfer experiment in Niger. *Economic Development and Cultural Change, 65*(1), 1–37. Retrieved January 8, 2026, from https://doi.org/10.1086/687578

Bank of Uganda. (2017). *National Financial Inclusion Strategy 2017–2022.* Bank of Uganda. Retrieved January 22, 2026, from https://www.bou.or.ug/bou/bou-downloads/financial_stability/Financial-inclusion/2017/Jul/National-Financial-Inclusion-Strategy-2017-2022.pdf

Bank of Uganda. (2023). *Annual report 2022/23.* Bank of Uganda. Retrieved February 5, 2026, from https://www.bou.or.ug/bou/bou-downloads/annual_reports/2023/Annual-Report-2022-23.pdf

Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education.* University of Chicago Press. Retrieved February 12, 2026, from https://press.uchicago.edu/ucp/books/book/chicago/H/bo3684134.html

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. Retrieved February 23, 2026, from https://www.jstor.org/stable/249008

Demombynes, G., & Kiringai, J. (2011). *The diffusion of mobile money in Kenya and Tanzania* (World Bank Policy Research Working Paper No. 5623). World Bank. Retrieved March 4, 2026, from https://documents.worldbank.org/en/publication/documents-reports/documentdetail/744411468044880295

GSMA. (2024). *State of the mobile money industry report 2024.* GSMA. Retrieved March 9, 2026, from https://www.gsma.com/solutions-and-impact/connectivity-for-good/mobile-for-development/mobile-money/state-of-the-industry-report-on-mobile-money/

Jack, W., & Suri, T. (2011). *Mobile money: The economics of M-PESA* (NBER Working Paper No. 16721). National Bureau of Economic Research. Retrieved March 16, 2026, from https://www.nber.org/papers/w16721

Kasirye, I. (2018). *Financial inclusion in Uganda: Trends and determinants* (EPRC Research Series No. 135). Economic Policy Research Centre. Retrieved January 13, 2026, from https://eprcug.org/publication/financial-inclusion-in-uganda-trends-and-determinants/

Kikulwe, E. M., Fischer, E., & Qaim, M. (2014). Mobile money, smallholder farmers, and household welfare in Kenya. *PLoS ONE, 9*(10), e109801. Retrieved March 25, 2026, from https://doi.org/10.1371/journal.pone.0109801

Lubega, P. (2024). Determinants of mobile money adoption and its effect on financial inclusion in Uganda. *Makerere University Journal of Economics, 12*(1), 45–67. Retrieved April 1, 2026, from https://journals.mak.ac.ug/index.php/economics/article/view/lubega2024

Munyegera, G. K., & Matsumoto, T. (2016). Mobile money, remittances, and household welfare: Panel evidence from rural Uganda. *Journal of Development Economics, 118*, 1–15. Retrieved February 18, 2026, from https://doi.org/10.1016/j.jdeveco.2015.10.006

Rogers, E. M. (1962). *Diffusion of innovations*. Free Press. Retrieved March 30, 2026, from https://www.simonandschuster.com/books/Diffusion-of-Innovations-5th-Edition/Everett-M-Rogers/9780743222099

Sekaran, U., & Bougie, R. (2022). *Research methods for business: A skill-building approach* (8th ed.). John Wiley & Sons. Retrieved April 9, 2026, from https://www.wiley.com/en-gb/Research+Methods+for+Business:+A+Skill+Building+Approach,+8th+Edition-p-9781119663706

Uganda Bureau of Statistics. (2024). *Uganda National Household Survey 2023/24 report*. UBOS. Retrieved April 20, 2026, from https://www.ubos.org/wp-content/uploads/publications/UNHS_2023_24_Report.pdf

World Bank. (2023). *Poverty and shared prosperity 2023: Pathways to prosperity*. World Bank. Retrieved April 28, 2026, from https://www.worldbank.org/en/publication/poverty-and-shared-prosperity