MAKERERE UNIVERSITY

DETERMINANTS OF LOW INSURANCE UPTAKE AMONG UGANDAN HOUSEHOLDS.

BY

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DECLARATION

I, AYEBALE JOANAH declare that to the best of my knowledge, this study is original and has not been submitted for any other degree award to this university or any other University for an academic award.

Signature ....AJL.......... Date..........18/08/2026..........

REG,. NO. 23/U/0335

APPROVAL

This proposal has been submitted for examination with the approval of the following supervisor:

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LIST OF ABBREVIATIONS

GDP: Gross Domestic Product

IRA: Insurance Regulatory Authority

FSDU: Financial Sector Deepening Uganda

OECD: Organisation for Economic Co-operation and Development

ID4D: Identification for Development Initiative

KYC: Know Your Customer

CGAP: Consultative Group to Assist the Poor

UBOS: Uganda Bureau of Statistics

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ABSTRACT

Despite modest growth in gross written premiums over the past decade, insurance penetration in Uganda remains below 1% of GDP, reflecting persistently low household uptake and a limited understanding of the demographic, socioeconomic and attitudinal factors that shape enrolment decisions. This study examined the determinants of low insurance uptake among Ugandan households, with specific objectives to assess the effects of demographic factors (age, place of residence and level of education), socioeconomic factors (income level and employment status) and attitudinal factors (insurance literacy and perceived trust) on insurance uptake. The study adopted a quantitative, cross-sectional design using secondary data from the nationally representative FinScope Uganda 2023 Survey. Data were analysed in three stages using STATA: univariate analysis to describe sample characteristics, bivariate analysis using a simple complementary log-log regression to test unadjusted associations between each independent variable and insurance uptake, and multivariate analysis using a multivariable complementary log-log model to test the study's hypotheses while controlling for other covariates. Only 2.61% of respondents held insurance. At the bivariate level, age, place of residence, education, employment status and income were all significantly associated with uptake. After adjustment, age lost significance, while place of residence, level of education, employment status (for paid employment and NPISH) and income level remained significant predictors, with income level and education emerging as the strongest and most consistent determinants. Insurance literacy and perceived trust could not be empirically tested because the available measures were observed only among the small number of respondents who already held a policy and had filed a claim. The study concludes that low insurance uptake among Ugandan households is primarily a demographic and socioeconomic phenomenon, driven mainly by affordability, education, place of residence and access to formal employment rather than age, and recommends affordability-focused product design, simplified consumer education, expanded rural distribution channels and workplace-linked group schemes for informal workers, alongside further research using data able to independently measure insurance literacy and trust

CHAPTER ONE

INTRODUCTION

1.0 Introduction

This chapter introduces the study on the determinants of low insurance uptake among Ugandan households. It presents the background to the study, problem statement, objectives, hypotheses, conceptual framework, scope and significance of the study. The chapter sets the stage for understanding why, despite the recorded growth of Uganda's insurance industry in monetary terms, the proportion of households that actually purchase and hold insurance products remains persistently low.

1.1 Background to the study

Insurance is a mechanism that enables households to pool and transfer risk, thereby reducing vulnerability to income shocks arising from illness, accidents, death, or other adverse events. Globally, insurance penetration measured as total gross premiums as a share of GDP averages around 5-6%, though it is considerably higher in advanced economies where insurance is deeply embedded in the financial-protection architecture (IAIS, 2025; OECD, 2025). In contrast, Sub-Saharan Africa and East Africa continue to experience low insurance penetration, averaging only about 1.5-2.5% of GDP (Ministry of Finance, 2025b; OECD, 2026). Within East Africa, penetration is highest in Kenya at around 2.2%, and lowest in Tanzania and Uganda, both below 1% of GDP (Ministry of Finance, 2025b).

In Uganda specifically, household uptake of insurance products remains strikingly low, with penetration estimated at just 0.87% of GDP below the East African average and far short of global standards (Insurance Regulatory Authority, 2022; Ministry of Finance, 2025a). This persistently low uptake limits the ability of many Ugandan households to protect assets and smooth consumption against shocks such as illness, accidents or crop failure, particularly in rural and informal-sector settings (FSDU, 2018; Medard, Yawe, & Bosco, 2022). By contrast, demand-side household survey data shows that only 2% of adults personally hold a formal insurance policy in their own name, rising to approximately 5% when beneficiaries who are covered under someone else’s policy are included (FSD Uganda, 2024).

Understanding the determinants of low insurance uptake is therefore essential for designing effective interventions. Insight into the relative importance of factors such as income constraints, mistrust and lack of information can inform context-specific strategies to expand coverage, enhance financial inclusion and strengthen household resilience to shocks (FSDU, 2018; Ministry of Finance, 2025b). This study seeks to systematically examine the key determinants underlying low insurance uptake among Ugandan households, with a view to informing policy, regulatory and market-based reforms aimed at building a more inclusive and sustainable insurance ecosystem in Uganda.

1.2 Problem Statement

Insurance protects households from financial shocks such as; accidents, illness, business loss and property damage, improving economic resilience and long-term welfare (Akello, 2022; Bah M, 2022). Widespread coverage would support financial inclusion, reduce reliance on informal coping and strengthen broader economic stability (Akello, 2022; Bah M, 2022).

In practice however, insurance uptake among Ugandan households remains low, with insurance penetration; measured by premiums as a share of GDP still below 1%, despite modest growth in gross written premiums over the past decade (IRA, 2020, 2022). Barriers to insurance uptake have been linked to low trust in insurers, weak regulation and product designs that poorly match local risks and payment capacities (Akello, 2022; IRA, 2020, 2022). Even then, there is a limited understanding of the socio-economic, demographic and institutional factors that affect coverage.

This study seeks to examine the determinants of low insurance uptake among Ugandan households and generate evidence-based recommendations for improving insurance coverage and financial protection. The study will identify the demographic, socioeconomic and attitudinal factors limiting participation in insurance schemes and assess their influence on enrolment decisions. The findings will help policymakers, insurers and regulators design affordable and accessible insurance products, strengthen consumer awareness, improve regulatory frameworks and expand inclusive insurance coverage to enhance household resilience and sustainable economic development in Uganda.

1.3 Study Objectives

The main objective of the study was to examine the determinants of low insurance uptake among Ugandan households.

1.3.1 Specific Objectives

I. To assess the effect of demographic factors like age, place of residence and level of education on insurance uptake among Ugandan households.

II. To determine the influence of socioeconomic factors like income level and employment status on insurance uptake among Ugandan households.

III. To examine the effect of attitudinal factors like insurance literacy and perceived trust in insurance providers on household insurance uptake in Uganda.

1.4 Study Hypothesis

Objective One: To assess the effect of demographic factors like age, place of residence and level of education on insurance uptake among Ugandan households.

H11**:** There is no significant relationship between age and insurance uptake among Ugandan households.

H12: There is no significant relationship between place of residence and insurance uptake among Ugandan households.

H13: There is no significant relationship between level of education and insurance uptake among Ugandan households.

Objective Two: To determine the influence of socioeconomic factors like income level and employment status on insurance uptake among Ugandan households.

H21: There is no significant relationship between income and insurance uptake among Ugandan households.

H22: There is no significant relationship between employment status and insurance uptake among Ugandan households.

Objective Three: To examine the effect of attitudinal factors like insurance literacy and perceived trust in insurance providers on household insurance uptake in Uganda.

H31: There is no significant relationship between insurance literacy and insurance uptake among Ugandan households.

H32: There is no significant relationship between perceived trust in insurance providers and insurance uptake among Ugandan households.

1.5 Conceptual Framework

The conceptual framework presents the expected relationships among independent variables (demographic factors, socioeconomic characteristics and insurance literacy and perceived trust in insurance providers) and the dependent variable (insurance uptake) among Ugandan households.

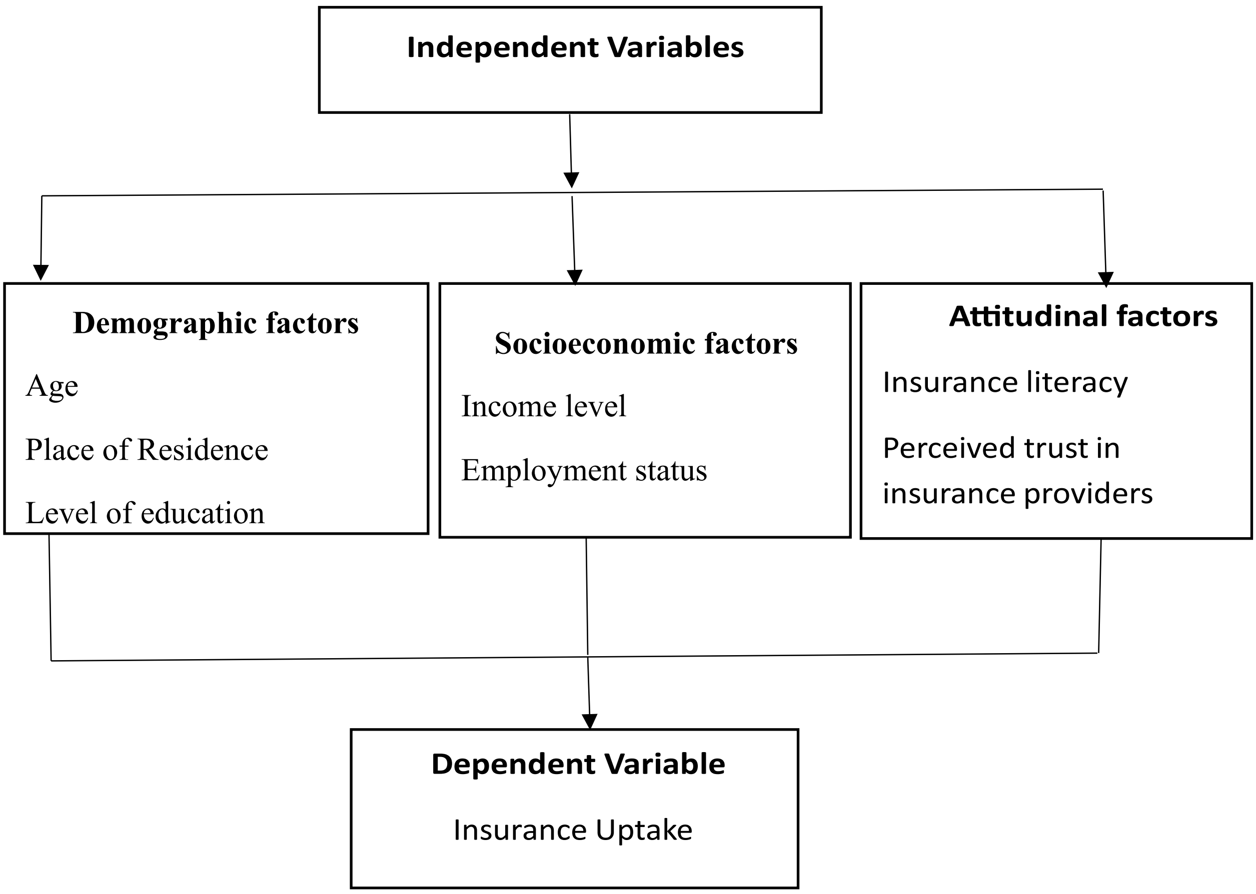

Figure 1.1 Conceptual Framework

The conceptual framework links demographic factors (age, place of residence, education), socioeconomic factors (income, employment status) and insurance literacy and perceived trust in insurance providers to insurance uptake among Ugandan households. Studies on insurance literacy and trust (Kiwanuka & Sibindi, 2025) and financial inclusion reports (FSDU, 2018) identify key determinants like socioeconomic status (income, education, employment), demographics (age, place of residence) and household attitudes (literacy, trust). (Kiwanuka & Sibindi, 2025).

1.6 Study Scope

The study focuses on Uganda at the national level, drawing from national reports and Ugandaspecific studies. Relevant, East African regional comparisons with Kenya, Tanzania will be included to contextualize Uganda's low penetration. The target population is Ugandan households, including formal and informal-sector workers, rural and urban populations. Determinants examined are demographic factors, socioeconomic characteristics and insurance literacy and trust in insurance providers. Literature and data from 2015-2026 will be reviewed to ensure current evidence while including foundational theoretical work where necessary. The study also covers insurance types for example general insurance, life insurance, health insurance, microinsurance and agricultural insurance on a household-level.

1.7 Significance of the Study

This study will contribute to both academic knowledge and policy practice in Uganda's insurance and financial-inclusion landscape. The research will provide empirical evidence on the specific determinants of low insurance uptake among Ugandan households, filling a gap in the existing literature that has largely focused on regional or sector-specific analyses such as health insurance only (Makerere University Dissertation, 2026; Medard et al., 2022) explicitly integrating insurance literacy and trust into a comprehensive household-level model. The study will enrich theoretical understanding of insurance demand in low-income and informal-sector contexts.

Insurance providers and microfinance institutions can use the results to redesign products for example microinsurance, flexible-premium schemes and distribution models like mobile-based and agent-network models that are more accessible and attractive to informal-sector workers and rural households. By identifying barriers to uptake, the study will help create targeted interventions that increase awareness, affordability and trust, thereby enhancing household financial resilience to shocks such as health emergencies, crop failure and income.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This chapter reviews literature related to the determinants of low insurance uptake among households, with particular focus on Uganda and other comparable developing-country contexts. It presents the theoretical and empirical literature structured around the three broad categories of determinants examined in this study that is demographic factors, socioeconomic characteristics and insurance literacy and perceived trust. For each variable discussed, the corresponding hypothesis is presented. The chapter also identifies gaps in existing studies and shows how the current study contributes to knowledge on low insurance uptake among Ugandan households.

2.1 Insurance Uptake

Insurance uptake refers to the extent to which individuals or households acquire and hold an insurance policy, whether through direct purchase, employer-based cover or membership in a scheme that provides a payout following a defined loss event. This understanding is consistent with national reports, which measure insurance uptake in Uganda both in terms of market-level penetration or gross premiums as a share of GDP and in terms of the proportion of individuals who personally hold a policy (FSD Uganda, 2018). Uptake is important because it reflects the extent to which households have converted the theoretical protection that insurance offers into an actual financial safety net against shocks such as illness, accidents, death or property loss. Despite modest growth in Uganda's insurance industry in monetary terms, uptake at the household level remains low, with only a small share of adults personally holding a policy in their own name (FSD Uganda, 2024). This gap between industry-level growth and householdlevel uptake is what this study seeks to explain by examining the demographic, socioeconomic and attitudinal factors that shape whether a household ultimately takes up insurance.

2.2 Demographic factors and Insurance Uptake

Demographic factors refer to the basic biological and social characteristics of individuals and households, including age, sex, marital status, level of education, household size and place of residence. These factors heavily influence insurance uptake by shaping an individual's financial capacity, their perceived risk of experiencing a life or health event and their understanding of how insurance products function (Aliu Ismaila Daudu, 2022).

In the Ugandan and wider African literature, demographic characteristics are consistently linked to differences in awareness, affordability and perceived need for insurance among households. Musoke et al. (2022) found that age and other demographic factors shaped women's demand for health insurance in Uganda, while Nahabwe (2022) showed that place of residence was strongly associated with insurance uptake among Ugandan women. Similarly, Alesane and Anang (2018) found marital status to be an important predictor of health insurance uptake among rural households in Ghana. These findings suggest that demographic characteristics shape not only whether a household is aware of insurance, but also whether it perceives a need for it. Therefore, this study examines age, gender, level of education, marital status, place of residence, and household size as demographic factors that may influence insurance uptake among Ugandan households.

Age

Older individuals typically have a higher uptake of health, life and critical illness policies because they face higher health risks and become more aware of their own mortality (Musoke, Ssekiziyivu, Mukoki, & Ashaba, 2022). Younger adults often delay purchasing insurance, viewing themselves as invulnerable or prioritizing immediate financial needs over long-term protection (Muremyi et al., 2025). Countries with a larger share of older, financially settled adults tend to have higher overall demand for insurance (Nebolsina, 2020). However, very young adults may have neither the income nor the felt need to buy insurance, while the oldest adults, especially those past retirement may reduce their coverage once their children are grown and their major assets are already secured.

In my view, age captures more than years lived. It reflects how far along an individual's lifecycle needs have shifted from immediate consumption toward protecting income, health and dependants. A young unmarried adult may see little urgency in cover, while a middle-aged parent balancing school fees, health risks and asset protection may value insurance far more, even where formal awareness is similar. Because Uganda's population remains predominantly young, this life-cycle effect may partly explain why overall uptake stays low even as the country's insurance sector nominally grows (Nebolsina, 2020).

Therefore, this study hypothesizes that there is no significant relationship between age and uptake among Ugandan households.

Gender

Gender significantly impacts insurance uptake because deep-rooted structural inequalities in income, employment types and asset ownership grant men much greater access to formal coverage than women. Data indicates that men are far more likely to secure corporate positions featuring employer-sponsored healthcare and own high-value registered assets that necessitate property or motor policies. Conversely, a massive portion of the female adult population is concentrated in volatile informal or agricultural economies, leaving them financially excluded from traditional insurers. As a result, statistical data such as findings from the Financial Sector Deepening (FSD) Uganda Report confirms that women heavily dominate the informal insurance sector, relying instead on village savings groups, community burial societies, and peer-to-peer safety nets (FSD Uganda, 2018).

In my view, gender differences in insurance uptake in Uganda are less about willingness to protect against risk and more about unequal access to income-generating opportunities, collateral, and formal financial products. Women may recognise the value of insurance just as much as men, yet be structurally unable to convert that recognition into a policy because their earnings are irregular or tied up in informal group savings. This suggests that closing the gender gap requires product design that meets women where their money already moves, such as mobile money and group-based schemes, rather than awareness campaigns alone (UN Women, 2025)

Level of Education

Higher educational attainment leads to greater financial literacy and a clearer understanding of how risk-pooling and insurance policies work (Mwinuka, Echoka, & Nyaberi, 2022). Uneducated or less-educated populations may struggle to comprehend complex policy jargon, which often leads to distrust and lower subscription rates (Musoke et al., 2022). A panel study of 42 African countries examining the institutional and demographic determinants of insurance demand found that education has an ambiguous relationship with insurance consumption. Although higher education is theoretically expected to raise risk awareness and demand for protection, several empirical studies instead find a weak or negative relationship, implying that general education does not automatically translate into insurance uptake where broader institutional weaknesses and trust deficits remain unresolved (Bah & Abila, 2024).

In my view, education matters for insurance uptake mainly through the confidence it gives households to interpret contracts, premiums and claims procedures, rather than through income alone. A household head with limited formal education may still afford a policy but avoid it out of uncertainty about what is being promised, particularly where product language is technical.

Therefore, this study hypothesizes that there is no significant relationship between level of education and insurance uptake among Ugandan households.

Marital Status

Married individuals and those with dependents (children or aging parents) show significantly higher uptake rates for life insurance, as they prioritize securing their family's financial future in the event of their death. Single individuals with no dependents often see less immediate need for long-term or comprehensive life coverage (I.A, 2022). In a study on rural health insurance uptake, married individuals in Kenya were found to be up to ten times more likely to take up health insurance cover than unmarried individuals, an effect attributed to the pooling of household financial resources and the shared responsibility for dependents that marriage typically entails (Alesane & Anang, 2018).

In my view, marital status is important because it changes who bears financial responsibility if a household loses an income earner. Married individuals with children or dependants have a concrete reason to protect that income stream, while single individuals without dependants may not see an immediate beneficiary for a payout. This suggests that marketing life and health products around household protection, rather than individual protection, may resonate more strongly in the Ugandan context.

Place of Residence

Place of residence determines insurance uptake by dictating an individual's proximity to financial provider networks, the nature of their economic risk and their access to usable service infrastructure. Urban areas feature highly concentrated insurance marketing, digital access and mandatory policy frameworks that naturally drive higher enrolment. In contrast, rural populations face severely depressed formal uptake. For instance, a landmark study from Makerere University revealed that women in urban centres can be up to nine times more likely to take up health insurance than those in rural areas (Nahabwe, 2022). This rural-urban divide persists because rural populations lack nearby accredited facilities such as hospitals or banks to make coverage practical, suffer from highly volatile agricultural incomes and are largely neglected by traditional indemnity products (Sharif, 2026).

This spatial disadvantage is compounded by the occupational structure of rural Uganda. FinScope survey findings show that only about 3 percent of Uganda's adult population is employed in the formal sector around which traditional insurance products have historically been designed, while roughly 48 percent of the population depends on agriculture and a further 15 percent on casual labour, pushing the majority of rural households toward informal, noncontractual risk-coping mechanisms instead of formal insurance (Joel Muhumuza, 2019).

In my view, place of residence is less about physical distance to an insurance office and more about the surrounding financial infrastructure a household is embedded in. Urban households are typically closer to banks, agents and employers who already interact with formal insurance, so uptake spreads through familiarity as well as access. Rural households, by contrast, are often served by informal risk-sharing mechanisms that substitute for insurance, meaning providers may need to work through existing agricultural or community structures rather than urban-style distribution channels.

Therefore, this study hypothesizes that there is no significant relationship between place of residence and insurance uptake among Ugandan households.

Household size

Larger families balance a higher demand for health or life coverage against a severely strained household budget. This economic tension often causes them to scale back to basic microinsurance or forgo policies entirely (Namugenyi, 2019). This is broadly supported by a large review of 54 studies on community-based health insurance in low and middle-income countries. It found that household size affects uptake differently depending on the region. In Sub-Saharan Africa, larger households were more likely to enrol, possibly because they can share the fixed cost of a policy among more members, while in Asia, larger households were less likely to enrol, likely because each extra member adds to the premium cost (Dror et al., 2016).

In my view, household size cuts both ways, and its effect likely depends on how a household is organised rather than its size alone. A large household with several income earners may find it easier to pool resources for a shared policy, while a large household dependent on a single earner may find premiums unaffordable however much it may want cover.

2.3 Socioeconomic Factors and Insurance Uptake

Socioeconomic factors are the combined social and economic measures that define an individual's or a group's position within a society. These factors focus heavily on financial leverage, social status and institutional access. They directly dictate insurance uptake by determining a household's financial capacity to absorb premium costs and their cognitive awareness of formal risk management. Individuals with low socioeconomic status must prioritize immediate survival needs like food and rent, making formal insurance an out-of-reach luxury (Boutayeb & Helmert, 2011).

Empirical evidence also shows that socioeconomic characteristics are closely linked to a household's capacity to sustain insurance contributions over time. Bah and Abila (2024) found that broader economic capacity was a key driver of insurance demand across African countries, while Yego, Nkurunziza, and Kasozi (2023) showed that income and wealth were among the strongest predictors of insurance uptake among Kenyan households. Kaonga et al. (2026) further noted that informal and casual employment, which is common among Ugandan households, is associated with income volatility that makes fixed premium schedules difficult to sustain. These findings suggest that socioeconomic position shapes not only whether a household can initially afford insurance, but also whether it can maintain coverage over time. Therefore, this study examines income level, employment status, asset ownership and financial-inclusion proxies as socioeconomic factors that may influence insurance uptake among Ugandan households.

Income Level

This is the most critical driver of insurance adoption. Higher disposable income allows households to pay regular premiums comfortably. For low-income individuals, premiums represent an immediate financial loss for an uncertain, future payout, which suppresses uptake (Akhter & Khan, 2017). Panel evidence from 42 African countries confirms that broader economic capacity, alongside institutional quality, shapes total insurance demand across the continent (Bah & Abila, 2024), while a machine-learning based study of Kenyan households using national FinAccess survey data ranked poverty vulnerability and income among the most important predictors of insurance uptake, concluding that affordability remains a significant barrier to enrolment even where awareness of insurance products is otherwise high (Yego, Nkurunziza, & Kasozi, 2023).

In my view, income is the clearest constraint on insurance uptake because, unlike attitudes or awareness, it directly determines whether a premium can be paid at all. Even a household that fully understands and values insurance will not purchase it if doing so competes with food, rent or school fees. This is why affordability-focused product design, such as small, flexible premiums timed to income cycles, may matter as much as financial literacy campaigns in raising uptake among lower-income Ugandan households.

Therefore, this study hypothesizes that there is no significant relationship between income and insurance uptake among Ugandan households.

Level of Employment

Formal, salaried employment frequently comes with mandatory or subsidized group health, life or disability insurance schemes. Informal, casual or seasonal workers lack these institutional structures and suffer from highly volatile revenues that do not support fixed premium schedules (Kaonga et al., 2026).

Evidence from rural south-western Uganda specifically supports this pattern in reverse as well. A household's engagement in rural casual/ informal work was found to be a significant positive predictor of community-based health insurance enrolment when combined with knowledge of insurance premiums and social capital built through membership in voluntary groups, suggesting that informally employed households can still be drawn into insurance schemes when trust and awareness barriers are addressed directly, even without the institutional structure that formal employment provides (Nshakira-Rukundo, Mussa, Nshakira, Gerber, & von Braun, 2019).

In my view, employment status matters less for the formal-informal label itself and more for what it signals about income predictability. A formally employed worker with a steady monthly salary can plan around a fixed premium, while an informally employed worker with fluctuating daily or seasonal earnings cannot commit to the same schedule even with comparable total income. This suggests that flexible, income-linked premium structures could extend coverage to informally employed households without requiring a shift in employment status itself.

Therefore, this study hypothesizes that there is no significant relationship between employment status and insurance uptake in Uganda.

Asset Ownership

Owning high-value, legally registered assets such as a home, commercial property or a vehicle creates an immediate, logical demand for protection. Furthermore, financial institutions often mandate property or auto insurance as a prerequisite for approving mortgages or asset-backed loans (Kirk, 2025). A Kenyan study found that a household's wealth level, not just its income, was one of the strongest predictors of insurance uptake showing that owning assets can drive insurance demand on its own, separate from how much a household earns (Yego et al., 2023). In Uganda, where formal registration of assets such as land is still uneven between urban and rural areas, asset ownership may also show how well a household is connected to the formal economic and legal systems that insurance products are usually built around.

In my view, asset ownership signals both something to protect and a household's broader connection to formal economic systems, which may explain why it predicts insurance uptake even after accounting for income. A household with a registered property or vehicle has both the incentive and, often, the documentation trail that makes formal insurance easier to access. Where asset registration itself is uneven, as in much of rural Uganda, this may mean asset ownership operates as much as a proxy for formal-system access as for wealth.

Financial-Inclusion Proxies

Access to mobile phones, the internet, computers and official ID documents function as financial-inclusion proxies that dictate insurance uptake by providing the mandatory legal and digital infrastructure necessary to clear entry barriers. According to data from the World Bank Group Identification for Development (ID4D) Initiative, lacking official identity documentation acts as an absolute regulatory barrier that locks out roughly 26 percent of unbanked adults in low-income regions due to strict Know Your Customer (KYC) laws (Group, 2021). Once legal identity is verified, mobile technology and internet connectivity serve as transactional and informational gateways. Research featured by the Consultative Group to Assist the Poor (CGAP) demonstrates that these digital transactional platforms allow insurers to bypass expensive traditional brick-and-mortar banking systems (Lyman & Lauer, 2015). By leveraging these tech channels, providers can dramatically increase retail enrolment, manage commercial group schemes via computers and collect tiny, flexible micro-premiums directly through everyday mobile money wallets to cover previously excluded populations.

A study of individuals who had accessed insurance products through digital platforms found that digital literacy significantly and positively predicts insurtech adoption, which in turn partially mediates the relationship between digital literacy and overall insurance inclusion, positioning mobile and digital access not merely as a convenience but as an active driver of uptake in regions where physical branch networks are scarce (Kiwanuka & Sibindi, 2023).

In my view, financial-inclusion proxies such as mobile phone and identification ownership matter because they remove practical, not just financial, obstacles to enrolling in and maintaining an insurance policy. A household may be willing and able to pay a premium yet still be excluded if it lacks the identification documents insurers require or a reliable channel for making payments. This suggests that digital and identification infrastructure gaps, rather than attitudes toward insurance, may be an underappreciated barrier to uptake among otherwise willing Ugandan households.

2.4 Attitudinal Factors

Insurance literacy and perceived trust are attitudinal factors that determine whether a household converts awareness and financial capacity into an actual insurance purchase. Unlike demographic and socioeconomic characteristics, which largely describe who a household is, these factors describe what a household believes about insurance and the institutions that provide it. Kiwanuka and Sibindi (2023) found that insurance literacy and perceived trust jointly explained a substantial share of variation in insurance inclusion in Uganda, while Mpuuga, Yawe, and Muwanga (2020) identified awareness as one of the most consistent predictors of insurance demand nationally. These findings suggest that even where households are demographically and economically positioned to purchase insurance, low literacy or weak trust in providers can still suppress uptake. Therefore, this study examines insurance literacy and perceived trust in insurance providers as attitudinal factors that may influence insurance uptake among Ugandan households

Insurance Literacy

Insurance literacy refers to the knowledge, skills, attitudes and practical understanding that allow households to evaluate insurance products and use them effectively. In Uganda, insurance literacy has a significant positive effect on insurance inclusion and its components of knowledge, skills and attitude each positively predict inclusion, while behaviour was not significant (Kiwanuka & Sibindi, 2023). In Uganda, awareness was the only variable reported as highly significant in all demand models (Mpuuga, Yawe, & Muwanga, 2020), and respondents unaware of nearby schemes were 99% less likely to enrol in Mbarara (Kangwagye, Bright, Atukunda, Basaza, & Bajunirwe, 2022). Low awareness also emerged in qualitative evidence among farming households and in nationally representative access data, where only 23.5% were aware and just 1.4% reported being insured (Keinerugaba, Wamono, Wandiembe, & Oyem, 2025; Otieno et al., 2025)

In my view, insurance literacy operates mainly by reducing the psychological distance between a household and an unfamiliar financial product. A household that understands how premiums, claims and payouts work is better placed to judge whether a product fits its needs, whereas a household that does not understand these may avoid insurance altogether regardless of its underlying risk exposure.

Therefore, this study hypothesizes that there is no significant relationship between insurance literacy and insurance uptake among Ugandan households.

Perceived Trust

Perceived trust refers to the confidence households hold that insurance providers will act in good faith and honour their obligations, particularly at the point of a claim. Trust appears to be the strongest relational determinant. In Uganda, perceived trust explained more variation in insurance inclusion than perceived value or literacy and the full model of trust, value and literacy explained 63.2% of variation in inclusion (Kiwanuka & Sibindi, 2023). Concerns about misuse of funds can discourage enrolment (Kangwagye et al., 2022), while bad prior experiences have a stronger negative effect on trust than good experiences which have a positive one.

Product confidence also depends on design and delivery. Agricultural insurance reviews identify product quality, design, affordability, information, sociocultural factors and government support as the six major uptake drivers in Africa (Nshakira-Rukundo, Kamau, & Baumüller, 2021), and Ugandan coffee index insurance research argues that efficient claims handling, low transaction costs and cooperative delivery channels are critical for adoption at scale (Asseldonk, Muwonge, Musuya, & Abuce, 2020). Together, these findings suggest that perceived trust in Uganda is shaped not only by an individual's general disposition toward financial institutions but also by the concrete, observable reliability of the specific product and channel through which insurance is offered.

In my view, perceived trust functions as a gatekeeper that determines whether literacy and affordability translate into an actual purchase. A household may understand a product and be able to afford it, yet still decline to buy if it doubts that a claim will be honoured fairly and promptly. This suggests that improving claims-handling practices and transparency may do more to raise uptake in Uganda than product design changes alone, since trust deficits can undo the effect of otherwise well-designed and affordable products.

Therefore, this study hypothesizes that there is no significant relationship between insurance literacy and insurance uptake among Ugandan households.

2.5 Summary of Literature Review and Research Gap

The reviewed literature shows that insurance uptake among Ugandan households is shaped by a combination of demographic, socioeconomic and attitudinal factors. Studies from Uganda and other African countries indicate that age, gender, education, marital status, place of residence and household size influence how households perceive the need for insurance and their exposure to insurance markets, while income, employment status, asset ownership, and financial-inclusion proxies determine whether households can afford and access insurance products. The literature further shows that insurance literacy and perceived trust in providers act as attitudinal gatekeepers that determine whether demographically and economically wellpositioned households ultimately convert that potential into an actual policy.

However, most existing Ugandan studies have focused narrowly on specific insurance types, particularly health insurance, or on specific population subgroups, with limited empirical evidence that examines demographic, socioeconomic, and attitudinal determinants of insurance uptake together within a single household-level model using recent, nationally representative data. This creates a gap in understanding how these three categories of factors jointly shape low insurance uptake among Ugandan households. Therefore, this study seeks to address this gap by examining the determinants of low insurance uptake among Ugandan households using FinScope Uganda 2023 Survey data.

CHAPTER THREE

RESEARCH METHODOLOGY

3.0 Introduction

This chapter presents the methodology that was used to examine the determinants of low insurance uptake among Ugandan households. It outlines the research design, study population, sampling design and sample size, study variables, data management, data analysis techniques, study limitations and ethical considerations. The chapter also explains how the FinScope Uganda 2023 data was used to analyse the relationship between selected demographic, socioeconomic and attitudinal factors and low insurance uptake among Ugandan households.

3.1 Research Design

This study adopted a quantitative, cross-sectional research design using secondary data from the FinScope Uganda 2023 Survey (FSD Uganda, 2024). The FinScope survey is a nationally representative household survey that has been conducted in Uganda since 2006, with the 2023 round being its fifth wave. It measures how individuals source income and manage their financial lives, including engagement with both formal and informal financial services such as insurance (FSD Uganda, 2024). Because the survey captures insurance uptake alongside a wide range of demographic, socioeconomic and attitudinal variables in a single cross-section, it provided a suitable secondary data source for examining the determinants of low insurance uptake among Ugandan households.

3.2 Study Population

The study population comprised adult Ugandans aged 16 years and above who are potential consumers of insurance products. This population includes both rural and urban residents and spans all four regions of the country that is Central, Eastern, Western and Northern, making it appropriate for examining household-level determinants of insurance uptake across diverse demographic and geographic contexts.

3.3 Sampling Design and Sample size

The original FinScope 2023 survey employed a three-stage stratified sampling design to draw a nationally representative sample (FSD Uganda, 2024). The first stage involved geographic representation in which enumeration areas were selected by the Uganda Bureau of Statistics

(UBOS) to ensure national, regional and urban-rural representativeness. The dataset confirmed 319 unique enumeration areas among the achieved sample. The second stage involved household representation with households randomly selected within each enumeration area. The third stage involved individual representation in which one adult aged 16 years or older was randomly selected from each sampled household for interview. Against a targeted sample of 3,200 individual respondents, the survey achieved 3,176 completed interviews, representing a response rate of 99%.

This achieved sample of 3,176 formed the sampling frame for the descriptive, univariate and bivariate analyses in this study, which used all available non-missing cases for each variable individually. However, because two of the independent variables central to this study, income level and employment status, had missing data, the multivariate model that jointly tested the study's hypotheses was estimated on a smaller complete-case sample.

3.4 Study Variables

The study consisted of one dependent variable and selected independent variables. The dependent variable was insurance uptake, while the independent variables included demographic, socioeconomic and attitudinal factors. The measurement and scale of each variable are presented in Table 3.1.

3.5 Data Management

Data management involved importing, cleaning and preparing the relevant modules of the FinScope Uganda 2023 dataset using STATA. Since the study used individual-level data drawn from a single cross-sectional survey, the demographic, socioeconomic and attitudinal variables required for analysis were extracted from the corresponding sections of the dataset and merged using the unique respondent identifier. After merging, the dataset was checked for duplicate records, out-of-range values and inconsistencies between related variables. Variables were recoded into the categories presented in Table 3.1, and cases with missing values on income and employment status were handled through listwise deletion in the multivariate model. The final analytic dataset was restricted to respondents aged 16 years and above with complete information on the dependent variable and was securely stored and used strictly for the purposes of this study.

Table 3. 1Measurement of Study Variables

Variable Category	Variable	Category/Measurement	Scale of Measurement
Dependent variable	Insurance Uptake	1 = Has insurance 0 = Does not have insurance	Binary
	Age	1 = 16–25 2 = 26–35 3 = 36–45 4 = 46–60 5 = 60+	Ordinal
Demographic factors	Gender	0 = Male 1 = Female 1 = Rural	Nominal
	Place of residence	2 = Urban	Binary
	Education Level	1= No formal education 2 = Primary 3= Secondary 4= Specialised training 5= Degree and above 6 = Don't know	Ordinal
	Employment status	1= Self-employed 2= Paid employment 3= Working with NPISH 4= Unemployed 5 = Don't know/Refused	Nominal
Socioeconomic factors	Income level	1 = Low (<UGX 250,000) 2 = Middle (UGX 250,001–1,000,000) 3 = High (>UGX 1,000,000)	Ordinal
Attitudinal	Insurance literacy/ trust	0 = Low trust/poor experience 1 = Moderate 2 = High trust/positive experience	Ordinal

3.6 Data Analysis

Data analysis was conducted in STATA and was done in three stages. Univariate analysis to describe the characteristics of the sample, bivariate analysis to test the association between each independent variable and insurance uptake and multivariate analysis to test the study's hypotheses while controlling for the effects of other variables simultaneously.

3.6.1 Univariate Analysis

Univariate analysis was used to describe the individual characteristics of the sample independently of one another. For categorical variables, including insurance uptake, place of residence, education level and employment status, frequencies and percentages were computed to summarise the distribution of respondents across categories. For continuous and near continuous variables, such as age, measures of central tendency such as mean, median and dispersion such as standard deviation and range were computed in addition to the grouped percentage distributions.

3.6.2 Bivariate Analysis

Bivariate analysis was conducted to test the unadjusted association between each independent variable and insurance uptake, using a simple (univariable) complementary log-log regression model. The simple complementary log-log model is specified as:

$$Log\ (log\ (\frac{p}{1-p}\ )) = \alpha + \beta_i X_i + \varepsilon$$

where p is the probability of insurance uptake, α is the constant term, X_i is a single independent variable entered one at a time for example age group, place of residence, education level, employment status or income level, β_i is its coefficient, and ε is the error term. A separate model was run for each independent variable and statistical significance was assessed at the 5% level.

3.6.3 Multivariate Analysis

Multivariate analysis was conducted using a multivariable complementary log-log regression model in which all independent variables were entered simultaneously to test the study's hypotheses while controlling for the effects of other covariates. The complementary log-log link was used instead of the more conventional logit link because insurance uptake is a rare event in this sample. Unlike the symmetric logit link, the complementary log-log link is asymmetric and approaches its extreme values at different rates, which better approximates the shape of the response probability curve when the outcome of interest is rare and avoids the underestimation of the probability of the rare event that a symmetric link can produce. The multivariable model is specified as:

$$Log\ (log\ (\frac{p}{1-p}) = \alpha + \beta_1 age + \beta_2 place\ of\ residence + \beta_3 education\ level + \beta_4 employment\ status + \beta_5 income\ level + \varepsilon$$

where p is the probability of insurance uptake, α is the constant term, β is the corresponding vector of coefficients and ε is the error term. Coefficients were interpreted in terms of their effect on the complementary log-log of the probability of insurance uptake, with statistical significance assessed at the 5% level.

3.7 Study Limitations

This study is subject to a number of limitations arising from the design and content of the FinScope Uganda 2023 dataset, which was collected for a broader financial-inclusion agenda rather than specifically to examine the determinants of insurance uptake.

Limited coverage of insurance literacy and trust items. The only available proxy items for insurance literacy and perceived trust were asked and answered exclusively by respondents who already held an insurance policy and had made a claim, yielding valid responses for only 28 of the 3,176 respondents. This precluded their use as independent variables in the bivariate and multivariate models explaining insurance uptake across the full sample, since a variable that is only observable after uptake cannot logically explain uptake itself. This study is therefore unable to empirically test the influence of insurance literacy and perceived trust on uptake using this dataset, which represents a departure from the third specific objective.

Missing data. A substantial proportion of respondents had missing income data, largely because the income variable was only collected for respondents who reported an identifiable income source. Employment status also had a smaller share of missing responses. These cases are handled through listwise (complete-case) deletion. Respondents with missing values on income and employment status are excluded from the multivariate model, while the univariate and bivariate analyses use all available non-missing cases for each variable individually. This approach was adopted because the proportion of missingness on employment status is small and because income, while missing for a sizeable minority, is retained as a three-category variable to preserve as many complete cases as possible. Listwise deletion in the multivariate model may still reduce statistical power and could introduce bias if missingness is not random with respect to insurance uptake.

Fixed variable definitions. As a secondary dataset, the study is constrained to the variable definitions, question wording, and response categories used in the original FinScope survey instrument, which were not designed specifically around this study’s conceptual framework and could not be adapted or extended to capture constructs more precisely.

3.8 Ethical Considerations

This study used secondary data from the FinScope Uganda 2023 Survey and did not involve direct contact with respondents. Because the dataset is anonymised and does not identify individual respondents, no additional consent procedures are required beyond those already obtained by FSD Uganda during the original data collection. The data was used strictly for academic purposes and confidentiality was maintained throughout the analysis and reporting process. Findings were presented in aggregate form through tables and statistical estimates and no attempt was made to identify or trace individual respondents. The study also ensured proper acknowledgement of the data source and of all literature used and the results were reported honestly and objectively without manipulation of findings to fit predetermined conclusions.

CHAPTER FOUR

PRESENTATION AND DISCUSSION OF RESULTS/ FINDINGS

4.0 Introduction

This chapter presents the results of the study on the determinants of low insurance uptake among Ugandan households. The results are presented in three stages. Univariate results, describing the demographic, socioeconomic and attitudinal characteristics of the sample. Bivariate results, examining the unadjusted association between each independent variable and insurance uptake using a simple complementary log-log regression model. Multivariate results, in which all independent variables are entered simultaneously to test the study's hypotheses while controlling for the effects of other covariates. The chapter also discusses the findings in relation to the study's objectives, hypotheses and the literature review.

4.1 Response Rate and Sample Characteristics

The FinScope Uganda 2023 Survey achieved 3,176 completed individual interviews against a targeted sample of 3,200, representing a response rate of 99%. This achieved sample of 3,176 forms the analytic base for the univariate and bivariate results presented in this chapter, with each variable analysed using all available non-missing cases. Income level had the greatest degree of missingness, being recorded for only 2,422 of the 3,176 respondents. Level of education and employment status were recorded for the full sample of 3,176 respondents, but seven participants (0.22%) were unsure of their educational background, while 40 participants (1.26%) didn’t know or declined to state their employment status. Because none of the respondents in these two categories held insurance, they are excluded only from the bivariate models and the multivariate model which causes the regression to predict that category perfectly and drop it automatically.

4.2 Univariate Results

This section presents the frequency distribution of the dependent variable, insurance uptake and of the demographic, socioeconomic and attitudinal characteristics of respondents in the sample.

Table 4. 1: Univariate distribution of respondents

Variable	Category	Frequency	Percentage (%)
Insurance Uptake	No insurance	3093	97.39
	Has insurance	83	2.61
Age group	16-25	816	25.69
	26-35	905	28.49
	36-45	579	18.23
	46-60	562	17.70
	60+	314	9.89
Place of residence	Rural	2210	69.58
	Urban	966	30.42
Sex of respondent	Male	1424	44.84
	Female	1752	55.16
Level of education	No education	526	16.56
	Primary	1408	44.33
	Secondary	891	28.05
	Specialised training	248	7.81
	Degree and above	96	3.02
	Don't know	7	0.22
Employment status	Self employed	1977	62.25
	Paid employment	217	6.83
	Working with NPISH	17	0.54
	Unemployed	925	29.12
	Don't know/ Refused	40	1.26
Income level	Low income	1721	71.06
	Middle income	594	24.53
	High income	107	4.42
Perceived Trust	Would recommend	4	14.29
	Would not recommend	24	85.71
Claims experience	Fair/ Not good	14	50.00
	Satisfactory	14	50.00
Trust score	Low trust	2	7.14
	Moderate trust	14	50.00
	High trust	12	42.86

4.2.1 Insurance Uptake

Of the 3,176 respondents, only 83 (3%) reported having an existing insurance policy, while the overwhelming majority, 3,093 (97%), had no insurance cover. This confirms the low insurance uptake pattern.

4.2.2 Demographic Characteristics

Age was recorded as a continuous variable in completed years for all 3,176 respondents. The average respondent was about 38 years old with a median age of 34 years, indicating a slight positive (right) skew consistent with the concentration of younger adults in the sample. Ages ranged from 16 to 100 years. 44.84% of the respondents were male while the majority, 55.16% were female.

Regarding place of residence, 69.58% resided in rural areas while 30.42% resided in urban areas which is consistent with Uganda's national rural-urban population distribution. With respect to education, the largest share of respondents had attained only a primary education (44.33%), followed by secondary education (28.05%), while only a small minority had attained a degree or higher qualification (3.02%), and 16.56% reported no formal education at all.

4.2.3 Socioeconomic Characteristics

The majority of respondents were self-employed (62.25%), while a further 29.12% were unemployed. Only 6.83% of the respondents were in paid employment or working with a nonprofit institution serving households, NPISH (0.54%). On income, 754 respondents (23.74%) had no income value recorded and are shown as missing, among the remaining 2,422 respondents with valid income data, the majority (71.06%) fell into the low-income category (below UGX 250,000), 24.53% fell into the middle-income category, and only 4.42% reported high income (above UGX 1,000,000).

4.2.4 Insurance Literacy and Perceived Trust

The indirect measures of perceived trust and claims experience in the FinScope Uganda 2023 dataset were restricted to respondents who held an insurance policy and had filed a claim, resulting in valid data for only 28 out of the 3,176 participants. Among this small sub-sample, the majority (85.71%) reported that they would recommend their insurance provider, and 50.00% reported a satisfactory claims experience. On the composite trust score, half of respondents (50.00%) fell into the moderate-trust category, 42.86% into the high-trust category, and only 7.14% into the low-trust category. Because these items are observable only for respondents who had already taken up insurance, they cannot logically be used to explain uptake itself and are therefore not carried forward into the bivariate or multivariate models.

4.3 Bivariate Results

This section presents the unadjusted association between each independent variable and insurance uptake, estimated using a simple (univariable) complementary log-log regression model for each variable. Statistical significance is assessed at the 5% level throughout.

Table 4.2 presents the bivariate complementary log-log results.

Table 4. 2: Bivariate Complementary Log-Log Results

Variable	Category	Coef.	z	p-value	95% CI
Age group	26-35 (Ref:18-25)	1.219 (0.426)	2.860	0.004	0.384 - 2.053
	36-45 (Ref:18-25)	1.503 (0.434)	3.460	0.001	0.653 - 2.354
	46-60 (Ref:18-25)	1.622 (0.430)	3.780	0.000	0.781 - 2.464
	60+ (Ref:18-25)	0.398 (0.627)	0.630	0.526	-0.831 - 1.626
Residence	Urban (Ref: Rural)	1.262 (0.224)	5.630	0.000	0.822 - 1.702
Education	Primary (Ref: Degree)	-3.819 (0.341)	-11.210	0.000	-4.487 - -3.151]
	Secondary (Ref: Degree)	-2.794 (0.283)	-9.860	0.000	-3.350 - -2.239
	Specialised training (Ref: Degree)	-1.5878 (0.292)	-5.440	0.000	-2.160 - -1.015
Employment	Paid employment (Ref: Self employed)	2.027 (0.248)	8.170	0.000	1.541 - 2.514
	Working with NPISH (Ref: Self employed)	3.686 (0.379)	9.730	0.000	2.944 - 4.429
	Unemployed (Ref: Self employed)	-0.777 (0.390)	-1.990	0.046	-1.541 - -0.013
Income	Middle income (250k-1M) (Ref: Low income)	1.901 (0.300)	6.330	0.000	1.312 - 2.490
	High income (>1M) (Ref: Low income)	2.853 (0.354)	8.070	0.000	2.160 - 3.546

4.3.1 Age and Insurance Uptake

The overall model was statistically significant ($p = 0.0001$). Respondents aged 26-35, 36-45 and 46-60 years all had significantly higher log-log odds of insurance uptake than the youngest age group shown by the positive coefficients ($p < 0.01$ in each case), with the effect strongest among the 46-60 years group because respondents had the largest coefficient of 1.6225. However, the coefficient for respondents aged 60 and above was small and not statistically significant ($p = 0.526$), indicating that uptake among the oldest respondents was not significantly different from that of the youngest group. This pattern provides partial support that there is no significant relationship between age and insurance uptake, with the relationship holding for middle-aged groups but not extending to the oldest respondents.

4.3.2 Place of Residence and Insurance Uptake

The model was statistically significant overall with $p = 0.000$. Urban respondents had significantly higher log-log odds of insurance uptake than rural respondents with coefficient of 1.262 and p-value of $p < 0.001$, consistent with the hypothesised direction and providing evidence to reject the null hypothesis.

4.3.3 Level of Education and Insurance Uptake

The overall model was statistically significant (LR chi2(3) = 148.500, $p = 0.000$). Respondents with only primary, secondary or specialised training all had significantly lower log-log odds of insurance uptake than degree-holders ($p < 0.001$ in each case), with the size of the negative coefficient increasing as the level of education fell further below a degree. This monotonic pattern is strong evidence of a positive relationship between education and insurance uptake, supporting the rejection of the null hypothesis which states that there is no significant relationship between level of education and insurance uptake. Because respondents with no education and those who didn't know held no insurance, these groups perfectly predicted failure and were excluded from the regression. This dropped 533 observations, leaving an estimation sample of 2,643 participants. The Degree and above category was therefore utilized as the baseline reference group against which other categories were compared.

4.3.4 Employment Status and Insurance Uptake

The overall model was statistically significant (LR chi2(3) = 112.870, $p < 0.001$). Respondents in paid employment and those working with a non-profit institution serving households (NPISH) had significantly higher log-log odds of insurance uptake than the self-employed because they had positive coefficients ($p < 0.001$ in each case), while unemployed respondents had significantly lower log-log odds of uptake than the self-employed (coef. = -0.777, $p = 0.046$). These results provide evidence to reject the null hypothesis that there is no significant relationship between employment status and insurance uptake among Ugandan households. The 40 individuals who declined to state or did not know their employment status perfectly predicted failure. Consequently, they were omitted from the regression, leaving an estimation sample of 3,136.

4.3.5 Income Level and Insurance Uptake

The overall model was statistically significant (LR chi2(2) = 76.530, $p < 0.001$). Both middleincome and high-income respondents had significantly higher log-log odds of insurance uptake than low-income respondents ($p < 0.001$ in each case), with the coefficient rising from 1.9011 for middle income to 2.8531 for high income, indicating a clear response relationship between income and uptake. This provides strong evidence to reject the null hypothesis that there is no significant relationship between income level and insurance uptake among Ugandan households

4.3.6 Summary of Bivariate Results

All five demographic and socioeconomic variables considered were statistically significantly associated with insurance uptake at the bivariate level, providing initial evidence against each corresponding null hypothesis. Age was the only variable whose association was not fully consistent across all categories, as the effect did not extend to the oldest respondents.

4.4 Multivariate Results

The overall model was highly statistically significant (LR chi2(13) = 155.790, $p = 0.000$). Because of listwise deletion on the variables with missing data, particularly income level and employment status, the model is estimated on a complete-case sample of 2,038 respondents.

Table 4.3 presents the multivariable complementary log-log model, in which age group, place of residence, level of education, employment status and income level were entered simultaneously to test the study's hypotheses while controlling for the effects of the other covariates.

Table 4. 3: Multivariate Complementary Log-Log Model of Insurance Uptake

Variable	Category	Coef.	z	p-value	95% CI
Age group	26-35 (Ref:18-25)	0.482 (0.508)	0.950	0.343	-0.515 - 1.478
	36-45 (Ref:18-25)	0.589 (0.526)	1.120	0.264	-0.443 - 1.620
	46-60 (Ref:18-25)	0.906 (0.521)	1.740	0.082	-0.116 - 1.928
	60+ (Ref:18-25)	0.124 (0.758)	0.160	0.870	-1.362 - 1.610
Residence	Urban (Ref: Rural)	0.520 (0.260)	2.000	0.046	0.010 - 1.029
Education	Primary (Ref: Degree)	-2.439 (0.453)	-5.380	0.000	-3.328 - -1.551
	Secondary (Ref: Degree)	-1.770 (0.370)	-4.790	0.000	-2.495 - -1.046
	Specialised training (Ref: Degree)	-0.874 (0.337)	-2.600	0.009	-1.534 - -0.215
Employment	Paid employment (Ref: Self employed)	0.601 (0.301)	2.000	0.046	0.011 - 1.190
	Working with NPISH (Ref: Self employed)	1.239 (0.535)	2.320	0.020	0.191 - 2.287
	Unemployed (Ref: Self employed)	-0.398 (0.512)	-0.780	0.437	-1.401 - 0.605
Income	Middle income (Ref: Low income)	0.874 (0.334)	2.610	0.009	0.219 - 1.530
	High income (Ref: Low income)	1.419 (0.410)	3.460	0.001	0.615 - 2.222
Constant		-3.202 (0.636)	-5.030	0.000	-4.448 - -1.955

Once the other variables are controlled for, age group lost statistical significance in all categories except a marginal effect for the 46-60 years group (p = 0.082, significant only at the 10% level), indicating that much of the age effect observed at the bivariate stage was attributable to the other characteristics with which age is correlated, such as employment status and income. The coefficients also lose statistical significance after adjustment even for respondents in the 46-60 years category whose coefficient is significant only at the 10% level, not at the conventional 5% level.

Place of residence remains statistically significant after adjustment with urban residence coefficient of 0.5196 and p = 0.046, although the coefficient has fallen from 1.2620 in the bivariate model to 0.5196. This shows that urban residence still has an independent, positive association with insurance uptake even after accounting for income, education and employment. Level of education remains one of the statistically significant predictors of insurance uptake with all three coefficients remaining highly significant, and in the same monotonic order, in both the unadjusted and adjusted models.

Middle income coefficient of 0.8742 remains significantly positive after adjustment and highincome coefficient of 1.4186 also remains significantly positive and larger than the middleincome coefficient, although both coefficients are smaller than their bivariate counterparts (1.9011 and 2.8531 respectively). Respondents under paid employment have a coefficient of 0.6006 remains significant, though it has fallen substantially from 2.0273 in the bivariate model, and the p-value is now close to the 0.05 threshold (p= 0.046). Respondents working with NPISH have a coefficient of 1.2389 and remain significantly positive after adjustment, again smaller than the bivariate coefficient of 3.6863 but still the largest employment-related effect in the adjusted model. Unemployed respondents have a coefficient of -0.3982. This coefficient loses statistical significance after adjustment, the confidence interval now clearly spans zero, so unemployment is not independently associated with lower uptake once the other variables are controlled for.

4.5 Discussion of Findings

This section discusses the bivariate and multivariate results in relation to the study's three specific objectives and the literature reviewed.

4.5.1 Demographic Factors and Insurance Uptake

With respect to the first objective, the results provide mixed support for the role of demographic factors in insurance uptake. Age was significantly associated with uptake at the bivariate level, with middle-aged respondents (26-60 years) significantly more likely to hold insurance than the youngest group, consistent with the life-cycle reasoning (Musoke et al., 2022), where financial protection needs are expected to rise as individuals take on income, health and dependant-related responsibilities. However, the effect did not extend to respondents aged 60 and above, and lost statistical significance for all age groups once residence, education, employment and income were controlled for in the multivariate model. These findings indicate that the effect of age on uptake is not direct, but is instead mediated by socioeconomic factors such as employment status and income, which vary systematically across different life stages.

Place of residence was significantly associated with insurance uptake in both the bivariate and multivariate models, with urban respondents consistently more likely to hold insurance than rural respondents. This is consistent with (Nahabwe, 2022) that urban households are embedded in denser networks of banks, agents and employers through which formal insurance products circulate, while rural households remain more reliant on informal risk-sharing mechanisms. The persistence of this effect after adjusting for income and employment suggests that the urban-rural gap in uptake reflects differences in proximity to formal financial infrastructure, not simply differences in income.

Level of education showed the strongest and most consistent demographic effect on insurance uptake, with a clear monotonic pattern in which uptake fell progressively as educational attainment declined from a degree. This effect remained highly significant after controlling for income, employment, age and residence, suggesting that education operates through channels beyond affordability alone, such as the confidence to interpret insurance contracts and claims procedures discussed by (Mwinuka et al., 2022). This finding is more consistent with the education-uptake studies that found a positive relationship than with those reporting an ambiguous or weak effect, and suggests that in the Ugandan context, education continues to matter strongly for insurance uptake even after institutional and trust-related barriers are taken into account through other covariates in the model.

4.5.2 Socioeconomic Factors and Insurance Uptake

With respect to the second objective, both employment status and income level were significantly associated with insurance uptake. Respondents in paid employment and those working with an NPISH were significantly more likely to hold insurance than the self employed, consistent with (Kaonga et al., 2026) expectation that formal, salaried employment often comes bundled with group health, life or disability cover, while self-employed and informally employed respondents face irregular incomes that make fixed premium schedules harder to sustain. The negative association between unemployment and uptake observed at the bivariate stage did not persist after adjustment, suggesting that the apparent disadvantage of unemployed respondents in the unadjusted model was partly explained by their lower income and education levels rather than unemployment itself.

Income level proved to be the strongest socioeconomic predictor of uptake throughout the study, remaining highly significant in both the bivariate and multivariate models, with a clear response pattern in which higher income categories showed progressively larger effects on uptake. This directly supports (Akhter & Khan, 2017) reasoning that income is the clearest constraint on insurance uptake, since, unlike attitudes or awareness, it determines whether a premium can be paid at all. The consistency of this effect across both models suggests that affordability remains the single most binding constraint on household insurance uptake in Uganda, reinforcing the case made in the literature for affordability-focused product design, such as small, flexible premiums timed to income cycles, as a lever for expanding coverage.

4.5.3 Insurance Literacy and Perceived Trust

The third objective sought to examine the effect of insurance literacy and perceived trust in insurance providers on household insurance uptake. The indirect measures for these constructs within the FinScope Uganda 2023 dataset were restricted exclusively to the 28 respondents who both held an insurance policy and had filed a claim. Since a variable that is only observed after uptake cannot logically explain uptake itself, these items could not be used as independent variables in the bivariate or multivariate models, and Hypotheses H31 and H32 could therefore not be empirically tested using this dataset. This represents a departure from the third specific objective and means that the attitudinal literature by (Kiwanuka & Sibindi, 2023), particularly the strong role of trust found in prior Ugandan studies, could not be independently verified or refuted within the scope of this study.

Table 4. 4: Summary of Bivariate and Multivariate Hypothesis Testing.

Hypothesis	Variable	Bivariate Decision	Multivariate Decision
H11	Age	Reject null (partial significance for 26-60 years, not for 60+)	Fail to reject null (not significant after adjustment, except a marginal effect for 46-60 years)
H12	Place of residence	Reject null (significant)	Reject null (significant, p = 0.046)
H13	Level of education	Reject null (significant)	Reject null (significant, p < 0.01 for all categories)
H21	Income level	Reject null (significant)	Reject null (significant, p < 0.01 for both categories)
H22	Employment status	Reject null (significant)	Reject null (significant for paid employment and NPISH not for unemployed)

4.6 Chapter Summary

This chapter presented the univariate, bivariate and multivariate results on the determinants of low insurance uptake among Ugandan households. Only 2.61% of respondents held insurance, confirming the low-uptake pattern motivating the study. At the bivariate level, age, place of residence, level of education, employment status and income level were all significantly associated with insurance uptake. After adjusting for other covariates in the multivariate model, place of residence, level of education, employment status (for paid employment and NPISH) and income level remained statistically significant predictors, while age lost significance once other socioeconomic characteristics were controlled for. Income level and level of education emerged as the strongest and consistent predictors of insurance uptake across both models.
Insurance literacy and perceived trust could not be empirically tested due to a data limitation.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

This chapter presents the conclusions and recommendations for policy, practice and further research, arising from the study on the determinants of low insurance uptake among Ugandan households.

5.1 Conclusions

Based on the findings above, the study draws the following conclusions in relation to its specific objectives.

The study concludes that age is not an independent determinant of insurance uptake among Ugandan households once socioeconomic circumstances are taken into account. Place of residence, level of education, income and employment status are all genuine, independent determinants of insurance uptake. Rural residents are disadvantaged mainly by distance from formal financial infrastructure while education shapes uptake through channels beyond affordability, such as the capability to understand and engage with insurance products.

Affordability is the single most binding constraint on household insurance uptake in Uganda, given its consistent and strongly significant monotonic relationship with uptake across both the bivariate and multivariate models. Employment status matters mainly because paid or NPISH work provides access to workplace-linked group cover. The study also concludes that the influence of insurance literacy and perceived trust in insurance providers on uptake remains an open empirical question in the Ugandan context since the FinScope Uganda 2023 dataset lacks measures of these constructs independent of uptake itself.

Overall, the study concludes that low insurance uptake among Ugandan households is primarily a demographic and socioeconomic phenomenon, driven principally by education, income, place of residence and access to formal employment, rather than by age.

5.2 Recommendations for Policy and Practice

Insurance providers and regulators should design affordability-focused products for lowincome households, such as micro-insurance with small, flexible premiums timed to align with irregular or seasonal income cycles.

Given the strength of the education effect, insurance providers, regulators and consumer protection bodies should invest in simplified product design and targeted consumer education for households with lower educational attainment, using plain language, illustrated materials and community-based intermediaries rather than relying on written policy documents alone.

To close the urban-rural gap in uptake, insurance providers and mobile-money or microfinance partners should expand rural distribution channels, for example through agent networks, savings groups and mobile-based enrolment and premium payment, to reduce the physical and informational distance rural households face in accessing formal insurance.

Given the significantly higher uptake found among respondents in paid employment and those working with NPISHs, employers, cooperatives and industry associations, particularly in the informal and self-employed sectors, which account for the majority of the workforce in this sample, should be encouraged to develop group and voluntary insurance schemes that extend the workplace-linked access enjoyed by the formally employed to informal workers.

5.3 Areas for Future Research

Future studies should use primary data collection or a secondary dataset specifically designed around insurance behaviour to measure insurance literacy and perceived trust independently of insurance ownership, this would close the gap left by the FinScope Uganda 2023 dataset's limited attitudinal coverage.

Future research should also examine the specific mechanisms through which education and place of residence affect uptake, for example financial literacy, exposure to insurance agents or trust in institutions, to isolate causal mechanisms from unobserved household characteristics.

Finally, to address the high rate of non-response on income, future analyses should incorporate multiple imputation in addition to complete-case approaches, verifying if the study's conclusions hold under alternative missing data mechanisms.

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APPENDICES

Do-file Editor - Code

```
*INSURANCE UPTAKE---
recode j1 (1=1 "Has insurance") (2=0 "No insurance"), gen(insurance_uptake)
label variable insurance_uptake "Has an existing insurance policy"
numlabel _all, add

tab insurance_uptake, missing

*AGE GROUP---
gen age_group = .
replace age_group = 1 if age >= 16 & age <= 25
replace age_group = 2 if age >= 26 & age <= 35
replace age_group = 3 if age >= 36 & age <= 45
replace age_group = 4 if age >= 46 & age <= 60
replace age_group = 5 if age > 60 & age < .

label define age_lbl 1 "16-25" 2 "26-35" 3 "36-45" 4 "46-60" 5 "60+"
label values age_group age_lbl
label variable age_group "Age group"
numlabel age_lbl, add

tab  age_group

*RESIDENCE---
gen residence = .
replace residence = 1 if Rural_Urban == "Rural"
replace residence = 2 if Rural_Urban == "Urban"

label define res_lbl 1 "Rural" 2 "Urban"
label values residence res_lbl
label variable residence "Place of residence"
numlabel res_lbl, add

tab residence

*EDUCATION---
gen education_group = .
replace education_group = 1 if c4 == 1
replace education_group = 2 if c4 == 2
replace education_group = 3 if c4 == 3
replace education_group = 4 if inlist(c4, 4, 5, 6, 7, 8)
replace education_group = 5 if c4 == 9

```

Line: 1, Col: 21 CAP NUM OVR

Do-file Editor - Code

```

*EDUCATION---
gen education_group = .
replace education_group = 1 if c4 == 1
replace education_group = 2 if c4 == 2
replace education_group = 3 if c4 == 3
replace education_group = 4 if inlist(c4, 4, 5, 6, 7, 8)
replace education_group = 5 if c4 == 9

label define edu_lbl 1 "No formal education" 2 "Primary" 3 "Secondary" 4 "Tertiary/Vocational" 5 "Other"
label values education_group edu_lbl
label variable education_group "Highest level of education"
numlabel edu_lbl, add

tab education_group, missing

*EMPLOYMENT STATUS---
gen employment_status = .
replace employment_status = 1 if inlist(c5, 1, 2)
replace employment_status = 2 if inlist(c5, 3, 4)
replace employment_status = 3 if c5 == 6
replace employment_status = 4 if inlist(c5, 5, 7, 8, 9)
replace employment_status = 5 if inlist(c5, 10, 99)

* --- Make sure ALL 5 categories are labeled here ---
label define emp_lbl 1 "Self employed" 2 "Paid employment" 3 "Working with NPISH" 4 "Unemployed" 5 "Don't know/refused", replace
label values employment_status emp_lbl
label variable employment_status "Employment/income-source status"
numlabel _all, add

tab employment_status, missing

*INCOME LEVEL---
gen income_level = .
replace income_level = 1 if inlist(d3_31, 1, 2)
replace income_level = 2 if inlist(d3_31, 3, 4)
replace income_level = 3 if inlist(d3_31, 5, 6, 7)

label define inc_lbl 1 "Low income" 2 "Middle income" 3 "High income", replace
label values income_level inc_lbl
label variable income_level "Monthly income level (primary income source)"
numlabel _all, add
```

Do-file Editor - Code

File Edit View Language Project Tools

Code

```
label values income_level inc_lbl
label variable income_level "Monthly income level (primary income source)"
numlabel _all, add

tab income_level, missing

*INSURACE LITERACY AND TRUST---
tab j1, missing
misstable summarize j10_1 j10_2

* --- Perceived trust proxy (recommendation intent) ---
recode j10_2 (1=1 "Would recommend") (2=0 "Would not recommend"), gen(trust_proxy)
label variable trust_proxy "Perceived trust in insurance (recommendation proxy)"
numlabel _all, add
tab trust_proxy, missing

* --- Claims-handling experience (literacy/satisfaction proxy) ---
gen claims_experience = j10_1
label define exp_lbl 1 "Satisfactory" 2 "Fair" 3 "Not Good"
label values claims_experience exp_lbl
label variable claims_experience "Experience handling insurance/claims"
numlabel exp_lbl, add
tab claims_experience, missing

* --- Collapsed binary version (useful given small n) ---
capture drop claims_experience_bin
recode j10_1 (1=1 "Positive experience") (2 3=0 "Fair/Not good"), gen(claims_experience_bin)
label variable claims_experience_bin "Positive vs fair/poor claims experience"
numlabel _all, add
tab claims_experience_bin, missing

* --- Optional composite index ---
capture drop literacy_trust_index
egen literacy_trust_index = rowtotal(trust_proxy claims_experience_bin)
replace literacy_trust_index = . if missing(trust_proxy) & missing(claims_experience_bin)
label variable literacy_trust_index "Composite insurance literacy/trust proxy (0-2)"
tab literacy_trust_index, missing

* --- Descriptive cross-tab restricted to insured sub-sample only ---
tab trust_proxy insurance_uptake if j1==1, row
tab claims_experience insurance_uptake if j1==1, row
```