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**THE DETERMINANTS OF PROBABILITY OF DEFAULT FOR DIGITAL CREDIT
BY YOUTH IN NAIROBI, KENYA: MODERATING EFFECT OF LOAN SIZE**

MURURU BRENDA MWENDWA

070997

**A RESEARCH THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS
OF THE MASTER OF SCIENCE IN DEVELOPMENT FINANCE OF
STRATHMORE UNIVERSITY BUSINESS SCHOOL**



JUNE 2026

DECLARATION

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Brenda Mururu [Name of Candidate]



[Signature]

23/06/2026

[Date]

Approval

The thesis of Brenda Mururu was reviewed and approved by the following:

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Faculty Affiliation



Institution: Strathmore Business School

ABSTRACT

Digital credit has been widely recognized as a form of financial inclusion in modern financial markets, with its origins in Kenya dating back over a decade through M-Shwari. This has since evolved into a market with several independent Digital Credit Providers and banks offering digital credit which are regulated by the Central Bank of Kenya. Despite its benefits, digital credit had presented challenges, particularly around consumer data protection by digital lenders and the effect of these facilities on the borrowers' financial capability, often inducing debt distress. This is evidenced by the high rates of default that had been observed for these facilities in Kenya and other global markets. Consequently, the main objective of this study was to investigate the determinants of the probability of default for digital credit facilities by youth in Nairobi County. The specific objectives of the study were to determine the effects of borrower characteristics, loan characteristics, and lender characteristics on the probability of default for digital credit facilities by youth in Nairobi County. The borrower characteristics analysed included age, gender, default history, student loan status, marital status, level of income, occupation, and level of education. The loan characteristics investigated were the loan interest rate, loan tenure, and loan purpose. The lender characteristics explored were the lender's business model, the applied mode of payment, and the loan appraisal period. The study was based on the adverse selection theory and the financial intermediation theory. The population of interest for this study was the Nairobi County youth and the sample size was determined using Cochran's formula and through stratified random sampling. Primary data collection was done using structured questionnaires. A probit regression model was used to analyse the data. The study concluded that borrower characteristics, loan features, and lender practices have a positive and statistically significant influence on the probability of default on digital credit facilities among youth in Nairobi County. The study recommends that digital credit providers refine their assessment models, invest in financial literacy programs, and adopt flexible loan terms, while urging policymakers to implement regulations that enhance transparency, promote financial education, and reduce information asymmetry to improve youth access to credit and reduce default rates.

Key words: Digital credit, probability of default, youth, borrower characteristics, loan characteristics, lender characteristics, Digital Credit Providers, loan size

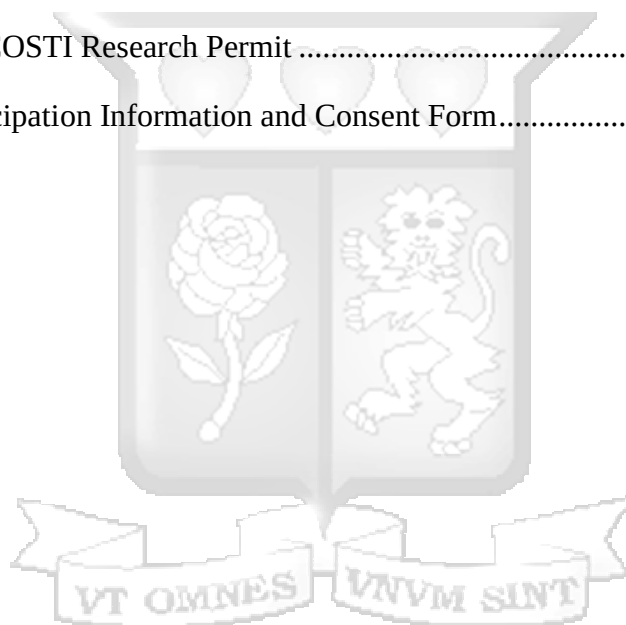
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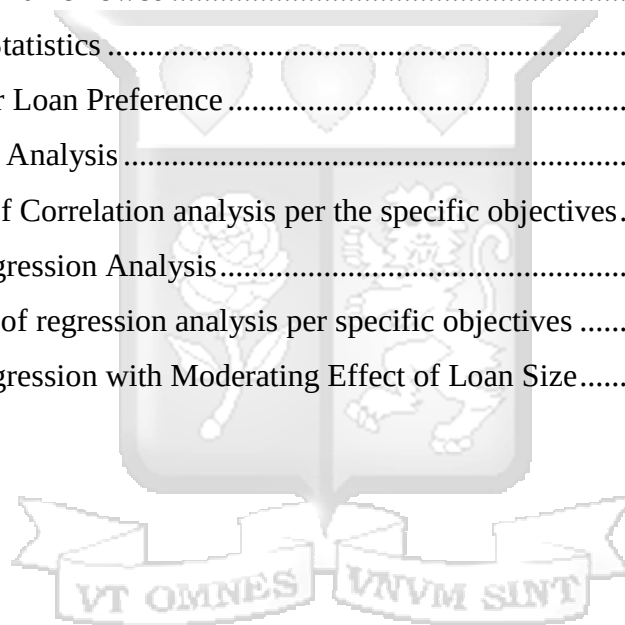
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LIST OF ABBREVIATIONS

CBK	Central Bank of Kenya
CRB	Credit Reference Bureau
DCP	Digital Credit Provider
MFI	Microfinance Institution
NACOSTI	National Commission for Science, Technology & Innovation
SACCO	Savings and Credit Cooperative Society
SME	Small and Medium Enterprise



DEFINITION OF TERMS

Digital Credit: Loans that are accessible online or through the use of mobile devices via a digital application (Kamau, 2021). These facilities are characterized by fast turnaround times for disbursement, often within 24 hours (Anderson & Reynolds, 2017) .

Probability of Default: The likelihood that a borrower will fail to meet the agreed-upon repayment obligations for a credit facility (Bob et al., 2018; Maggio & Yao, 2021).

Youth: In the context of the Kenyan Constitution, these are individuals who are between 18 and 35 years of age (The Government of Kenya, 2010).

Borrower Characteristics: The socio-economic and demographic and credit history factors like age, income, marital status, level of education, that are specific to an individual client which are used to assess whether they are credit worthy (Johnen & Mußhoff, 2023; Muthoni, 2016).

Loan Characteristics: The specific terms and features of a loan agreement, including the interest rate charged, the loan tenure (repayment period), and the intended purpose of the loan (Croux et al., 2020; Imai, 2022).

Lender Characteristics: The attributes describing the lending institution, such as its business model, the applied mode of payment, and the loan appraisal period (Maggio & Yao, 2021).

Digital Credit Providers (DCPs): Entities that use new innovative technologies to provide financing to both banked and unbanked populations outside of traditional banking structures (Eunsook & Kyeongwon, 2020).

Loan Size: The total amount of credit disbursed to a borrower, which serves as a moderating variable that can influence the effect of borrower, loan and lender characteristics on the probability of default (Featherstone et al., 2006).

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I express my profound gratitude to God for walking with me through this journey, my supervisor, Dr. Nyang'u for his exemplary guidance throughout the research process, my parents, family and friends for always offering their encouragement and support.



DEDICATION

I dedicate this work to my ever loving and supportive parents who have made this journey possible through the opportunities they have exposed me to in my life.



CHAPTER ONE: INTRODUCTION

1.1 Background of the study

Among the many current contemporary issues that several countries globally are focusing on, financial inclusion is a key issue. This is vital in achieving the first sustainable development goal of eradicating poverty (Neshovski, 2025). According to Goksu (2019), financial inclusion refers to using financial services to empower people's capabilities and improve their welfare which results in development that is all inclusive especially for the poor people, the young and female population.

Globally as of 2020, we had 67% of the population that had mobile phones access but there were still over 1.2 billion adults that lack access to traditional finance with the largest percentage in Sub-Saharan Africa and South Asia (Lyons et al., 2020). This created a niche for digital credit providers that seek to provide financing to both the banked and unbanked with an effort to also spread financial literacy.

Maggio and Yao (2021) describe digital credit providers as a disruptive force that has been witnessed in the financial services industry. They focus on provision of financial services using new innovative technologies for digital credit (Eunsook & Kyeongwon, 2020). Kamau (2021) defines digital credit as loans that are accessible online or by use of mobile devices through a digital application. The Global Fintech Index 2020 indicates that the leading countries in digital lending globally are United States, United Kingdom, Singapore, Switzerland, and Netherlands (Pauliukevičienė & Stankevičienė, 2021).

1.1.1 Determinants of probability of default on digital credit facilities

Digital credit is characterized by rapid processing, typically reaching the borrower within 24 hours, compared to other traditional credit facilities (Anderson & Reynolds, 2017). This is what attracts people to these loans since not all the digital lenders consider credit repayment history and the lengthy documentation that is required by banks and other traditional lenders. There are three key aspects that differentiate the digital lenders from traditional lenders in the lending process. The first one is based on the fast turnaround time for loan disbursement, the second is based on the automated process that is not reviewed by people, and the last one is that there is no need for in-person relations between the lender and borrower as is required by the traditional lenders like banks and microfinance institutions

Digital credit providers rely on data for repayment of previous digital loans for repeat borrowers while for the new borrowers, they rely on alternative data like the customers' mobile

money transaction data and balances as well as their activities on social media (Anderson & Reynolds, 2017). On the other hand, banks review one's eligibility for digital credit based on data provided by the Credit Reference Bureaus, review of previous credit facilities lent to the same customer and further analysis of the customer's income turnovers (Johnen et al., 2021). Banks carry out credit assessment by analysing the clients based on their demographic characteristics, their ability to pay back the loan within the agreed upon repayment period, and the assets owned before loan disbursement (Bob et al., 2018).

Borrower characteristics are traits that borrowers have if they are to gain access to financial services. Loan characteristics refer to the credit terms that the borrower signs up for in the loan agreement. These include the repayment amount, tenure, and interest rate. Borrower characteristics by themselves might not be able to explain default. It is essential to consider other aspects like loan characteristics that are more associated with loan repayment (Bob et al., 2018). This is why this study focused on borrower characteristics, loan characteristics and lender characteristics to have a better understanding of the determinants of probability of default for these credit facilities.

Extensive studies have been done but limited studies use individual borrowers' data as credit lenders hesitate to disclose their customers' data due to confidentiality. This study sought to address this by collecting data from borrowers directly. Significant factors in explaining mortgage loans default are gender, ethnicity, tenure of the loan and its interest rate. Male borrowers have a higher likelihood of default than female borrowers. The longer the period of loan repayment and a higher interest rate increase the probability of default (Abdul Adzis et al., 2021).

However, other studies indicate that female borrowers have a higher likelihood of default than males (Owusu-Manu et al., 2019). The borrower characteristics that are significant include gender, age, and the borrower's work sector. Additionally, the borrowers' perception of limitations to credit access also influences credit default. These factors include the collateral required, interest rate and the loan size (Owusu-Manu et al., 2019). The significant determinants of default for agricultural credit facilities are the borrower's age, the size and tenure of the loan (Savitha & Kumar K., 2016).

Existing studies have evaluated the determinants of probability of default on various credit facilities and there has been consensus that the main factors that determine default are socio-

demographic characteristics specific to the borrower, loan characteristics, lender characteristics and macro-economic factors.

1.1.2 Probability of default on digital credit facilities

In 2021 and 2022, the global digital loans delinquency rates were at a high of 8.7% and 4.7% respectively as the large fintech companies had to consider the provision for bad loans due to Covid-19. The digital lending industry seems to have stabilized from the Covid-19 effects given the 49% increase in the number of disbursed loans as well as 21% increase in the loan value disbursed globally in 2023 (Gonsalves, 2023). On the contrary, Kenya witnessed a huge ramp up in the uptake of digital credit in 2020 and 2021 because of Covid-19 (Michuki, 2022).

ETBFSI Research (2023) indicates that global digital lenders are shying away from new to credit customers due to the high default rates on digital loans. They have shifted to customers with high credit scores to enhance the performance of their loan portfolios. The global default rates for digital loans rose to 3.2% in 2023 compared to 0.9% for other lenders. According to TransUnion CIBIL, in 2023, the new to credit digital loans in India only accounted for 13% of total lending compared to 29% in 2019. However, in other markets like China, there has been an increased uptake of digital lending which is focusing on its middle-class population that is mostly comprised of young people. Fintech has revolutionized business in China by influencing how people interact with vendors and how vendors interact with their markets. Digital credit disbursed loans worth \$170 billion globally in 2017 (Kharas & Dooley, 2020).

Sub-Saharan Africa has embraced digital credit since the traditional access to finance is very restricted. As of 2014, 34% of the adult population in Sub-Saharan Africa had a mobile money account with East Africa recording the highest penetration at 55% (Blechman, 2016). Kenya and Tanzania have been at the forefront in embracing digital lending. Tanzania has 4 digital lenders that were established between 2014 and 2016. These include M-Pawa and Nivushe (Anderson & Reynolds, 2017). Additionally, CGAP indicates that circa 50% of Kenyans and 56% of Tanzanians who have borrowed digital credit facilities have had late loan repayments with 12% and 31%, respectively, defaulting fully (Izaguirre, 2018).

According to FSD Kenya, the usage of digital loan applications in Kenya grew from 0.6% in 2016 to 8.3% in 2019. The movement that began with M-Shwari in 2012 had more than sixty lenders in 2019 (Gwer, 2019). The Global Findex 2021 survey also indicates that 30% of adults had used their mobile money accounts to borrow money in 2021 (Demirgüç-Kunt et al., 2022).

As of June 2024, there are 58 licensed digital credit providers in Kenya, including Tala, which are regulated by the CBK (Central Bank of Kenya, 2024). The initiative to register them emanated in 2022 following several concerns of data privacy violation by digital credit providers. In terms of the other credit providers in the market, as of 2021, we had 39 commercial banks with 564 branches countrywide, 59,000 mobile agents and 37 SACCO branches (Central Bank of Kenya et al., 2021). However, even with all these players in the financial markets, there is still need for information sharing in the Kenyan financial markets with regards to digital loans. In 2019, only one bank was consistent on sharing information on its digital loans performance with Credit Reference Bureaus and only one non-bank lender shared the information with the three authorized Credit Reference Bureaus i.e. TransUnion CRB Africa Limited, Metropol Credit Reference Bureau Limited Kenya and Credit Info Credit Reference Bureau Limited (Gibbins, 2019).

Based on the 2024 FinAccess Household survey (Central Bank of Kenya et al., 2024), 16.6% of borrowers in Kenya had fully defaulted on loans up from 10.7% in 2021. Of this, 52% were male and 48% were female. In 2021, the default rate for loans from mobile banking was at 51% and for digital loans was at 46% (Central Bank of Kenya et al., 2021). These were the loans with the highest default rates while the default rate on personal loans and business loans from a bank stood at 22.1%. These findings were consistent with the results from the (2019) FinAccess Household survey. This creates the need to explore the determinants of probability of default for digital credit facilities by youth in Nairobi County.

Various methodologies have been applied to predict the probability of default including binomial logistic regression, probit regression model, use of machine learning and artificial intelligence in the developed countries to determine the level of risk and creditworthiness attached to a particular borrower especially in cases where there is no previous lending history for the digital loans. The use of these various methodologies has led to conflicting outcomes on the most critical determinants of probability of default (Kumar et al., 2021). This study applied the probit regression approach that has been applied in several previous studies (Banasik et al., 1999; Croux et al., 2020; Volkwein & Szelest, 1995; Zurada & Barker, 2007).

1.1.3 Youth in Nairobi as the context

Based on the 2024 FinAccess Household survey (Central Bank of Kenya et al., 2024), 93.7% of the Nairobi County population of adults (18 years+) have financial products and services access.

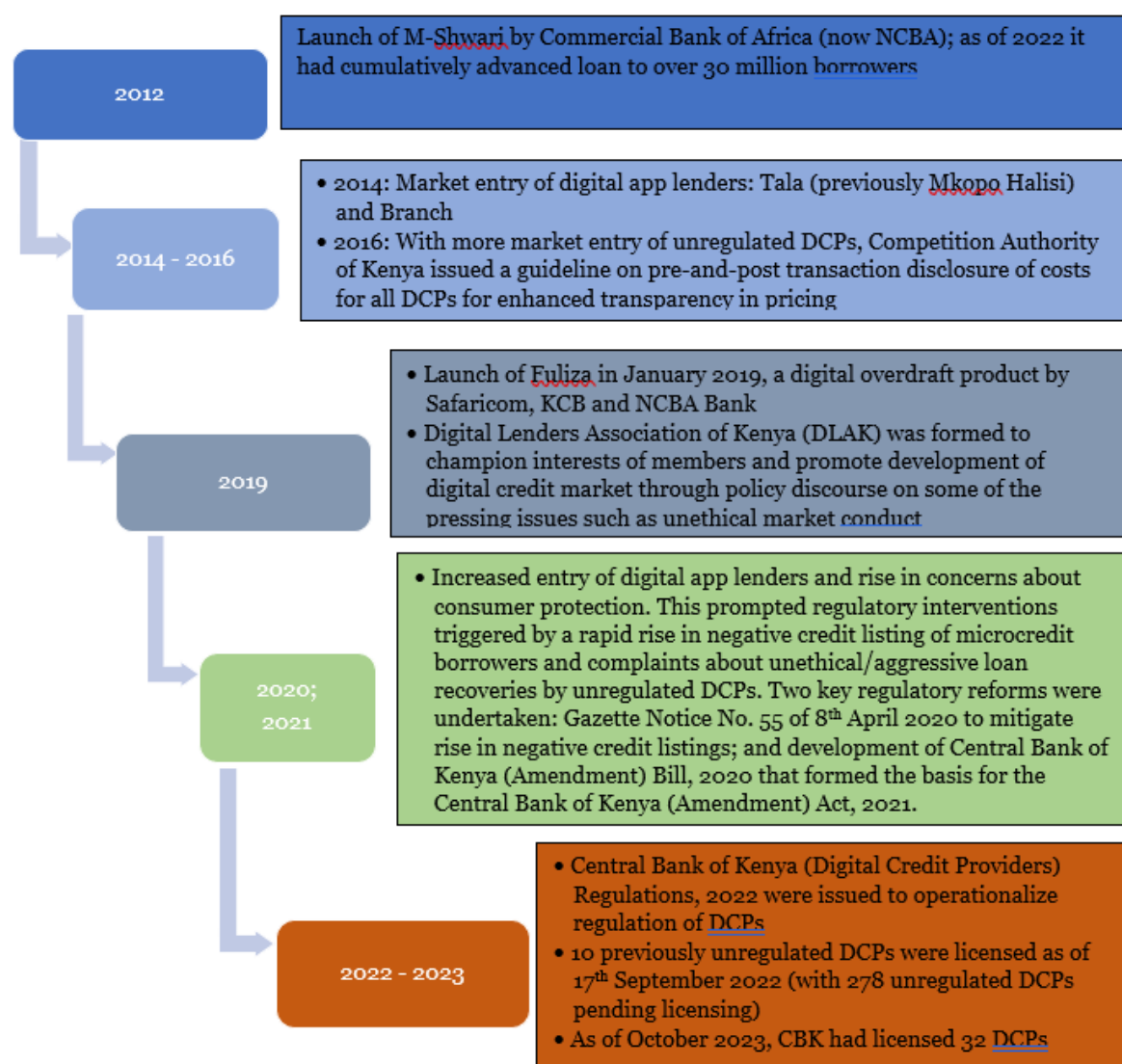
One of these financial products is digital credit which offers a platform for people to access loans through mobile banking and applications (Michuki, 2022). The majority users of digital credit are youth who are male, individuals dwelling in urban areas and those with a higher level of education (Kamau, 2021; KIPPRA, 2023). Most youth digital loan borrowers believe that digital credit facilities have helped them get better access to financing (Wathome, 2020).

According to ETBFSI Research (2023), delinquency rates as of 2023 varied across various age segments. However, the highest delinquency rate was from borrowers aged below 25 years at 5%, 3% for those between the ages of 26-45 and those above 45 at 1%. One of the most important findings from the FinAccess survey 2021 was that 52% of the credit defaulters in Kenya were below 35 years of age and more than 70% were earning below Ksh. 25,000 per month (Michuki, 2022). This emphasizes the need for contextualizing the determinants of the probability of default by youth on digital credit facilities.

From the perspective of financial literacy, circa 69% of the population of adults have heard of CRB reports and 70% are aware of the cost of borrowing. In terms of financial usage, 72% of the population use banks and mobile bank services while 94% use mobile money accounts. The high usage of mobile money accounts is explained by the need for mobile money to address financial needs of these youth especially during the Covid-19 pandemic which encouraged people to go cashless to reduce its spread within the country (Central Bank of Kenya et al., 2021).

Since young people represent the majority of those failing to repay digital loans (Wathome, 2020), many find themselves caught in cycles of indebtedness. This situation restricts their ability to obtain future financing if they are reported negatively to credit bureaus (Michuki, 2022). Frequently, young borrowers acquire new loans from unlicensed platforms to settle previous debts, a strategy that is not viable over the long term. This is one of the aspects that this study investigated to understand the borrower's purpose for taking up the digital loan.

With the noted increase in the uptake of digital lending services within these markets and the high rates of default on these facilities by youth, this study sought to review the determinants of the probability of default among this population.



Source: Author's illustration based on review of literature and regulatory reforms

Figure 1: Evolution of the digital credit market in Kenya

(KIPPRA, 2023)

1.2 Statement of the problem

While the growth of digital lending has transformed financial markets by boosting accessibility, the frequency of non-repayment in this area has surged, exceeding the rates found in traditional credit. Specifically, digital loan defaults in Kenya reached 16% during the 2016–2018 period, a figure notably higher than the 12% default rate recorded for general private sector credit (Johnen et al., 2021; Sommer, 2021; World Bank, 2024).

From the 2019 FinAccess survey, digital credit default rates in Kenya were at 14% while the default rates for semi-formal and formal credit markets stood at 7% and 6% respectively. As at 2023, the global digital credit default rates varied depending on geographical context with Mexico's standing at 27% and Kenya and Nigeria's at 7%. This has made the digital creditors more vigilant in their credit risk assessment of potential borrowers (ETBFSI, 2023; Wang et al., 2020). Digital Credit Providers (DCPs) rely heavily on hard information from credit reports which leads to adverse selection that can lock out credit worthy borrowers and misallocate funds to defaulters (Maggio & Yao, 2021).

There is extensive literature that identifies the determinants of probability of default for various credit facilities, specifically borrower characteristics (Croux et al., 2020; Johnen & Mußhoff, 2023; Muthoni, 2016; Wamalwa et al., 2019), loan characteristics (Adem et al., 2012; Croux et al., 2020; Njenga & Kavindah, 2021), and lender characteristics (Burlando et al., 2023; Felix & Wachira, 2018; Gubbins, 2019). Despite the youth being the largest consumer base for digital credit and characterized by high credit default risk, there are relatively few studies that have investigated the determinants of probability of default on digital credit facilities by youth in Nairobi County, Kenya. This shows that there is a population gap in previous studies that this study sought to investigate (Kamau, 2021; Michuki, 2022; Nzisa & Kithandi, 2023).

However, the results of these studies have been contradictory with regards to the most significant determinants of probability of default. Previous studies have mostly focused on the demand side of the determinants of probability of default, specifically borrower characteristics while ignoring the supply side which explores lender and loan characteristics. This study aims to investigate the demand and supply side (Johnen et al., 2021; Muthini & Ndede, 2022). Additionally, most previous studies in Kenya have narrowed their focus on the probability of default for traditional forms of credit like banks, SACCOs and MFIs (Bob et al., 2018;

Burlando et al., 2023; Kamau, 2021; Muthini & Ndede, 2022). Finally, there have been contradictory results in the best methodology in predicting the probability of default with some arguing that logistic regression is the best regression (Costa e Silva et al., 2020; Croux et al., 2020; Featherstone et al., 2006; Jouault & Featherstone, 2011; Khedr et al., 2021) while others support machine learning (Bussmann et al., 2021; Khedr et al., 2021; Kumar et al., 2021; Mhlanga, 2021).

Against this background of gaps in previous studies and the rapid growth of the digital lending space, this study sought to investigate the determinants of the probability of default on digital credit facilities by the youth in Nairobi County. This would contribute to improving the credit risk assessment process by establishing the borrower, loan and lender characteristics that have the most significant effect on the probability of default and reduce the risk of adverse selection.

1.3 Research Objectives

1.3.1 General objective

The study sought to investigate the determinants of probability of default for digital credit facilities by youth in Nairobi County

1.3.2 Specific objectives

The specific objectives of the study were:

- i. To determine the effect of borrower characteristics on the probability of default for digital credit facilities by youth in Nairobi County
- ii. To establish the effect of loan characteristics on the probability of default for digital credit facilities by youth in Nairobi County
- iii. To examine the effect of lender characteristics on the probability of default for digital credit facilities by youth in Nairobi County
- iv. To investigate the moderating effect of loan size on the relationship between borrower, loan, and lender characteristics and the probability of default for digital credit facilities by youth in Nairobi County

1.4 Research questions

The study answered the following questions:

- i. What is the effect of borrower characteristics on the probability of default for digital credit facilities by youth in Nairobi County?

- ii. What is the effect of loan characteristics on the probability of default for digital credit facilities by youth in Nairobi County?
- iii. What is the effect of lender characteristics on the probability of default for digital credit facilities by youth in Nairobi County?
- iv. What is the moderating effect of loan size on the relationship between borrower, loan, and lender characteristics and the probability of default for digital credit facilities by youth in Nairobi County?

1.5 Scope of the study

The study's main population was the youth who had access to financial products and services, including digital and mobile banking loans, which totalled 1,765,922 (Refer to Section 3.4). According to the Constitution of Kenya 2010, a person is defined as youth if they have attained the age of eighteen years but have not reached the age of thirty-five years (The Government of Kenya, 2010). The digital credit facilities reviewed in the study were those offered by Branch, Tala, KCB-Mpesa, Equity Eazzy loan, M-Coop Cash, M-Shwari, Timiza, and Fuliza. These facilities were chosen due to their popularity in the Kenyan digital lending market (Edoardo Totolo, 2018). Data collection was done between May and June 2025 and the sample consisted of 384 borrowers with an 88% response rate. A quantitative analysis approach was applied using probit regression model.

1.6 Significance of the study

Digital credit has taken the world by storm with a lot of its aspects yet to be fully explored with regards to its scalability, regulation, pricing among other issues. This study aimed to provide more clarity on the default aspect and how that can be used to inform better pricing mechanisms for digital credit facilities. The study is expected to be beneficial to the following:

1.6.1 Policy makers and regulators

The study assisted to inform policies that the policy makers like the Ministry of ICT and Youth Affairs, Capital Markets Authority and the Central Bank of Kenya can come up with to regulate the exorbitant interest rates on digital credit facilities lent to the youth and protect the consumers from illegal use of their personal data in determining their creditworthiness by fintech companies.

1.6.2 Digital credit lenders

This study aimed to inform the pricing of future digital loans by digital credit lenders by determining the probability of default of individuals based on the lender, borrower, and loan characteristics.

1.6.3 Academicians and researchers

This study aimed to provide insight to academicians and researchers on how digital lending credit assessment is done and more clarity on the default aspects of the lending facilities offered by both parties. With this, there will be proposals on other areas of study that can be taken up in the future based on the findings from this study.

1.7 Summary of the study

This chapter has built the foundation for the study by outlining the background, research objectives, problem statement, scope and significance of the study. The main objective of this study was to investigate the determinants of probability of default for digital credit facilities by youth in Nairobi County. Chapter two includes a review of the underpinning theories for this study and the existing literature bringing out the relevant research gaps that will be addressed by this study. Chapter three entails the research philosophy applied in this study, the research design, population of the study, sampling and data collection method and instrument. Chapter four discusses the data analysis and presentation, including the descriptive analysis of the study responses, the correlation tests, and the probit regression analysis between the independent and dependent variables. Chapter five focuses on the discussions, conclusion and recommendations of the study.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This chapter takes a deeper look into the theoretical foundation of the study and the empirical studies carried out in determining the probability of default for digital credit facilities. This supports the need to take on a proactive rather than a reactive approach to credit risk management. This chapter brings out the gaps that have been identified from previous research and how this study sought to address those gaps.

There is a chronological breakdown of the two theories underpinning this study followed by the empirical review of previous research, their findings and future areas of research recommended. The empirical review includes the logic that ties up the theoretical review to the empirical work done and links them to the objectives of the study and the research questions that this study sought to address. This informs the summary of the key research gaps, the conceptual framework of the study and the operationalization of variables that the researcher applied in this study.

2.2 Theoretical review

This section presents two underlying theories for this research, their background, strengths, and criticisms brought forward by other studies. The application of a multi-theory framework allows the study to focus on the demand and the supply sides of credit and the risks associated with both sides that can lead to default. Financial intermediation theory introduces the innovation by financial institutions in digital lending and the challenges faced as a result. The adverse selection theory explains the risks due to information asymmetry in the credit markets.

2.2.1 Adverse selection theory

This theory was developed by Akerlof in 1970 and it postulates that information asymmetry is a critical challenge that faces transactions in the credit markets (Akerlof, 1970). In a perfect

market, the borrowers and lenders would have perfect and equal information about each party. However, in the credit market, from the lender's perspective, borrowers tend to have more information about their credit worthiness, based on their characteristics and due to this, lenders extend loans to borrowers who end up being defaulters which leads to losses for the lenders (Wachira & Kihara, 2023). In the context of this study, this theory explains how the limited knowledge of borrower characteristics in the lending markets, especially for the youth who do not have a significant credit history, can lead to default. This could also lead to credit worthy borrowers being locked out of the credit market.

Pagano and Jappelli (1993) recognize the impact of adverse selection on the credit lending markets. They constructed a model advocating for the exchange of data as a strategy to counter information asymmetry. Consequently, their work highlights the vital role of Credit Reference Bureaus (CRBs) in offering transparency regarding a borrower's past credit repayment history which leads to an increase in lending activity. To support this, Cohen and Siegelman (2010) also reveal that there exists adverse selection in the insurance industry.

Huang and Thomas (2014) determine that there is a simple relationship between the actual default risk of a credit card borrower and their perceived risk by the lender. The expected profits forecasted by the lender are not that far off from the optimal possible profit in the market. However, due to adverse selection, there is a reduction on the actual profit realized.

There is a link between a borrower's financial literacy level and their state of indebtedness in the Kenyan digital credit market. The borrowers with a higher financial literacy have a lower likelihood of borrowing digital credit compared to those who have lower financial literacy. This is because the more financially literate borrowers have a better understanding of the risks tied to digital credit. The individuals with lower financial literacy are those who have less income and have lower levels of education. Given this context, DCPs attract borrowers with a higher likelihood of default which is in support of the adverse selection theory (Wamalwa et al., 2019).

In support of the adverse selection theory, Johnen et al. (2021) indicate that the borrowers who seek digital credit in Kenya are those who lack access to credit in the formal credit market due to being considered to be high risk borrowers. They acknowledge that understanding the rate of default on these credit facilities warrants consideration of other elements outside of borrower characteristics, for example the loan characteristics like interest rates charged on the loans.

Adverse selection can also be evaluated from the borrower's perspective given that some lenders do not share all the loan details like the terms and conditions, upfront with the borrowers and this could lead to borrowers taking on loans that they are unable to service. These terms include loan characteristics like the interest rates, transaction fees and the required repayment period (Wachira & Kihara, 2023).

Critiques of this theory have indicated that while the adverse selection theory plays a role in default risk, there are other factors that contribute to default. The adverse selection theory tends to focus on the borrower characteristics that the lenders are unaware of that can lead to the less credit worthy borrowers defaulting. However, there are outside factors like the loan characteristics, lender characteristics and modern credit risk assessment tools that can also lead to default. For example, the borrowing cost, the loan repayment period and the shortcoming of limited credit information sharing for digital credit facilities (Francis et al., 2017). In support of this, Siegelman (2004) argues that there are other factors that are unforeseen to insurance policy holders that are not considered by the adverse selection theory whose case is also applicable in credit markets where there is need to focus on other factors outside the borrower characteristics that can influence default.

According to Johnen and Mußhoff (2023), while the adverse selection way of assessing credit risk works, it cannot be used to fully understand the nature of digital lending. There is need to consider alternative data and modern tools in credit risk assessment (Anderson & Reynolds, 2017). In support of this, Mhlanga (2021) explores the use of alternative data in credit risk assessment in growing markets to promote financial inclusion. The use of artificial intelligence could greatly reduce adverse selection as it provides more information on the credit worthiness of the borrower by reviewing their patterns on various platforms. According to Kashangaki (2019), one key consequence of information asymmetry is a small regulated formal credit market and an equally robust but potentially extractive unregulated informal market as exists in Kenya.

From the different proponents and opposers described above, there is some aspect of adverse selection that can be considered by lenders in the financial industry. This theory informs the need to assess the probability of default on digital credit facilities by youth in Nairobi County which is what this study sought to investigate. Based on the findings of this study, previous default history and unstable income are significant determinants to the theory. Since the youth have limited credit histories which lenders might not have visibility at the point of lending, the

information asymmetry is at its peak, forcing lenders to rely on "lender-side" characteristics like aggressive appraisal periods, which the study found significantly increases default probability. With such a proactive approach, digital lenders can adopt a credit risk model that can be applied in determining the credit worthiness of a potential borrower for digital credit. This gives them leverage on information they might not have about the borrower by mirroring their characteristics with those of previous borrowers and how their facilities were conducted.

2.2.2 Financial Intermediation Theory

The theory of financial intermediation was initiated by Gurley and Shaw in 1956 (Gurley & Shaw, 1956). It posits that financial intermediaries exist to lower the transaction costs, to mitigate information asymmetry and due to regulatory factors within financial markets (Scholtens & Wensveen, 2003). Financial intermediaries facilitate improved liquidity through reducing transaction costs and manage risk profiles by reducing information asymmetry. This theory is key to this study as the digital credit lenders play an intermediary role in the financial markets. Financial intermediaries exploit benefits in the transaction technology including costs related to risk, searching and monitoring (Alam & Nazim Ali, 2021). This theory shows how digital lenders evaluate borrower risk and integrate that in their pricing strategies, including the interest rates charged. Given that different lenders have different credit lending practices, it helps to explain how lender and loan characteristics can determine the probability of default.

The emergence of digital lending has had a significant impact on the financial services sector especially the banking industry. DCPs powered by fintech have further reduced transaction costs in credit markets and enhanced financial inclusion from an access dimension. Reduction of transaction costs caused by technology has also reduced barriers to entry in financial markets which explains the huge increase in the digital credit providers in Kenya over the recent years (Molnár, 2018). However, even though fintech has led to the innovations in the financial markets, it is unlikely that banks will disappear from the markets. This is because the digital credit providers play a supplementary role to banks. Consequently, this study investigated the lender and loan characteristics for digital credit lenders and their role in determining the probability of default for digital credit facilities.

Based on the recent reviews of the financial intermediation theory, information-based theories provide a better explanation to the existence of financial intermediaries. Modern financial markets stemming from the development of new financial instruments and technology

advancement have led to enhanced roles of financial institutions. Albeit there is a change in the financial intermediaries' role, their existence remains fundamental (Alam & Nazim Ali, 2021). Scholtens and Wensveen (2003) argue that there is a need to view financial intermediaries from an evolutionary perspective whereby their form changes with time and place. Banks have been forced to adopt technology in some of their processes like online banking, mobile banking and bancassurance like NCBA and Equity bank in Kenya (Alam & Nazim Ali, 2021). This emphasizes the need to investigate the determinants of probability of default for the digital credit facilities offered by banks which have developed their own digital credit facilities or partnered with mobile networks to provide facilities like Fuliza.

The controversy introduced in the modern financial markets with respect to the financial intermediation theory is whether the risk management role of financial intermediaries supersedes the reduction of transaction costs and information asymmetry. In these markets, financial innovation centers on risk management specifically in terms of minimizing credit risk, currency risk and interest rate risk. Additionally, the financial intermediaries do not fully eliminate information asymmetry which means that the market imperfections are maintained (Scholtens & Wensveen, 2003).

The diverse types of intermediaries and their innovation in the financial markets suggests that the need for financial intermediaries still exists. With technology innovations, traditional transaction costs take a different form where they transform into the costs of gathering information, selection, and processing (Scholtens & Wensveen, 2003). Due to information asymmetry by credit borrowers, bank loans signal the credit worthiness of borrowers in a way that other forms of credit do not (Bhattacharya & Thakor, 1993). Banks ration credit if they have less information about the ability of the borrower to pay back or if they believe that the borrower will make choices that affect the bank's return (Bhattacharya & Thakor, 1993).

In summary, one of the strengths of the financial intermediation theory is that it is well suited for explaining default within the context of banks and other lenders as supported by Bhattacharya and Thakor (1993). Secondly, it provides a risk management framework for financial institutions (Scholtens & Wensveen, 2003). It covers the influence of borrower characteristics, lender behaviour, loan characteristics and the regulatory environment in explaining the existence of financial intermediaries.

Based on various previous studies, one of the downsides of the financial intermediation theory is that even though it reduces information asymmetry, it does not account for the other

dynamics of the financial markets. Secondly, it does not fully cover the complexities of default in the ever-evolving financial markets (Alam & Nazim Ali, 2021). The financial intermediation theory was applied in this study to explain the supply side of digital credit, more specifically showing the role of DCPs and banks in the digital credit market and how their business models and the structure of their digital loan facilities determine the probability of default. This study reviewed the financial intermediation theory aspect of reducing information asymmetry from the lenders' side. This was done by evaluating borrower characteristics, loan and lender characteristics and the extent to which they can predict the probability of default in digital credit facilities. The study established that structural loan elements, particularly steep interest charges and brief repayment periods, are major catalysts for default. This suggests that financial institutions have fallen short of their responsibilities by offering generic digital products that do not account for the fluctuating financial circumstances of the youth demographic

2.3 Empirical review

2.3.1 Borrower characteristics and digital credit facilities

Existing literature has brought out the relevance of borrower characteristics in explaining the probability of default (Johnen et al., 2021). Borrower characteristics are demographic, socio-economic (Johnen & Mußhoff, 2023) and credit history factors linked to the individual client who borrows credit (Muthoni, 2016).

Volkwein and Szelest (1995) establish that borrower characteristics like marital status, age, income, gender, occupation, education and race were the best predictors of default compared to college institutional factors that had a negligible effect on default behaviour. Banasik et al.(1999) advance this by investigating additional borrower characteristics like age and employment and loan characteristics like the purpose of the loan and loan term that are also examined by Zurada and Barker (2007). Education is a strong socio-demographic borrower characteristic that is significant in the digital credit uptake and subsequently a critical factor in predicting the probability of default (Johnen & Mußhoff, 2023; Wamalwa et al., 2019). Financially literate borrowers with a higher level of education are more conscious of the terms and conditions of the loan and how it affects their repayment.

Hakim and Haddad (1999) discover that high default rate has a negative correlation with a borrower's income and positively correlated with borrowers with many dependents. In alignment with this, Muthoni (2016) explains that the key borrower characteristics when investigating default are the borrower's credit history, age, number of dependents and loan

diversion where the loan was not used for its intended purpose; with emphasis on future studies to focus on facilities offered by commercial banks. Additional key borrower characteristics in other studies include gender, marital status, financial literacy, monthly income, education, occupation, urban residence, and vulnerability to external shocks (Adem et al., 2012; Costa e Silva et al., 2020; Croux et al., 2020; Johnen et al., 2021; Kamau, 2021; Khedr et al., 2021; Maina, 2020; Muthini & Ndede, 2022). Maggio and Yao (2021) support that a borrower's credit history determines their probability of default such that those with a thin credit file are more likely to default. However, the findings on borrower's age being a significant borrower characteristic in explaining default (Costa e Silva et al., 2020; Maina, 2020; Muthoni, 2016) conflicts with those of Hakim and Haddad (1999) who establish that the relationship between the borrower's age and default is inconclusive. Unlike, Johnen et al. (2021) who indicate that digital loans are borrowed more by casuals and self-employed than those with formal jobs, Kamau (2021) states that the majority of the digital credit borrowers are formally employed.

Gardner and Mills (1989) examine the characteristics of borrowers and loan contracts related to resolution of past due accounts to establish the probability of default using chi-square tests and logit regression. Borrower location, reason for delinquency and previous credit history at the time of delinquency are the most significant characteristics that offer more information as compared to the characteristics considered at loan origination with the probability of default being doubled for a first-time defaulter. Banasik et al. (1999) apply the proportional hazard model in determining the probability of default which they deem superior to Gardner and Mills (1989) methodology of logistic regression.

Zurada and Barker (2007) establish that memory-based reasoning, a machine learning technique is the best methodology compared to logistic regression in prediction of default. To support this, Gui (2019) suggests the need to rely on machine learning algorithms to predict default as using the logistic regression deems borrower characteristics like age, education level and marital status as insignificant variables in explaining default. In contrast, Costa e Silva et al. (2020) use logistic regression in predicting default and find the most significant variables in predicting default are the interest rate spread, loan term, borrower's age, income, credit cards and tax echelon.

Guided by the previous studies, the key borrower characteristics that used in this study were age, gender, default history, student loan, marital status, level of income, occupation and level of education.

2.3.2 Loan characteristics and digital credit facilities

Loan characteristics are the features distinctive to the loan disbursed to the borrower by the lender. Featherstone et al. (2006) emphasize the need to investigate loan specific characteristics in predicting loan default and establish that the loan amount is significant in predicting loan default using the binary logistic regression model (Imayi, 2022). In support of this, Jouault and Featherstone (2011) evaluate loans by a French bank and discover additional loan characteristics like loan tenure and leverage that have a positive correlation with default while profitability and liquidity have a negative correlation with loan default. Additionally, Adem et al. (2012) carry out a study to model bank loan default in Kenya and identify loan tenure as a statistically significant variable that can predict default (Costa e Silva et al., 2020).

Croux et al. (2020) investigate loan characteristics, individual applicant characteristics, macroeconomic variables, and institutional investor risk characteristics to determine default on digital loans and establish the loan purpose as a good predictor of default. For example, a borrower whose purpose is to fund a small business is more likely to default as compared to one taking the loan for a wedding.

The loan interest rate charged is a key characteristic in determining the probability of default on digital credit facilities. DCPs are more exposed to adverse selection than banks and the higher the interest rate on a DCP facility, the higher the probability of default (Costa e Silva et al., 2020; Maggio & Yao, 2021; Njenga & Kavindah, 2021). This is aligned with the key aspects that a borrower considers when taking a digital loan which include the interest rate, accessibility, loan repayment terms (Kamau, 2021). Digital loans are more significantly likely to be in default 15 months after origination since the borrowers spend the funds rather than consolidating their debts (Maggio & Yao, 2021).

2.3.3 Lender characteristics and digital credit facilities

Lender characteristics are those that describe the attributes of the lender institution, in this case, the Digital Credit Providers and the banks that lend money to borrowers in credit markets. Previous studies highlight the role of lender characteristics in determining the probability of default. The business model of the digital lender determines which data can be retrieved, applied, and shared once a customer seeks and is granted a loan. In case the business model constitutes a partnership with a regulated lender, financial data like borrowers' mobile money transactions will most likely determine the lender's credit decision (Gubbins, 2019). Maggio and Yao (2021) evaluate banks and DCPs and discover that DCPs tend to start with less

creditworthy borrowers then attract more creditworthy borrowers as they increase their market share. DCPs sometimes must focus on other aspects like rent payment history, utility bills and education in assessing the creditworthiness of new borrowers with minimal credit history (Maggio & Yao, 2021) while banks use credit risk rating systems when vetting customers who have applied for new loans (Featherstone et al., 2006).

There are three main categories of business models for digital credit: Bank-Telco like M-Shwari which are small ticket sizes with high interest rates that are offered on the mobile money platform of a Telecommunications company with the bank providing capital. Secondly, Bank-Fintech which are larger ticket sizes offered through a fintech application with capital provision from the bank like WeBank in China. The third category is Non-Bank Fintech, which are digital loans, provided by fintech firms without the intermediation of the bank like Tala and Branch (CEGA & IPA, 2024). Additionally, most digital borrowers are interested in bank-owned digital credit applications linked to their mobile service providers like KCB Mpesa and Mshwari rather than those owned by independent digital credit providers (Michuki, 2022). This creates the need to investigate whether the lender characteristics are indeed a determinant of the probability of default for digital credit facilities.

Felix and Wachira (2018) investigate the lender characteristics that influence the default of loans by SMEs in Kitui County in Kenya. Mode of payment and the structure of interest rate are positively correlated to loan default. They recommend that lenders ease their lending policies and future studies to investigate additional factors that influence loan default. Some lenders take advantage of the fact that some borrowers are not privy to the terms and conditions and end up charging high fees for overdue payment penalties (Veronica et al., 2022).

The loan appraisal period which feeds into the loan disbursement influences the likelihood of default for digital credit facilities. Burlando et al. (2023) investigate a digital lender in Mexico and determine that increasing the period before loan disbursement from ten to twenty hours reduces the probability of default by 21%. Borrowers change their initial purpose of the loan due to the delay in accessing the funds. This could be caused by a change in the borrowers' preferences or if the delay changes the person who decides how the loan shall be used, especially in a married household.

2.3.4 Loan size as a moderating variable

The loan size refers to the amount of credit disbursed to the borrower by the lender. The loan size can change the impact of the borrower, loan and lender characteristics on the probability of default (Featherstone et al., 2006). Previous studies have brought out inconsistencies in the loan size's significance in predicting the probability of default, its role in credit models, and the direction of its impact on default.

Some of the previous studies (Featherstone et al., 2006; Imai, 2022; Savitha & Kumar K., 2016; Xu, 2025) indicate that loan size is statistically significant in predicting the probability of default while other studies argue that the effect of loan size on default is not constant across the loan portfolio and could lead to different probabilities of default depending on the size of the loan (Dendramis et al., 2025; Lohmann & Ohliger, 2024).

The loan size could impact the borrower's perception of risk related to default such that if the loan size is small, they could consider default as opposed to when the size is large where there are more severe consequences of default (Shen & Chen, 2023). Additionally, the loan size could influence the effect of loan characteristics on credit default like loan purpose where a borrower could easily divert a small loan and use it for the purpose it was not intended for as compared to a large loan whose structure and repayment is more rigid (Xu, 2025). In the context of these previous studies, the loan size was essential as a moderating variable in this study to show the interaction between borrower, lender and loan characteristics and the probability of default.

2.4 Summary of literature and research gaps

There is existing past literature that has been carried out to determine the probability of default with a huge focus on borrower characteristics due to adverse selection. There is information asymmetry in the credit markets that leaves lenders at a disadvantage since the borrowers have more information on their credit eligibility than the lenders do.

Table 2.1: Summary of literature and research gaps

Author(s) (Year)	Title	Methodology	Findings	Research Gaps
Johnten et al. (2021)	Promises and Pitfalls of Digital Credit: Empirical Evidence from Kenya	Descriptive analysis; representative survey data; comparative analysis across credit market types	Digital credit accounts for 90% of default blacklisting in Kenya compared to formal and semi-formal credit. It increases the opportunities for borrowing but its sustainability is threatened by high default rates	Empirical gap and knowledge gap: Limited empirical research on whether digital credit reaches excluded populations like the youth. There is unclear extent to which borrowers and lenders lead to high default rates. There is need to compare this across different lenders
Costa e Silva et al. (2020)	A logistic regression model for consumer default risk	Logistic regression model on credit scoring data from financial institution	Default increases with: loan spread, loan term, borrower's age and low income while it decreases with: more credit cards owned, salary in same bank institution	Population gap: The study focused on only one institution which limits generalizability and only looks at consumer loans in one geographical scope, Portugal. There is need to explore additional lending institutions in other locations. It does not also address the significance of loan size

Muthini & Ndede (2022)	Socio-Economic Factors and Table Banking Loans Default Levels Among Women Groups in Machakos County, Kenya	Descriptive cross-sectional design; structured questionnaires; chi-square tests; regression analysis	The study revealed that lower default is characterized by higher income, higher literacy, higher household demand and more borrowing experience. Loan purpose is also significant such that if the loan is used for an income generating purpose like a business, it reduces the default level	Population gap and geographic gap: The study was limited to Machakos County and flagged the need for studies in other regional context. The population was limited to women in informal groups. There is a need to study default in other groups and beyond the socio-economic factors
Burlando et al. (2023)	Too Fast, Too Furious? Digital Credit Delivery Speed and Repayment Rates	Regression-discontinuity design; unique administrative data from digital lender; causal identification	Faster delivery of digital credit significantly increases the probability of default. Slowing down the delivery time can lead to reduced likelihood of default and increase the digital lender's probability	Knowledge gap: The study did not focus on loan characteristics and how they impact the likelihood of default. There is need to also study individual characteristics and a different geographical context for generalizability
Kamau (2021)	Digital Credit in Kenya: A Survey of Costs, Uses and Borrowers	Mixed methods research design and regression analysis	Employment status is the only factor with a statistically significant effect on loan uptake	Population gap and knowledge gap: The statistical insignificance of age contradicts theory and emphasizes the need to explore

	Considerations in Relation to Loan Uptake		while age and loan considerations do not	additional borrower characteristics. The study recommends future research on digital credit to focus on the youth population
Maggio & Yao (2021)	Fintech Borrowers: Lax Screening or Cream-Skimming?	Comparative individual-level data; matched pairs analysis; multiple lender types	Fintech borrowers are significantly more likely to default than those borrowing from traditional banks	Empirical gap and knowledge gap: There is need to research why fintech borrowers default more than those who borrow from traditional lenders even though their characteristics are similar. There is also need to understand how lender characteristics influence the likelihood of default
Hakim & Haddad (1999)	Borrower Attributes and the Risk of Default of Conventional Mortgages	Maximum likelihood failure time model (duration analysis); nationwide sample of 9,000 mortgages	Small loan mortgages, low income, high number of dependents increases the probability of default. Older borrowers have a low likelihood of default	Empirical gap: The findings of the study were inconsistent with previous literature on the effect of loan size on the likelihood of default. There is need to explore other credit facilities for generalizability

Lee et al. (2022)	A comparative study on determinants of housing mortgage prepayment of individual borrowers	Time-comparative analysis; accelerated time failure model versus logit versus Cox proportional risk model	Younger borrowers prefer shorter maturity for their mortgage loans. The borrower's debt-to-income ratio effect is context-dependent	Empirical gap: Since the debt-to-income and loan size effect on repayment is dependent on context, there is need to explore varied context with other loan products
Khedr et al. (2021)	A New Prediction Approach for Preventing Default Customers from Applying Personal Loans Using Machine Learning	Machine learning classifier comparison; decision tree, and other classifiers; feature selection analysis	The most important determinants of prediction of default are income, loan size and activity with loan size being the most statistically significant determinant	Empirical gap: There is need to explore the interaction between loan size and income for future credit default prediction
Busmann et al. (2021)	Explainable Machine Learning in Credit Risk Management	Explainable AI model, correlation networks and Shapley values	Default risk can be predicted using financial characteristics clusters. While all borrowers have some similar financial characteristics, it is possible to group them to explain default	Knowledge gap and empirical gap: There is need to group borrowers based on different characteristics since a one-size-fits-all approach on modelling credit default risk is inappropriate
Kumar et al. (2021)	Machine Learning Technologies for Digital Credit Scoring in Rural	Systematic literature review, documentary	Machine learning is offering new hope for credit access for historically excluded populations	Empirical and population gap: Limited research on optimal credit risk modelling for specific credit

	Finance: A Literature Review	and conceptual analysis	(farm holders, rural youth, and women). Machine learning methods can reduce human bias in loan decision-making	contexts like the youth. There is need to explore how to evaluate borrowers with no previous credit history and how to blend traditional and digital methods ethically
Mhlanga (2021)	Financial Inclusion in Emerging Economies: The Application of Machine Learning and Artificial Intelligence in Credit Risk Assessment	Literature review, documentary and conceptual analysis	Alternative data reduces adverse selection in credit lending. Enables serious credit risk analysis using borrower behaviour	Knowledge gap: Limited research on the use of alternative data for excluded populations. There have been ethical challenges in the use of alternative data which needs a regulation framework
Croux et al. (2020)	Important Factors Determining Fintech Loan Default: Evidence from a LendingClub Consumer Platform	Multiple empirical approaches and robustness checks	Loan characteristics, specifically loan maturity, loan purpose and loan terms, were statistically significant and robust in determining loan default. The borrower characteristics that were statistically significant were home ownership and occupation. Macroeconomic variable are also	Empirical and methodological gap: Loan repayment period is underestimated in determining loan default and should be explored in future studies

			significant. The results are robust across empirical approaches	
Featherstone et al. (2006)	Determining the Probability of Default and Risk-Rating Class for Loans in the Seventh Farm Credit District Portfolio	Probability of default modelling	The most significant determinants of probability of default are repayment capacity, owner equity and loan purpose	Empirical gap: Repayment capacity comes up as the most significant determinant compared to loan size which is contradictory with the findings of previous studies. There is need to explore the effect of loan size on the probability of default
Wang et al. (2020)	Why do borrowers default on online loans? An inquiry of their psychology mechanism	Structural equation modelling and a two-stage psychological model	Moral norms, economic and social strains have a significant effect on a borrower's likelihood to default	Population gap: Youth-specific social, economic and psychological factors need to be examined

Source: Author (2026)

2.5 Conceptual Framework

Figure 2.1 presents the conceptual framework for this study with a focus on the independent variables, dependent variable, and the moderating variable.

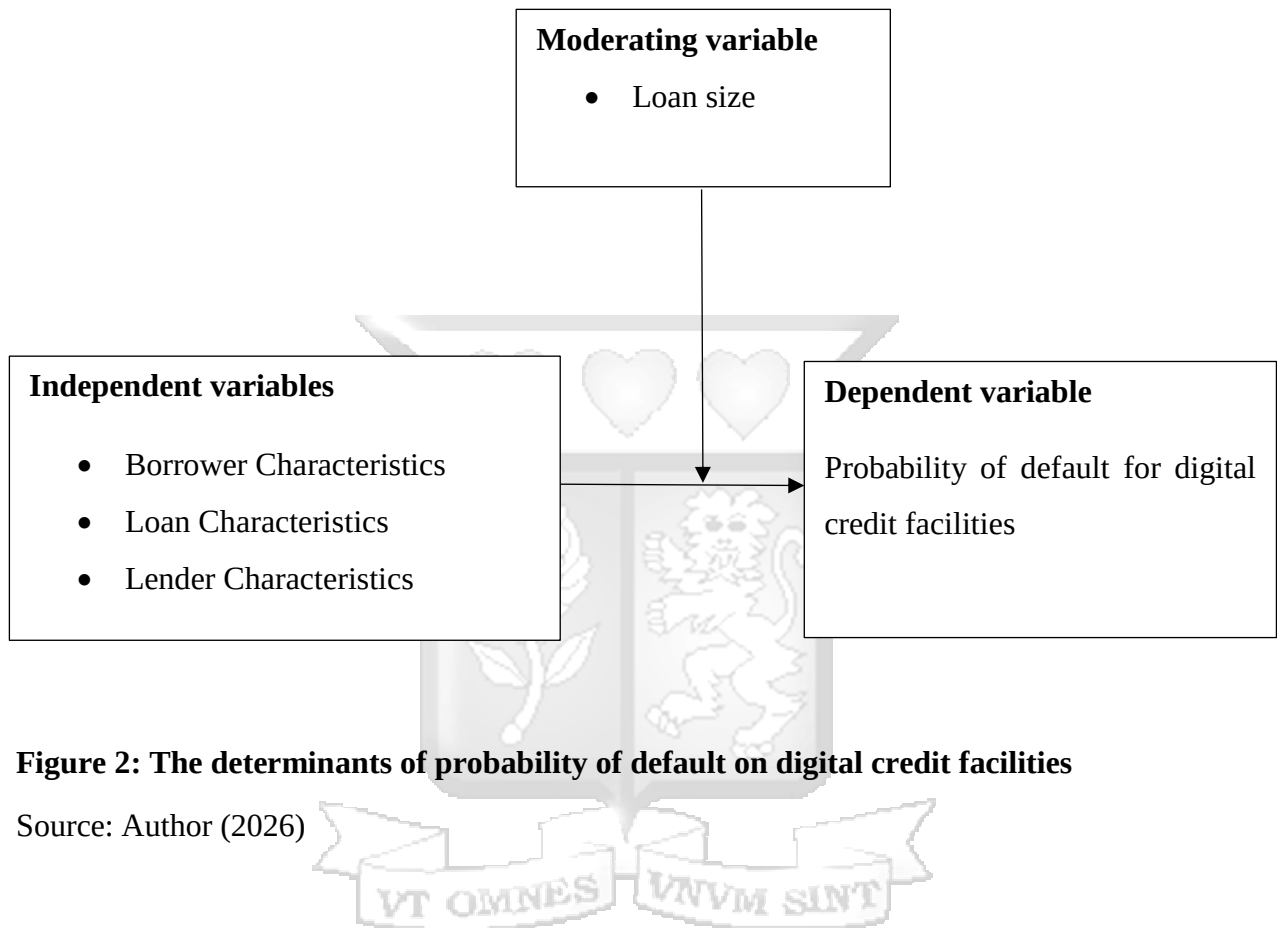


Figure 2: The determinants of probability of default on digital credit facilities

Source: Author (2026)

2.6 Operationalisation of the study's variables

Based on the conceptual framework outlined in section 2.5, the following variables will be considered in the present study.

Table 2.2: Operationalization of Variables

Variable	Type of variable	Measurement	Literature source	Data source	Theory supported
Dependent variable					
Probability of default on digital facilities	Ratio	The likelihood of default between 0 and 1	Gardner and Mills (1989); Maggio and Yao (2021)	Questionnaire	Adverse selection
Independent (test) variables					
Borrower characteristics					
Age	Ordinal	The number of years the borrower has been in existence in categories (18-25, 26-30, 31-35)	Adem et al. (2012), Costa e Silva et al. (2020), Hakim and Haddad(1999), Johnen et al. (2021)	Questionnaire	Adverse selection

Variable	Type of variable	Measurement	Literature source	Data source	Theory supported
Gender	Nominal	The gender of the borrower in categories (Male or Female)	Adem et al. (2012), Johnen et al. (2021)	Questionnaire	Adverse selection
Default history	Nominal	Assessed by the borrower's indication of ever defaulting on a credit facility before (Yes, No)	Maggio and Yao (2021), Muthini and Ndede (2022)	Questionnaire	Adverse selection
Student loan	Nominal	Indicated by whether the borrower ever took a student loan by the time of borrowing (Yes, No)	Maggio and Yao (2021), Volkwein and Szelest (1995)	Questionnaire	Adverse selection
Marital Status	Nominal	Marital status of the borrower as at the time of the study (Single, Married, Divorced/Separated, Widowed)	Maggio and Yao (2021), Adem et al. (2012)	Questionnaire	Adverse selection
Level of Income	Ordinal	The borrower's range of level of income as at the time of the study	Johnen et al. (2021),	Questionnaire	Adverse selection

Variable	Type of variable	Measurement	Literature source	Data source	Theory supported
		(0- 20,000; 21,000- 50,000; >50,000)	Khedr et al. (2021), Maggio and Yao (2021) Muthini and Ndede (2022)		
Occupation	Nominal	The borrower's occupation as at the time of the study under 3 categories (Employed, self-employed and un-employed)	Adem et al. (2012), Croux et al.(2020), Johnen et al. (2021), Kamau (2021), Maggio and Yao (2021)	Questionnaire	Adverse selection
Level of education	Ordinal	The highest attainment of education by the borrower (no	Johnen et al. (2021),	Questionnaire	Adverse selection

Variable	Type of variable	Measurement	Literature source	Data source	Theory supported
		formal education, primary, secondary, tertiary)	Maggio and Yao (2021), Volkwein and Szelest (1995)		
Loan characteristics					
Interest rate	Ordinal	5-point Likert scale	Costa e Silva et al. (2020), Maggio and Yao (2021), Njenga & Kavindah (2021)	Questionnaire	Financial intermediation
Loan tenure	Ordinal	The repayment period for the digital loan borrowed (1 month, 2-3 months, 4-5 months, 6-12 months, Over 12 months)	Adem et al. (2012), Costa e Silva et al. (2020), Croux et al.(2020), Jouault and Featherstone (2011),	Questionnaire	Adverse selection

Variable	Type of variable	Measurement	Literature source	Data source	Theory supported
			Maggio and Yao (2021)		
Loan purpose	Nominal	The reason for the borrower taking the loan based on a list of different reasons	Croux et al. (2020), Maggio and Yao (2021), Nzisa and Kithandi (2023)	Questionnaire	Adverse selection
Lender characteristics					
Business model	Nominal	The type of digital lender that lent a digital loan to the borrower, DCPs and/or banks	Gubbins (2019), Jouault and Featherstone (2011), Maggio and Yao (2021), Michuki (2022)	Questionnaire	Financial intermediation

Variable	Type of variable	Measurement	Literature source	Data source	Theory supported
Mode of payment	Nominal	The payment tool which the loan was paid back to the lender by the borrower (Standing order, Cash deposits, Checkoff, Mobile Money)	Felix and Wachira (2018), Veronicah et al. (2022)	Questionnaire	Financial intermediation
Loan appraisal period	Ordinal	The period it took for the loan to be disbursed to the borrower from application for the digital loan -24 hours, 36 hours, 48 hours, Above 48 hours	Anderson and Reynolds (2017), Burlando et al. (2023)	Questionnaire	Financial intermediation
Moderating variable					
Loan Size	Ordinal	The amount of the digital loan borrowed based on ranges of different amounts	Jouault and Featherstone (2011), Maggio and Yao (2021),	Questionnaire	Adverse selection

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

This chapter discusses the details on the research methodology to be undertaken in the study. The outlay of the chapter includes the research philosophy followed by the research design, population and sampling, data collection methods, data analysis, research quality and finally the ethical considerations of the study.

3.2 Research philosophy

Research philosophy is described as the system of beliefs and assumptions about the development of knowledge (Saunders et al., 2023). Ontology is concerned with the assumptions regarding the nature of reality, based on what the researcher believed the world to be like, which in turn shaped how the world was perceived and understood. This ontological view of reality influenced different ways of obtaining knowledge, which was defined as methodology (Saunders et al., 2023).

The epistemological orientation of this study was positivism. Under this paradigm, knowledge and reality are derived from empirical data rather than absolute universal truths (Saunders et al., 2023), ensuring that findings are grounded in observable evidence. This stance was chosen to meet the study's general objective to investigate determinants of probability of default for digital credit facilities by youth in Nairobi County. This was based on the positivism orientation such that causes determine outcomes and effects. In this study, a causal explanation and prediction was sought by determining the probability of default from the borrower, loan, and lender characteristics for digital credit facilities

The role of theory in this research was deductive. The study was guided by two main theoretical frameworks. The first was the financial intermediation theory, which recognized the essential role of financial intermediaries in the financial markets. As proposed by Gurley and Shaw (1956), one of the key roles of financial intermediaries was to reduce information asymmetry—a core focus of this study, which aimed to predict the probability of default on credit facilities issued by digital lenders and banks. Additionally, the study drew from the adverse selection theory (Akerlof, 1970), which argued that borrowers possess private information about their creditworthiness that lenders cannot access. This information gap often leads lenders to offer

loans to high-risk individuals while excluding creditworthy borrowers, based on flawed credit assessment criteria. This theory also applied to the context of lender and loan characteristics that may be unknown to borrowers at the time of accessing credit yet could significantly contribute to their risk of default.

3.3 Research design

The research design outlines the process that was followed in collection of data and its analysis to address the research questions. In this study, the research design was a quantitative cross sectional design with an exploratory approach. This is because the study surveyed youth digital credit borrowers simultaneously to establish the relationship between borrower, loan and lender characteristics and the probability of default for digital credit facilities.

3.4 Population of the study

Based on the Kenya Housing and Population Census (Kenya National Bureau of Statistics, 2019), the total population of youth in Nairobi County is 1,884,655. Additionally, the Constitution of Kenya (2010) states that the legal definition of youth in Kenya are persons between the ages of 18 and 35. This was the population of interest in this study. From this population, stratified random sampling was applied such that the study focused on the youth that have borrowed digital credit facilities from banks, DCPs and those who have borrowed from both banks and DCPs based on the data collected from the structured questionnaire. Once they are classified under these three categories, a random sample was then selected. With this, we can establish the borrower, lender and loan characteristics and consequently determine the probability of default. This technique ensured that there was proper representation of the population groups in the sample.

Table 3.1: Target Population

	Population
Number of youths in Nairobi County based on the 2019 Kenya Housing and Population Census (Kenya National Bureau of Statistics, 2019)	1,884,655
According to the 2024 FinAccess survey report by Central Bank of Kenya, the level of access to financial products and services in Nairobi County including digital and mobile banking loans is 93.7% (Central Bank of Kenya et al., 2024)	$93.7\% \times 1,884,655 = 1,765,922$
Target population	1,765,922

3.5 Sampling

To determine a statistically significant sample for a large demographic, the study applied Cochran's formula. By setting a 95% confidence level, a 5% margin of error, and a 0.5 variability factor, a target sample size of 384 respondents was established.

Cochran's formula is given by:

$$n_o = \frac{Z^2 pq}{e^2}$$

$$n_o = \frac{1.96^2 \times 0.5 \times 0.5}{0.05^2} = 384$$

Where;

Z is the z-value based on the confidence level

p is the estimated proportion of the population

q is $1 - p$

e is the desired level of precision (the margin of error)

n_o is the sample size

The sampling design used was stratified random sampling since the individuals were classified into three main strata; those who have borrowed digital loans from banks only, those who have

borrowed digital loans from DCPs only and those who have borrowed from both institutions. The 384 respondents were distributed based on the population of the 11 sub-counties in Nairobi based on the 2019 Census (Kenya National Bureau of Statistics, 2019) as represented in table 3 below.

Table 3.2: Distribution of Sample size across Sub-Counties

Sub-County	Population	Sample size
Dagoretti	172,822	37
Embakasi	426,083	93
Kamukunji	107,398	23
Kasarani	324,918	71
Kibra	67,785	15
Lang'ata	73,155	16
Makadara	75,924	16
Mathare	83,515	18
Njiru	234,089	51
Starehe	90,792	20
Westlands	109,440	24
TOTAL	1,765,922	384

Source: (Central Bank of Kenya et al., 2024; Kenya National Bureau of Statistics, 2019)

3.6 Data collection method and instrument

The data for this study comprised of quantitative data and consisted of primary data only. A structured questionnaire was used as the data collection instrument. This was administered face

to face to ensure a high response rate for the study. The questionnaire included closed-ended questions, including Likert scale items. It was divided into four categories: Section A collected data on the respondent's demographic characteristics. Section B gathered information on the loan characteristics to gain insights into the digital loans that they had borrowed. Section C collected data on the lender characteristics of the loans borrowed. Section D examined the default status of the loans borrowed.

3.7 Data analysis

Zurada and Barker (2007) emphasized the value of machine learning techniques—such as logistic regression, memory-based reasoning, and other predictive methods—as effective tools for optimizing credit assessment by identifying creditworthy borrowers and minimizing risk by excluding those likely to default. While logistic regression has been widely employed in prior studies to estimate the probability of default (Croux et al., 2020; Featherstone et al., 2006; Jouault & Featherstone, 2011; Khedr et al., 2021), this study adopted the probit regression model as the preferred estimation technique.

This model was selected due to its robustness in handling binary dependent variables and its theoretical alignment with the assumption of a normally distributed error term. Unlike logistic regression, which uses a logistic (S-shaped) function, the probit model assumes that the underlying latent variable follows a standard normal distribution. This assumption is particularly aligned with analyzing credit default behaviour, which is often influenced by a range of subtle and continuous socio-economic factors. Secondly, the probit regression model assumes normally distributed errors which aligns with the normally distributed borrower characteristics and prevents over inflation of the probability of default when we have extremes of the borrower income and loan size. Thirdly, previous studies on credit default have also applied the probit regression model (Johnen et al., 2021; Ouyang et al., 2021).

The dependent variable of this study is the probability of default. While the observed outcome, “Default Status” is recorded as a binary variable—where 1 represented a defaulted loan and 0 represented a loan in good standing, the study utilizes a probit regression model to estimate the underlying likelihood of this occurrence. Consequently, the response variable Y is treated as a dichotomous indicator that allows the model to calculate the estimated probability of default as a function of independent borrower, loan, and lender characteristics.

The probit model is expressed as:

Probability of default $Y = 1$ or 0

.....Equation 1

$$\begin{aligned} & \text{Probability of default for digital credit facility}_i \\ &= \beta_0 + \beta_1 * \text{Borrower characteristics}_i + \beta_2 \\ & \quad * \text{Loan Characteristics} + \beta_3 * \text{Lender characteristics}_i + \beta_4 \\ & \quad * \text{Loan size}_i + \varepsilon_i \end{aligned}$$

3.8 Research quality

This section reveals the validity and reliability of the study to determine its quality.

3.8.1 Validity

Validity refers to the extent to which a research instrument measures what it is intended to measure and performs its intended purpose. This study focused on both content validity and criterion validity. Content validity is the degree to which an instrument reflects the entire scope of the concept it aims to measure. In this study, content validity was established through a review of relevant literature from previous studies. Additionally, it was determined through an expert review by the supervising lecturer, who assessed whether the data collection instrument effectively served its intended purpose in the context of the study. Construct validity, as described by Taherdoost (2016), refers to how well the instrument transforms an abstract concept (construct) into a measurable and observable reality. A pilot test was also conducted on 10% of the sample size (39 respondents) to test the face validity of the questionnaire and its ability to collect the required information for the study. The pilot test confirmed that the questionnaire was comprehensive and relevant to the target population and only minor adjustments were made to improve the flow of the questionnaire.

Criterion validity is the magnitude to which a measurement is related to an outcome, and it is often used to predict future behaviour or results. In this study, criterion validity was ensured by evaluating the ability of the test to accurately predict the probability of default for digital credit facilities (Taherdoost, 2016).

3.8.2 Reliability of the research

Reliability relates to the extent to which results of the study remain consistent over time and provide an accurate representation of the total population of the study. Internal consistency is mostly measured by the Cronbach Alpha coefficient. This was applied in this study due to the

use of Likert scales in the questionnaire. Most studies agree on an internal consistency coefficient of 0.70 (Taherdoost, 2016).

Table 3.3: Cronbach's Alpha Coefficient

Construct	Number of Items	Cronbach's Alpha	Interpretation
Borrower Characteristics	8	0.81	Reliable
Loan Characteristics	5	0.76	Reliable
Lender Characteristics	4	0.84	Reliable
Probability of Default (DV)	5	0.79	Reliable

The results demonstrate that all constructs, including the dependent variable—probability of default, meet the acceptable threshold for internal consistency. The Cronbach's Alpha of 0.81 for borrower characteristics indicates reliable measurement of attributes like financial discipline, income regularity, and repayment history. A score of 0.76 for loan characteristics confirms that variables such as loan amount, interest rate, and tenure were measured consistently. Lender characteristics yielded a Cronbach's Alpha of 0.84, showing strong agreement among items concerning lender communication, credit scoring, and flexibility in repayment options. The dependent variable—probability of default—scored 0.79, suggesting the items effectively captured respondents' likelihood of defaulting based on their perceptions and past behaviour. These reliability results confirm that the instrument is suitable for assessing both the independent and dependent variables in the study.

3.9 Ethical considerations

Approval was sought from the National Commission for Science, Technology, and Innovation (NACOSTI) to conduct the research. An introduction letter from Strathmore University was also presented to the individuals who filled out the questionnaire. The research was conducted in line with the principles of research integrity outlined by Strathmore University with approval sought from the Strathmore University Institutional Scientific and Ethics Research Committee (SU-ISERC).

3.10 Summary of Research Methodology

This study was based on the pragmatism research philosophy, which allowed for both inductive and deductive approaches. The research design was quantitative cross sectional data with an

exploratory approach. The data were collected through the administration of questionnaires and analysed using the probit regression model.



CHAPTER FOUR: PRESENTATION OF RESULTS

4.1 Introduction

Chapter 4 encompasses the study's response rate, participant bio-demographic characteristics, contextual background, descriptive statistics of responses, correlation analysis, and probit regression findings examining relationships between the independent and dependent variables.

4.2 Response Rate

The study aimed to investigate the determinants of the probability of default for digital credit facilities among youth in Nairobi County. A representative sample of 384 youth aged between 18 and 35 years was targeted using stratified random sampling for proper representation of key borrower subgroups. The stratification was grounded on the type of lender: (i) banks only, (ii) digital credit providers (DCPs) only, and (iii) both banks and DCPs. This classification enabled the study to analyse borrower, lender, and loan characteristics, which were central to understanding default behaviour. Structured questionnaires were used to collect quantitative data relevant to the objectives of the study. Out of the 384 questionnaires administered, 336 were properly completed and returned, representing an 88% response rate, which is regarded as highly satisfactory for a survey-based study. According to Arora (2003), a response rate above 65% in large-sample questionnaire studies indicates strong participation and enhances the credibility of the research.

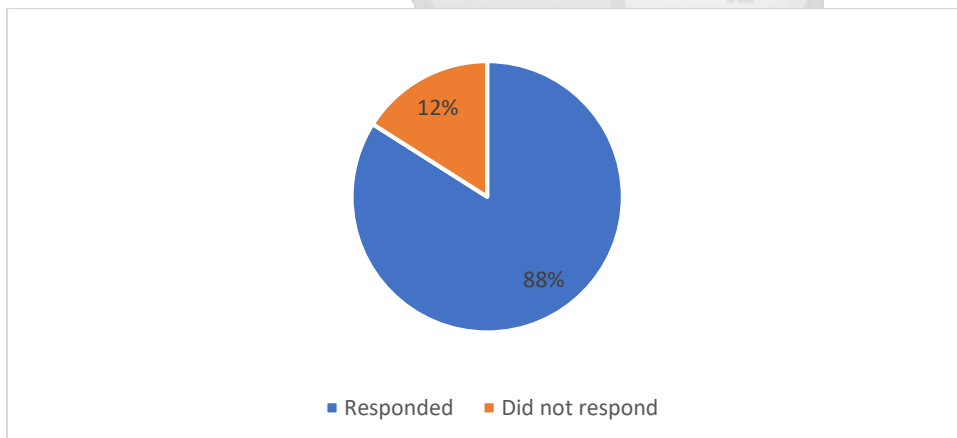


Figure 3: Response Rate

4.3 Descriptive Statistics

4.3.1 Borrower Characteristics Summary Statistics

The study sought to determine the demographic and socio-economic characteristics of the respondents under Section A of the questionnaire, which focused on borrower characteristics. This information was critical to assess the sample's representation and enhance the validity of the study's findings in relation to the broader population of youth in Nairobi County. By understanding these characteristics, the study was able to explore how demographic factors influence the probability of default on digital credit facilities. The borrower characteristics captured included gender, marital status, age bracket, level of education, employment status, monthly income, and the presence of current or past student loans. These factors provided a comprehensive profile of the respondents and offered important insights into their financial backgrounds and borrowing behaviour, which were relevant in determining their creditworthiness and likelihood of default. The findings of the study are as shown in subsequent sub-headings to address the objective to determine the effect of borrower characteristics on the probability of default for digital credit facilities by youth in Nairobi County.

Table 4.1: Borrower Characteristics Summary Statistics

	Frequency	Percent
Gender		
Male	226	67.3
Female	110	32.7
Marital Status		
Single	106	31.5
Married	155	46.1
Divorced/Separated	46	13.7
Widowed	29	8.6
Age		
18-25	44	13.1
26-30	162	48.2
31-35	130	38.7
Highest level of education		
No formal education	34	10.1

Primary	41	12.2
Secondary	68	20.2
Tertiary (College/University)	193	57.4
Outstanding Student Loan		
Yes	151	78.2
No	42	21.8
Employment Status		
Employed	131	39
Self- employed	83	24.7
Unemployed	122	36.3
Monthly Income levels		
0- 20,000	41	19.2
21,000- 50,000	79	36.9
>50,000	94	43.9
History of Student Loan Uptake		
Yes	126	72.4
No	48	27.6

Table 4.1 illustrates that the gender distribution of the respondents was such that 226 (67.3%) were male while 110 (32.7%) were female, reflecting a significant male dominance among youth borrowers of digital credit facilities in Nairobi County. This disparity suggests that male youth may be more actively engaged in borrowing from digital credit platforms, potentially due to greater access to financial resources, higher participation in income-generating activities, or differing financial risk preferences compared to their female counterparts. The underrepresentation of female borrowers could imply barriers such as limited financial literacy, lower access to digital devices, or cultural and socio-economic constraints that hinder their engagement with digital credit. These findings have important implications for financial inclusion strategies, highlighting the need for gender-sensitive policies and interventions focused on easing young women's access to and utilization of digital credit services effectively.

Table 4.1 indicates that the marital status of respondents was such that 46.1% were married, followed by single (31.5%), divorced/separated (13.7%), and widowed (8.6%). This distribution suggests that a substantial portion of youth borrowers bear familial and financial responsibilities, which may influence their borrowing behaviour and repayment priorities. Married individuals, for instance, may have more pressing financial needs—such as housing, childcare, or household expenses—that compel them to seek digital credit but may also expose them to a higher default risk. On the other hand, single respondents may have more financial flexibility and potentially fewer obligations, which could enhance their repayment capacity. The presence of divorced, separated, and widowed youth in the borrowing pool also points to the vulnerability of certain demographic subgroups who may use credit as a coping mechanism during periods of financial instability. These variations emphasize the need to consider marital status as a key socio-economic factor when assessing the probability of default in digital lending.

Table 4.1 reveals that the distribution of the age of the respondents was such those aged 26–30 years (48.2%), 31–35 years (38.7%), and the youngest group, 18–25 years (13.1%). This distribution indicates that majority of digital credit borrowers among youth in Nairobi fall within their late-20s to mid-30s, which aligns with the phase in life where individuals are likely to be establishing careers, starting businesses, or supporting families — all of which may necessitate access to credit. The relatively lower representation of the 18–25 age group may reflect limited financial independence, lower income levels, or greater caution among younger borrowers. These findings show the importance of age in determining the probability of default, as financial behaviour, stability, and repayment ability tend to evolve with age and life stage.

The majority of the respondents, 193 (57.4%), indicated tertiary education (college or university) as their highest education level, respondents with secondary education (20.2%), primary education (12.2%), and no formal education (10.1%). This alludes that digital credit facilities are predominantly accessed by relatively well-educated youth, who may be more financially literate, technologically savvy, and confident in navigating digital lending platforms. The strong representation of tertiary-educated borrowers may also indicate that this group has a higher likelihood to engage in formal or semi-formal economic activities that increase their credit demand. However, the presence of borrowers with only basic or no education underscores potential risks related to financial literacy gaps, as these individuals may have limited understanding of loan terms, repayment obligations, and the long-term

consequences of default. Therefore, education level emerges as a major determinant in access to and responsible use of digital credit, with implications for designing borrower education programs and credit risk assessment models that are sensitive to varying literacy levels.

Of the respondents with tertiary education, 151 (78.2%), currently have an outstanding student loan, while only 42 (21.8%) do not. This high prevalence of existing student debt among youth borrowers suggests a significant financial burden that may impact their ability to repay additional credit such as digital loans. The overlap between educational debt and digital credit use raises concerns about debt accumulation and repayment stress, particularly for those with limited or unstable income sources. The findings imply that student loan obligations may be a key factor influencing the probability of default, as they reduce disposable income and can result in over-indebtedness when combined with other borrowing. This highlights the importance for lenders and policymakers to assess the total debt exposure of borrowers when issuing digital credit, and to promote financial education initiatives that help youth manage multiple credit lines responsibly.

131 respondents (39%) were employed, 83 (24.7%) were self-employed, and 122 (36.3%) were unemployed. This distribution reflects a relatively balanced spread across employment categories, though it is noteworthy that over one-third of the respondents lacked formal employment. The high proportion of unemployed youth suggests potential financial instability and a limited capacity to consistently meet repayment obligations, which may contribute to an increase in the probability of default on digital credit. Meanwhile, the self-employed group, though representing entrepreneurial initiative, may face irregular income flows that also affect repayment behaviour. Employed respondents, with more stable income, are presumably more creditworthy, yet the fact that even many employed youth still access digital credit highlights the pervasive need for short-term financing across all groups. These findings emphasize the importance of considering employment status as a critical variable in credit risk assessment, with implications for loan product design and borrower support strategies tailored to varying income reliability.

The monthly income levels of respondents who reported being employed or self-employed (n = 214). The largest share, 94 respondents (43.9%), earned more than Ksh. 50,000, followed by 79 (36.9%) earning between Ksh. 21,000 and 50,000, and 41 (19.2%) earning Ksh. 0–20,000. This income distribution suggests that a substantial portion of youth borrowers accessing digital credit have relatively high or moderate earnings, which may positively influence their

ability to meet loan obligations. However, the presence of borrowers in the lowest income bracket raises concerns about financial vulnerability and the likelihood of default, particularly if they rely on digital loans to supplement insufficient income. While higher income levels generally indicate better repayment capacity, it is also possible that higher earners take on larger loans, which may increase default risk if not managed prudently. This highlights the gravity of income as a predictor of default probability and suggest the need for income-sensitive lending practices and borrower education to promote responsible borrowing and repayment.

The findings of this study revealed that 126 respondents (72.4%) have a history of taking a student loan, while 48 respondents (27.6%) do not. This high prevalence of student loan uptake suggests that a sizable proportion of youth borrowers have prior experience with formal credit systems, which may influence their current borrowing behaviour, including their likelihood of default on digital loans. Those with student loans may have developed an understanding of loan repayment processes, potentially improving their financial management skills. However, the substantial student loan burden could also contribute to financial strain, as these respondents may already be managing multiple debt obligations. The existence of student loans may result to over-indebtedness, limiting the ability of the youth to keep up with new credit obligations, and increases their likelihood to default. These findings highlight the importance of considering existing debt obligations when evaluating creditworthiness, as prior borrowing history significantly impacts financial behaviour and repayment capacity.

4.3.2 Loan Characteristics Summary Statistics

The results below are linked to the study's aim to establish the effect of loan characteristics on the probability of default for digital credit facilities by youth in Nairobi County.

Table 4.2: Loan Characteristics Summary Statistics

	Frequency	Percent
Awareness of loan interest rates and charges		
Yes	261	77.7
No	75	22.3
Loan Repayment Period		
1 month	12	3.6
2–3 months	18	5.4
4–5 months	99	29.5
6–12 months	102	30.4
Over 12 months	105	31.3
Purpose of Borrowing Digital Loans		
For paying school fees	179	53.3
For buying airtime	25	7.4
For a big home improvement purchase (electronics, furniture)	41	12.2
For my personal business	28	8.3
For meeting day-to-day needs like food	17	5.1
For paying medical bills	14	4.2
For paying off other debts	10	3
For betting	13	3.9
For buying a car	9	2.6

Table 4.2 shows that a significant portion of respondents, 261 (77.7%), were aware of the interest rates and charges levied on the digital loans they borrowed, while 75 (22.3%) were not aware of these financial terms. The high level of awareness suggests that most youth borrowers in Nairobi County are generally informed about the costs associated with borrowing digital loans. This awareness could reflect improvements in financial literacy and the transparency of digital lending platforms, which likely provide borrowers with clear information about loan terms before they commit. However, the fact that 22.3% of respondents were unaware of the interest rates and charges raises concerns about the potential risks associated with digital borrowing. Borrowers who are not fully aware of the loan terms may face unexpected financial burdens, leading to repayment difficulties and an increased likelihood of default. This finding underscores the importance of continued efforts to educate borrowers about the full costs of

digital loans and to ensure that digital credit providers maintain transparency in their lending practices.

The most common repayment term remains over 12 months (31.3%), followed closely by 6–12 months (30.4%), showing that the majority of youth prefer longer repayment windows that ease their monthly financial burden, even if it might result in higher interest accumulation. Meanwhile, short-term repayment options like 4–5 months (29.5%) still attract a significant portion of borrowers who might be financially disciplined or have predictable income streams. Interestingly, only 12 respondents (3.6%) and 18 respondents (5.4%) chose 1-month and 2–3 month terms respectively. These shorter repayment windows could be unappealing due to high repayment pressure, limited grace periods, or penalties often associated with quick turnaround times. The broad distribution of responses reflects diverse financial behaviours and capacities among youth borrowers. It suggests that digital lenders should provide flexible repayment options that cater to different user profiles—from those capable of short-term repayment to those needing longer repayment periods due to lower or irregular incomes.

A significant majority (53.3%) borrow to pay school fees, emphasizing a pressing need for structured educational financing tailored to academic calendars, possibly with grace periods and affordable interest rates to ease repayment burdens. Beyond education, a noteworthy proportion seek loans for asset-building purposes such as home improvement (12.2%) and personal business ventures (8.3%), indicating a demand for medium-sized credit products that can facilitate entrepreneurship and household development. Meanwhile, smaller percentages borrow for daily necessities like airtime (7.4%), food (5.1%), and medical expenses (4.2%), underlining how digital credit is used in bridging short-term financial gaps, though such micro-loans may increase default risk if borrowers lack financial literacy or income stability. Alarming, 3.9% of respondents reported borrowing for betting—a risky behaviour that may reflect over-indebtedness or poor financial judgment—while others used credit to repay existing debt (3.0%) or purchase vehicles (2.6%), both of which signal potential strain on repayment capacity. Collectively, these findings highlight the need for tiered digital credit offerings that reflect the spectrum of borrower needs, from urgent micro-consumption to long-term investments, alongside robust borrower assessment and financial literacy initiatives to ensure responsible borrowing and minimize default rates among youth.

By asking respondents to rate factors such as interest rate, bank charges, and loan tenure, the study explores the primary considerations that drive borrowing behaviour among youth in

Nairobi County. The results will help to identify which elements are most important to youth when deciding whether to take on digital credit, and whether these factors are perceived as beneficial or detrimental to their financial well-being. Understanding these influences can guide digital credit providers in designing loan products that address the needs and preferences of their niche market better.

Table 4.3: Factors Influencing the Decision to Borrow a Digital Loan

	N	Mean	Std. Deviation
Interest rate	336	4.137	1.022
Bank charges	336	3.970	0.768
Loan Tenure	336	4.631	0.647

Table 4.3 posits that majority of the respondents strongly agreed that loan tenure is the most influential factor in their decision to borrow a digital loan (mean = 4.631, SD = 0.647). This advises that youth borrowers in Nairobi County prioritize flexibility in the repayment period, with many preferring loans that offer longer repayment durations. The relatively low standard deviation indicates that this factor is consistently important across respondents, highlighting the importance of manageable loan terms in preventing financial strain. Additionally, a large number of respondents strongly indicated that interest rate is an important consideration when deciding to borrow a digital loan (mean = 4.137, SD = 1.022). While there is some variability in responses, the mean score reflects that interest rate is a crucial factor for youth borrowers, with many keenly aware of how it impacts the overall cost of the loan. Further, respondents agreed that bank charges influence their borrowing decisions (mean = 3.970, SD = 0.768). Therefore, the respondents are sensitive to the additional costs associated with digital loans, with most viewing bank charges as a significant consideration in their decision to borrow. These findings suggest that digital credit providers should focus on offering flexible loan terms with competitive interest rates and minimal bank charges to align with the financial preferences of youth borrowers.

4.3.3 Lender Characteristics Summary Statistics

The study sought to determine the effect of lender characteristics on the probability of default for digital credit facilities by youth in Nairobi County.

Table 4.4: Lender Characteristics Summary Statistics

	Frequency	Percent
Digital Lender		
M-Shwari	52	15.50%
KCB Mpesa	16	4.80%
Eazzy Banking	79	23.50%
M-Coop Cash	100	29.80%
Timiza	48	14.30%
Branch	21	6.30%
Tala	20	6.00%
Key Attractors to Digital Lenders		
Loan approval process	28	8.3
Loan limit amount	65	19.3
Interest rate and other applicable fees	110	32.7
Mode of Loan Repayment		
Standing order	16	4.8
Cash deposits	66	19.6
Checkoff	92	27.4
Mobile Money	162	48.2
Loan Disbursement Time		
24 hours	16	4.8
36 hours	48	14.3
48 hours	80	23.8
Above 48 hours	192	57.1

Centred on the indications from the respondents (29.8%), M-Coop Cash was the most popular digital lender among youth in Nairobi County. This suggests that the Co-operative Bank's digital lending platform is effectively addressing the financial needs of this demographic—likely due to a combination of user-friendly features, favorable loan terms, and strong institutional trust. Eazzy Banking, operated by Equity Bank, followed closely at 23.5%, further reinforcing the dominance of bank-backed digital lending platforms. M-Shwari, a longstanding and widely used product, was the third most preferred lender at 15.5%, indicating its continued relevance in the market. Timiza (14.3%) also maintained a strong presence, while Branch (6.3%) and Tala (6.0%), which are non-bank mobile lending apps, registered relatively lower preferences. KCB Mpesa, despite its early entry into the digital lending space, had the least number of users (4.8%), suggesting it may be losing ground to more innovative or better-marketed competitors. These findings illustrate a clear trend: youth borrowers are increasingly leaning toward bank-affiliated digital lenders, likely valuing the security, structure, and reliability they offer. The data highlights the competitive nature of the digital credit market and underscores the need for lenders—especially underperforming platforms—to improve their value propositions through better customer experiences, tailored products, and enhanced digital engagement strategies.

Table 4.4 shows that the loan repayment period was the most important factor attracting youth borrowers to digital lenders, with 39.6% of respondents citing it as the primary motivator. This suggests that flexible or longer repayment terms are particularly appealing to young borrowers, who may have limited or inconsistent income streams. The interest rate and other applicable fees followed closely at 32.7%, indicating that cost-related factors are crucial in selecting a lender. The loan limit amount was selected by 19.3% of respondents, emphasizing the prominence of access to sufficient credit to meet their borrowing needs. Interestingly, only 8.3% were influenced by the loan approval process, implying that while speed and ease of access are important, they may be less of a differentiator compared to more practical considerations such as repayment terms and total cost of borrowing. These insights emphasize the need for digital lenders to offer competitive rates and flexible repayment structures to remain attractive to the youth demographic.

The results from Table 4.4 show that mobile money is the most widely used mode of loan repayment among youth borrowers in Nairobi County, with 48.2% of respondents indicating it

as their preferred repayment method. This underscores the centrality of mobile financial services in Kenya's digital credit ecosystem, likely because of their accessibility, convenience and integration with popular digital lending platforms. Checkoff systems, where loan repayments are automatically deducted from salaries or incomes, were used by 27.4% of respondents, reflecting a significant share of borrowers with formal or regular income streams. Cash deposits accounted for 19.6%, indicating that some borrowers still rely on traditional banking methods. Meanwhile, only 4.8% used standing orders, possibly due to the limited appeal of recurring payments among youth with variable incomes. These findings suggest that for digital lenders aiming to improve repayment rates and borrower satisfaction, optimizing mobile repayment solutions should be a key strategic focus.

Lastly, respondents reported how long it took to receive funds after loan approval—ranging from within 24 hours to over 48 hours. This metric helps gauge lender efficiency and responsiveness, which are critical to borrower satisfaction and may influence repeat borrowing and repayment behaviour. Fast disbursement may offer financial relief in urgent situations but could also lead to impulsive borrowing and increased default risk if not coupled with financial discipline.

Majority of the respondents (57.1%) received their digital loan disbursements after more than 48 hours, indicating a significant delay in the processing and release of funds. Only 23.8% of the respondents received their loans within 48 hours, while 14.3% and 4.8% reported receiving their loans within 36 hours and 24 hours, respectively. This delay in disbursement contradicts the common perception of digital credit being instantly accessible and may affect borrower satisfaction and trust in digital lenders. For youth borrowers who often seek digital loans to meet urgent financial needs, prolonged waiting times could drive them to seek alternative lenders or informal credit sources. These insights suggest a need for DCPs to streamline their loan approval and disbursement processes maintain their competitiveness in meeting the time-sensitive demands of the youth demographic.

4.3.4 Loan Size as the moderating variable

The study sought to determine the moderating effect of loan size. Respondents were asked to indicate the loan amounts that youth borrowers typically take out. By categorizing loan amounts, the study aims to investigate whether the loan size correlates with the likelihood of default. Smaller loan amounts (e.g., Ksh. 1,000–Ksh. 5,000) may be more easily managed and

repaid, while larger amounts (e.g., Ksh. 50,001–Ksh. 100,000 or more) could present significant financial strain. Understanding the distribution of loan sizes helps to gauge the financial burden faced by youth borrowers and their ability to meet repayment terms, providing a clear picture of the relationship between loan amount and default risk.

Table 4.5: Loan Amount Borrowed

	Frequency	Percent
Less than Ksh. 1000	44	13.1
Ksh. 1,000- Ksh. 5,000	32	9.5
Ksh. 5,001- Ksh. 10,000	81	24.1
Ksh. 10,001- Ksh. 50,000	145	43.2
Ksh. 50,001- Ksh. 100,000	34	10.1
Total	336	100

Table 4.5 provides a detailed breakdown of the loan amounts borrowed by youth in Nairobi County, revealing varying financial needs and borrowing capacities within this demographic. The largest proportion of respondents, 145 (43.2%), reported borrowing between Ksh. 10,001 and Ksh. 50,000, indicating that most youth depend on digital loans to finance moderately significant needs such as school fees, business expansion, or household investments. A smaller yet substantial group, 81 respondents (24.1%), borrowed between Ksh. 5,001 and Ksh. 10,000, while only 32 (9.5%) and 44 (13.1%) borrowed between Ksh. 1,000–5,000 and less than Ksh. 1,000, respectively. These figures suggest the presence of micro-borrowers who likely use loans to cover short-term needs such as food, airtime, or emergency expenses. Additionally, 34 respondents (10.1%) accessed higher loan amounts between Ksh. 50,001 to Ksh. 100,000, reflecting a small but noteworthy segment of youth with the ability or need to service larger credit facilities, possibly for significant expenditures like tuition or business capital. These findings underscore the importance of offering tiered digital credit products that align with borrowers’ financial goals and repayment abilities—ranging from microloans to higher-value credit options—to enhance access while minimizing the probability of default.

4.3.5 Probability of Default

This section sought to assess the likelihood and circumstances under which youth borrowers default on digital loans. Understanding default behaviour is critical to evaluating the

sustainability of digital credit products and identifying borrower profiles most at risk of financial delinquency. The section explored the types of loans borrowed, borrower preferences between bank-issued and third-party digital credit providers, and the perceived convenience and trustworthiness of these lenders. Additionally, the study examined actual experiences with default, including which type of lender was associated with non-repayment. The findings are crucial for informing the development of risk-based pricing models and borrower support strategies to reduce default rates among youth borrowers in Nairobi County.

Table 4.6: Summary Statistics

	Frequency	Percent
Type of loan borrowed		
Digital loan from a digital credit provider	70	20.8
Digital loan from a bank	91	27.1
Both above	175	52.1
Preferred Source of Digital Loan		
Digital credit provider	210	62.5
Bank	126	37.5
History of Loan Default		
Yes	74	22
No	262	78
Type of Loan in Default		
Digital loan from a bank	24	32.4
Digital loan from a digital credit provider	33	44.6
Both above	17	23.0

Table 4.6 indicates that majority of the respondents (52.1%) had borrowed from both banks and digital credit providers, suggesting that youth borrowers in Nairobi County tend to

diversify their credit sources depending on need, convenience, or loan conditions. Meanwhile, 27.1% reported borrowing exclusively from banks, while 20.8% had only taken loans from digital credit providers such as Tala or Branch. This distribution implies a growing reliance on digital lending ecosystems, with many borrowers interacting with both traditional and fintech platforms. The significant proportion of borrowers utilizing both channels underscores the evolving financial behaviour among youth, who appear to value the flexibility and accessibility of digital platforms while still engaging with formal banking institutions. This mixed borrowing behaviour is crucial when analysing default risks and borrower loyalty, as it suggests that digital financial services are not replacing banks but rather complementing them in the financial inclusion landscape.

A sizable proportion of the respondents (62.5%) prefer borrowing digital loans from digital credit providers, such as Tala or Branch, rather than traditional banks (37.5%). This preference indicates a higher level of comfort or satisfaction with the accessibility and convenience offered by digital lenders, which may include quicker loan processing times, easier application procedures, and fewer requirements compared to banks. The significant preference for digital credit providers highlights the growing role of fintech in the youth borrowing landscape, as these platforms often cater more directly to the needs and expectations of younger, tech-savvy borrowers. However, the fact that 37.5% still favour banks suggests that trust in formal financial institutions and possibly more favourable loan terms or customer service may still drive a portion of the population to seek loans from banks.

Grounded on the findings in Table 4.6, 22% of the respondents have experienced defaulting on a digital loan, while the majority (78%) reported never defaulting. This indicates that, although a significant portion of borrowers can manage their loan repayments successfully, a noteworthy minority has faced challenges in meeting their obligations. The relatively low default rate suggests that many youth borrowers potentially could repay their loans on time, but the 22% who have defaulted could represent a higher-risk group for lenders. Understanding the characteristics of these borrowers will be crucial in identifying the factors contributing to defaults and in developing strategies to reduce this risk.

Among those who have defaulted on a previous loan, 44.6% had defaulted on a digital loan from a digital credit provider, while 32.4% had defaulted on a loan from a bank. A smaller proportion (23%) reported defaulting on both types of loans. This indicates that digital credit providers, despite their widespread popularity and ease of access, might carry a higher default

risk compared to banks. The ease of borrowing and rapid disbursement offered by digital lenders could potentially lead to over-borrowing, which might contribute to higher default rates. Conversely, the lower default rates on bank loans suggests that bank borrowers may have a slightly higher capacity to manage their debt or are subject to stricter lending criteria, which could mitigate default risk. Understanding these patterns can help lenders develop more effective risk management strategies tailored to each type of lender.

Respondents rated several reasons for preferring a specific loan provider—such as ease of approval, speed of disbursement, convenience of repayment, fee structure, and perceived trust. These ratings reveal the most influential factors in lender selection and allow for comparison between different loan platforms.

Table 4.7: Reasons for Loan Preference

	N	Mean	Std. Deviation
The loan approval process is not complicated	336	4.464	0.772
The loan is disbursed to my account fast	336	4.185	0.938
The loan repayment process is convenient	336	4.113	0.983
I get access to the loan amount I want	336	4.074	0.767
I am not charged hefty fees to access the loan	336	4.211	0.857
I trust this credit provider more than others in the industry	336	3.833	0.997

The results from Table 4.7 highlight the fundamental factors that influence the respondents' choice of digital loan provider. The highest-rated factor was the ease of the loan approval process (mean = 4.464, SD = 0.772), which suggests that youth borrowers prioritize simplicity and speed in accessing credit. The second highest-rated was the speed of loan disbursement (mean = 4.185, SD = 0.938), indicating that timely access to funds is crucial for youth borrowers. The loan repayment process was also seen as a significant factor (mean = 4.113, SD = 0.983), as borrowers likely prefer convenient and manageable repayment options. While access to the desired loan amount (mean = 4.074, SD = 0.767) and relatively low fees (mean = 4.211, SD = 0.857) were also important, they ranked slightly lower than the approval process and disbursement speed. Trust in the credit provider (mean = 3.833, SD = 0.997) was the

lowest-rated. This indicates that while trust is a factor, it may not be as critical as other practical considerations such as loan approval and disbursement speed. This information reveals that digital lenders need to prioritize efficient, fast, and user-friendly processes to attract youth borrowers, while also maintaining competitive fee structures.

4.4 Correlation Analysis

The correlation analysis was done to show the association between the borrower, loan and lender characteristics, and the probability of default on digital credit facilities by youth in Nairobi County. The analysis aimed to uncover how these factors interact and contribute to the likelihood of default. The findings are as displayed in Table 4.8 below.



Table 4.8: Correlation Analysis

Variable s	Age	Gender	Default History	Student Loan	Marital Status	Income Level	Occupation	Education Level	Interest Rate	Loan Tenure	Loan Purpose	Business Model	Mode of Payment	Loan Appraisal Period	Probability of Default
Age	1.00	0.02	0.30	-0.10	0.20	0.40	0.35	0.28	0.15	0.20	0.10	0.08	0.05	0.07	0.32
Gender	0.02	1.00	-0.05	0.12	0.10	0.08	0.15	0.06	0.04	0.02	0.03	0.01	0.00	0.02	0.10
Default History	0.30	-0.05	1.00	0.25	0.18	0.45	0.40	0.33	0.35	0.30	0.20	0.12	0.10	0.15	0.55
Student Loan	-0.10	0.12	0.25	1.00	0.22	-0.05	-0.08	0.10	0.10	0.05	0.08	0.06	0.04	0.03	0.28
Marital Status	0.20	0.10	0.18	0.22	1.00	0.30	0.25	0.20	0.08	0.10	0.05	0.05	0.03	0.02	0.30
Income Level	0.40	0.08	0.45	-0.05	0.30	1.00	0.55	0.50	0.40	0.35	0.25	0.20	0.18	0.15	0.52
Occupation	0.35	0.15	0.40	-0.08	0.25	0.55	1.00	0.48	0.35	0.28	0.20	0.15	0.12	0.10	0.50
Education Level	0.28	0.06	0.33	0.10	0.20	0.50	0.48	1.00	0.30	0.25	0.22	0.18	0.16	0.12	0.45
Interest Rate	0.15	0.04	0.35	0.10	0.08	0.40	0.35	0.30	1.00	0.60	0.50	0.30	0.25	0.20	0.58
Loan Tenure	0.20	0.02	0.30	0.05	0.10	0.35	0.28	0.25	0.60	1.00	0.45	0.28	0.22	0.25	0.54
Loan Purpose	0.10	0.03	0.20	0.08	0.05	0.25	0.20	0.22	0.50	0.45	1.00	0.24	0.18	0.20	0.45
Business Model	0.08	0.01	0.12	0.06	0.05	0.20	0.15	0.18	0.30	0.28	0.24	1.00	0.40	0.50	0.32
Mode of Payment	0.05	0.00	0.10	0.04	0.03	0.18	0.12	0.16	0.25	0.22	0.18	0.40	1.00	0.45	0.30
Loan Appraisal Period	0.07	0.02	0.15	0.03	0.02	0.15	0.10	0.12	0.20	0.25	0.20	0.50	0.45	1.00	0.38
Probability of Default	0.32	0.10	0.55	0.28	0.30	0.52	0.50	0.45	0.58	0.54	0.45	0.32	0.30	0.38	1.00

Table 4.9: Summary of Correlation analysis per the specific objectives

Variables	Borrower Characteristics	Loan Characteristics	Lender Characteristics	Probability of Default
Borrower Characteristics	1	0.45	0.30	0.50
Loan Characteristics	0.45	1	0.55	0.60
Lender Characteristics	0.30	0.55	1	0.35
Probability of Default	0.50	0.60	0.35	1

The analysis above indicates numerous significant insights into the relationships between various borrower, loan and lender characteristics and the probability of default on loans. The findings highlight several factors that moderately to strongly influence a borrower's likelihood of default on loans.

One of the most notable findings is the positive correlation of 0.58 between the loan interest rate and probability of default, which is the highest in the matrix. This indicates a moderately strong positive relationship, suggesting that as interest rates increase, the default likelihood increases. Intuitively, as higher interest burdens can create repayment pressure on borrowers, particularly those with constrained or fluctuating incomes. In the context of youth borrowers, especially in urban areas like Nairobi County, higher interest rates may exacerbate financial strain, pushing them into default.

Another significant variable is default history, which has a correlation coefficient of 0.55 with the probability of default. This moderately strong positive relationship implies that past repayment behaviour is a strong predictor of future financial conduct. Individuals with a history of defaulting on loans are more likely to default again. This finding emphasizes the need for inclusion of historical credit behaviour into digital credit risk models to better anticipate and mitigate future losses.

Loan tenure also exhibits a strong correlation ($r = 0.54$) with default probability. This implies that loans with longer repayment periods tend to be associated with higher default risks. Over extended periods, borrowers' financial situations can change due to employment instability, health issues, or other socio-economic factors, increasing the chance of default. In youth-dominated segments, the likelihood of such disruptions may be even more pronounced due to precarious employment or lifestyle volatility.

Income level, often viewed as a key determinant of creditworthiness, shows a moderate positive correlation of 0.52 with default probability. Interestingly, this relationship proposes that higher income levels do not necessarily equate to lower default risk. This may indicate over-borrowing among higher-income individuals or income unpredictability among segments such as entrepreneurs or informal sector workers. For instance, some borrowers may inflate income expectations or rely on seasonal earnings, which may not sustain regular repayments.

Similarly, occupation type has a moderate correlation of 0.50 with the probability of default. This suggests that the nature of one's employment or professional engagement plays a role in determining repayment behaviour. Occupations characterized by instability or irregular income—common in the gig or informal economy—may increase vulnerability to default.

Education level is also positively correlated ($r = 0.45$) with default probability. This finding may seem counterintuitive, as education is traditionally linked with better financial decision-making. However, it could reflect a trend where more educated individuals have greater access to credit facilities, and greater confidence in managing credit, leading to over-borrowing or riskier financial behaviour. Among youth, higher education may not always translate to immediate income, which may in turn affect their repayment capacity.

Another variable with a moderate correlation is loan purpose, which registers a coefficient of 0.45. This implies that the reason for borrowing influences the likelihood of repayment. Loans taken for non-productive purposes, such as consumption or emergencies, may not generate income to support repayment, thereby increasing the risk of default. Lenders could consider integrating loan purpose more explicitly into their risk assessment frameworks.

The presence of a student loan shows a lower but still meaningful correlation ($r = 0.28$) with default risk. This indicates that a borrower with a student loan has a higher likelihood of default,

possibly due to lack of stable employment or financial independence. The transitional life stage of student borrowers may also contribute to inconsistent repayment behaviour.

Marital status and age show modest positive correlations with default risk ($r = 0.30$ and $r = 0.32$, respectively). These findings suggest that older or married individuals may have more financial responsibilities, which could affect their ability to meet debt obligations. However, they may also possess stronger support systems that mitigate default risk to some extent.

The loan appraisal period exhibits a correlation of 0.38, indicating that delays or inefficiencies in evaluating and approving loans may contribute to borrower disengagement or misalignment between credit need and disbursement timing, potentially increasing default risk.

Other variables such as the business model ($r = 0.32$) and mode of payment ($r = 0.30$) have moderate positive correlations with the probability of default. These findings suggest that how a loan is repaid and the structure of the borrower's financial ecosystem can influence repayment outcomes. For example, digital or mobile-based repayment modes may be more susceptible to disruptions in mobile money flows or irregular income.

Lastly, gender shows a weak correlation of 0.10, suggesting that it has minimal direct influence on loan default probability. This indicates that both male and female borrowers exhibit similar repayment behaviours when other variables are controlled for.

Overall, the correlation analysis underscores that interest rate, default history, loan tenure, income level, and occupation are the most critical variables influencing the probability of default. These findings can guide lenders, particularly digital credit providers, in refining their risk assessment criteria. In settings like Nairobi County, where youth make up a sizeable percentage of the borrowing population, it is critical to tailor credit products with an understanding of the socio-economic dynamics revealed in this analysis. By doing so, lenders can enhance repayment performance while promoting responsible borrowing practices.

4.5 Probit Regression Analysis

The probit analysis was conducted to explore the factors influencing the probability of default on digital credit facilities among youth in Nairobi County. Table 4.10 lays out the results which outline the key predictor variables: borrower characteristics, loan characteristics, and lender characteristics. These are accompanied by their respective coefficients, standard errors, Wald

statistics, and marginal effects. The probit model is suitable in this context as it assumes a normal distribution of the latent error term, making it appropriate for modelling binary outcomes such as loan default. The results relay that all three categories of variables significantly influence the probability of default.

Table 4.10: Probit Regression Analysis

Variable	Coefficient	Std. Error	z-Statistic	P-Value	Marginal Effect
Age	0.142	0.058	2.448	0.014	0.0345
Gender	0.065	0.052	1.25	0.211	0.016
Default History	0.492	0.083	5.928	0.000	0.1195
Student Loan	0.188	0.074	2.541	0.011	0.0456
Marital Status	0.158	0.069	2.29	0.022	0.0371
Income Level	0.378	0.081	4.667	0.000	0.0919
Occupation	0.352	0.076	4.632	0.000	0.0852
Education Level	0.298	0.072	4.139	0.000	0.0721
Interest Rate	0.476	0.079	6.025	0.000	0.1142
Loan Tenure	0.438	0.083	5.277	0.000	0.1048
Loan Purpose	0.325	0.07	4.643	0.000	0.0778
Business Model	0.21	0.065	3.231	0.001	0.0503
Mode of Payment	0.195	0.067	2.91	0.004	0.0462
Loan Appraisal Period	0.245	0.071	3.451	0.001	0.0581
Constant	-1.042	0.192	-5.427	0.000	—

Table 4.11: Summary of regression analysis per specific objectives

Predictor Variable	Coefficient	Standard Error	z-Statistic	P-Value	Marginal Effect (%)
Borrower					
Characteristics	0.259	0.071	3.487	0.032	0.0627
Loan					
Characteristics	0.413	0.077	5.315	0.000	0.0989
Lender					
Characteristics	0.217	0.068	3.197	0.002	0.0515
Constant	-1.042	0.192	-5.427	0.000	—

The findings from the detailed Probit regression model reveal that individual borrower characteristics, loan-specific features, and institutional (lender-related) attributes jointly exert a statistically robust positive influence on the probability of default on digital credit facilities among youth in Nairobi County. This indicates that variations in demographic, financial, and institutional factors meaningfully affect the likelihood of default by a young borrower. The model therefore underscores that both behavioural and structural variables contribute to loan default.

First, among the borrower characteristics, several variables were found to have a statistically significant positive effect on the likelihood of default. These include Age ($\beta = 0.142$, $p = 0.014$), Default History ($\beta = 0.492$, $p < 0.001$), Student Loan ($\beta = 0.188$, $p = 0.011$), Marital Status ($\beta = 0.158$, $p = 0.022$), Income Level ($\beta = 0.378$, $p < 0.001$), Occupation ($\beta = 0.352$, $p < 0.001$), and Education Level ($\beta = 0.298$, $p < 0.001$). The positive coefficient for age suggests that as youth borrowers get older within the target bracket, their likelihood of default slightly increases, possibly due to higher financial commitments or debt accumulation. The most significant predictor, default history, indicates that individuals who have defaulted previously are more likely to default again, reflecting persistent credit behaviour patterns.

The positive and significant coefficients for income level and occupation reveal that borrowers with irregular or lower-income jobs face higher repayment difficulties, especially when their income streams are unpredictable. The marginal effects of these variables, ranging between

3.4% and 9.2%, demonstrate that even small changes in borrower profiles can substantially influence repayment outcomes. Furthermore, the significance of education level highlights that while education enhances awareness and access to digital credit, it does not necessarily guarantee responsible credit behaviour; some educated youth may overborrow due to overconfidence in their future earnings. Overall, these findings suggest that borrower vulnerability stems not only from low income or lack of collateral but also from behavioural and experiential factors such as prior defaults, unstable employment, and inadequate financial literacy. Consequently, there is need for financial literacy programs targeting the youth, enhanced credit profiling, and the inclusion of behavioural indicators such as prior payment consistency and spending patterns within credit scoring algorithms for youth borrowers.

Secondly, the loan characteristics namely Interest Rate ($\beta = 0.476, p < 0.001$), Loan Tenure ($\beta = 0.438, p < 0.001$), and Loan Purpose ($\beta = 0.325, p < 0.001$) also exhibited a strong positive association with default. The high coefficient for interest rate suggests that the cost of borrowing is a key determinant of repayment performance; borrowers facing high or variable interest rates experience greater repayment stress, increasing the likelihood of delinquency. Similarly, longer loan tenures correlate with increased default probability, implying that the longer the repayment period, the higher the risk surrounding the borrower's ability to generate stable income or maintain repayment discipline. Loan purpose, which captures whether the loan is used for consumption or investment, was also significant—indicating that credit used for non-productive or short-term consumption tends to elevate default risk.

These findings collectively indicate that the pricing and structuring of the loan are critical in determining the repayment outcomes. When loan products are mismatched with borrowers' income cycles or repayment capacity, they can inadvertently push borrowers into default. Therefore, digital lenders should adopt flexible repayment models, offer tiered interest rates, and encourage productive loan use through tailored financial guidance. Structuring loans to reflect cash flow realities of youth borrowers especially those in informal or gig economies would help mitigate default rates and promote sustainable borrowing behaviour.

Thirdly, the lender-related characteristics, including Business Model ($\beta = 0.210, p = 0.001$), Mode of Payment ($\beta = 0.195, p = 0.004$), and Loan Appraisal Period ($\beta = 0.245, p = 0.001$), have a positive and statistically significant relationship with default probability. The significance of business model implies that institutional factors, such as whether the lender operates as a bank, microfinance, or fintech company, influence default outcomes. Digital-first

lenders relying on automated credit scoring systems may inadequately assess risk, particularly among borrowers lacking traditional credit histories. The positive relationship between mode of payment and default suggests that the repayment channels such as mobile wallets or online transfers—may affect repayment discipline, especially when payments are not automatically deducted or synchronized with borrowers' income receipts.

Similarly, a longer loan appraisal period, though meant to ensure due diligence, was associated with higher default risk, possibly because it delays disbursement or reflects inefficiencies in lender operations. These findings imply that institutional practices such as loan disbursement speed, customer support responsiveness, and transparency in loan terms can influence repayment behaviour. Hence, lenders should balance automation with human oversight, strengthen post-disbursement borrower engagement, and enhance customer service delivery. Financial institutions should also maintain transparent communication regarding charges, repayment schedules, and penalties to prevent borrower confusion or distrust that may lead to default.

In conclusion, the study demonstrates that digital loan default among youth is a multifaceted phenomenon influenced by personal, structural, and institutional factors. Borrower characteristics such as previous default history, income instability, and limited financial literacy interact with unfavorable loan features like high interest rates and long tenures, as well as with institutional weaknesses in appraisal and payment management. To curb the rising incidence of default, stakeholders including digital lenders, regulators, and financial educators should implement integrated strategies that combine borrower empowerment through financial education, development of flexible and affordable loan products, and promotion of ethical, data-driven lending practices. Such comprehensive interventions will not only reduce default risk but also enhance financial inclusion, credit sustainability, and youth empowerment within Kenya's rapidly evolving digital finance ecosystem.

4.5.1 Probit Regression with Moderating Effect of Loan Size

The probit regression analysis was extended to test for a moderating effect of loan size on the determinants of the default probability. The results are summarized in Table 4.12.

Table 4.12: Probit Regression with Moderating Effect of Loan Size

Variable Category	Coefficient	Std. Error	z-Statistic	P-Value	Marginal Effect
Borrower Characteristics (BC)	0.38	0.103	3.689	0.000	0.0942
Loan Characteristics (LC)	0.35	0.088	3.977	0.000	0.0864
Lender Characteristics (LDC)	0.31	0.084	3.69	0.000	0.0765
Loan Size (LS)	0.215	0.07	3.071	0.002	0.0532
BC × LS (Interaction Term 1)	0.13	0.051	2.549	0.011	0.0321
LC × LS (Interaction Term 2)	0.118	0.049	2.408	0.016	0.0295
LDC × LS (Interaction Term 3)	0.102	0.047	2.17	0.030	0.0258
Constant	-0.95	0.188	-5.053	0.000	—

The probit regression analysis incorporating interaction terms reveals important insights into how loan size moderates the relationship between borrower characteristics, loan characteristics, and lender characteristics with the probability of default on digital credit among youth in Nairobi County. The results indicate that each of the three primary predictor categories—borrower characteristics, loan characteristics, and lender characteristics—has a positive and statistically significant effect on the likelihood of default. These findings confirm that youth-related factors, institutional structures, and product design elements each contribute meaningfully to the dynamics of repayment behaviour in the digital lending environment.

Specifically, borrower characteristics exhibit a strong and significant influence on default, with a coefficient of 0.380 and a marginal effect of 9.42 percentage points. This means that as borrower-related risk factors—such as unstable employment, or limited income—intensify, the

probability of default among youth increases accordingly. These personal and socioeconomic dimensions are essential in determining whether a youth borrower can meet repayment obligations. Similarly, loan characteristics demonstrate a statistically significant effect (coefficient = 0.350) with a marginal influence of 8.64%. This underscores the role that loan design features—such as the loan interest rate, the loan repayment period, and loan size relative to income—have in shaping repayment behaviour. Less favorable loan terms, particularly those with limited flexibility or high cost, appear to elevate the risk of default. Lender characteristics also exhibit a significant positive relationship with default, with a coefficient of 0.310 and a marginal effect of 7.65%. This suggests that the practices and capacities of digital lenders—including their credit scoring systems, customer support quality, and transparency in loan communication—substantially affect the borrower's willingness to repay and their ability.

In addition to their independent effects, the study finds that loan size exerts a significant and positive main effect on the probability of default. The coefficient for loan size is 0.215, with a p-value of 0.002, indicating that larger loan amounts increase the likelihood of default among youth borrowers. This result is consistent with the understanding that higher loan burdens are harder to manage, particularly for young individuals who often rely on inconsistent or informal income sources. In this context, loan size functions as more than just a financial variable; it represents a stressor that, when misaligned with borrower capacity, can magnify default risk.

Importantly, the interaction effects between loan size and each of the three predictor categories provide further evidence that loan size acts as a moderator, intensifying the impact of the other variables on default outcomes. The interaction between borrower characteristics and loan size, with a coefficient of 0.130, is both positive and statistically significant ($p = 0.011$). This finding suggests that when youth borrowers with riskier profiles take on larger loans, the probability of default escalates disproportionately. In essence, borrower weaknesses—such as lack of experience in credit management or limited financial planning skills—are exacerbated under the weight of larger loan obligations. Consequently, youth who might otherwise manage smaller debts successfully may falter when given more substantial credit.

The moderating role of loan size is similarly evident in its interaction with loan characteristics. The positive and significant interaction coefficient of 0.118 ($p = 0.016$) indicates that the effect of unfavorable loan features is more evident when the loan size increases. For instance, short repayment timelines or high interest rates become more burdensome and detrimental to repayment when applied to larger loan amounts. Youth borrowers may find themselves

overwhelmed not only by the structure of the loan but by the financial pressure that accompanies higher loan values, leading to an increased likelihood of default.

Lastly, the interaction between lender characteristics and loan size is also positive and statistically significant, with a coefficient of 0.102 ($p = 0.030$). This relationship highlights that institutional weaknesses or inefficiencies—such as inadequate borrower risk assessment, lack of personalized loan terms, or automated and impersonal lending processes—can have a greater negative effect when the credit amounts involved are larger. In such cases, the risk of default rises not only because of borrower limitations or poor loan design, but also because institutional oversight fails to account for the increased risk posed by higher loan values. Lenders who apply a “one-size-fits-all” approach to credit may inadvertently contribute to rising default rates among youth when issuing larger loans without corresponding support or risk mitigation strategies.

In summary, these findings demonstrate that loan size is not only an independent determinant of default but also serves as a key moderator that amplifies the effects of borrower traits, loan design, and lender practices. This multifaceted interaction underscores the necessity for additional nuanced, risk-sensitive lending models that capture the varying capacities of youth borrowers. Financial institutions offering digital credit to youth in Nairobi County should consider implementing tiered or progressive lending limits, strengthening credit appraisal mechanisms, and ensuring that larger loans are accompanied by additional borrower education or support. Such measures would enhance credit sustainability, reduce the risk of over-indebtedness, and promote more responsible financial inclusion for the youth segment.

CHAPTER FIVE: DISCUSSIONS, CONCLUSION, CONTRIBUTIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter outlines a comprehensive overview of the study's findings, offering detailed discussion, conclusion, and recommendations based on the analysis of the determinants of loan default for digital credit facilities among youth in Nairobi County. This chapter begins by summarizing the key results and linking them to the study's objectives. It then explores the implications of these findings, followed by a conclusion that synthesizes the main insights derived from the analysis. The chapter also includes recommendations for improving digital lending practices, highlights the limitations of the study, and proposes future research areas to enhance understanding and inform policymaking in the field of digital credit.

5.2 Summary of Findings

The study investigated the determinants of the probability of default on digital credit facilities by youth in Nairobi County. Grounded by the findings, it was palpable that borrower characteristics, loan characteristics and lender characteristics all have a statistically significant positive effect on the probability of default for digital credit facilities by youth in Nairobi County. The study revealed that borrower characteristics, specifically the low income and history of previous default increased the probability of default. Loan characteristics like short loan tenure and high interest rates, contributed to the largest increase in the probability of default which showed the financial burdens that were mismatched with the youth's level of income. Lender characteristics had a significant positive effect on the probability of default. From the analysis of the moderating effect of the loan size, it was evident that larger loan amounts were a financial stressor that amplified the probability of default associated with the borrower, loan and lender characteristics. This led to the disproportionate escalation of the probability of default with the increase in loan size.

5.3 Discussion of Findings

This section entails a detailed discussion of the study findings grounded on the three specific research objectives. The discussion integrates the descriptive and inferential results of the study, interprets their implications, and relates the outcomes to existing empirical literature. It also highlights the alignment or difference of the current findings from those of prior studies, offering insights into potential controversies or confirmations in the literature.

5.3.1 Effect of Borrower Characteristics on the Probability of Default

The study found that borrower characteristics significantly influenced the probability of default on digital credit facilities among youth in Nairobi County. Probit regression analysis indicated that a rise in risk borrower factors—including erratic earnings, poor financial knowledge, or unstable employment—directly correlates with a higher chance of default. Furthermore, the preliminary data showed that a significant number of youth borrowers fit a high-risk profile characterized by a lack of collateral or irregular monthly income.

These findings support the Adverse Selection Theory (Akerlof, 1970), which suggests that lenders may inadvertently issue loans to high-risk borrowers due to information asymmetry. The results are consistent with those of Ghosh and Van Tassel (2011) and Wachira and Kihara (2023), who found that poor borrower profiling contributes significantly to default rates, especially in digital lending platforms where rigorous credit assessments are often bypassed. However, unlike studies by Njiru (2021), which downplayed the significance of demographic characteristics like the borrower's age and education in digital loan default, this study accentuates the relevance of deeper behavioural and socioeconomic traits, revealing a more nuanced understanding of borrower risk.

5.3.2 Effect of Loan Characteristics on the Probability of Default

Loan characteristics also had the strongest statistically significant influence on the probability of default. The probit regression results showed a positive coefficient indicating that certain loan features like high interest rates, short loan tenure, high interest rates, and small loan amounts, contributed to the likelihood of default increasing. Descriptive analysis showed that most of the loans accessed by youth had repayment durations of less than 30 days and carried high service fees.

These results are in alignment with the Financial Intermediation Theory, which argues that when loan terms are not well matched to borrower repayment capacities, default becomes more likely. The findings are consistent with research by Kamau and Mukabi (2020) and Mungai (2022), who reported that inflexible loan structures and hidden charges in digital loans exacerbate borrower distress, leading to high default rates. The current findings of this study indicate that the interaction of multiple loan characteristics creates a cumulative risk effect, reinforcing the importance of a holistic loan design.

5.3.3 Effect of Lender Characteristics on the Probability of Default

Lender characteristics had a significant positive influence on the probability of default. The analysis showed that weak lender practices—such as lack of due diligence, insufficient borrower screening, and limited post-disbursement monitoring—substantially contributed to higher default rates. Descriptive findings also showed that many digital credit providers did not engage in effective communication or borrower education post-loan disbursement.

These findings corroborate Financial Intermediation Theory, which underscores the role of intermediaries in reducing risk through borrower monitoring and information processing (Gurley & Shaw, 1956). The results align with those of Mbaka and Muturi (2020), who argued that digital lenders' failure to assess borrower risk adequately contributes to high non-performing loan rates. Additionally, the findings extend the work of Alam and Nazim Ali (2021), who emphasized that technology-driven lenders often prioritize speed and automation over risk evaluation, undermining the quality of credit decisions. This study adds weight to the argument that lender operational design and capacity are pivotal to mitigating default risk, especially in the context of youth borrowing where financial experience is often low.

5.3.4 Moderating Effect of Loan Size

The analysis revealed that loan size significantly moderates the association between borrower, loan and lender characteristics and the probability of default among youth borrowers. The interaction effects between loan size and each of the three predictor categories provide further evidence that loan size acts as a moderator, intensifying the impact of the other variables on default outcomes. The interaction between borrower characteristics and loan size, is both positive and statistically significant. This finding implies that when youth borrowers with riskier profiles take on larger loans, the probability of default escalates disproportionately. In essence, borrower weaknesses—such as lack of experience in credit management or limited financial planning skills—are exacerbated under the weight of larger loan obligations. Consequently, youth who might otherwise manage smaller debts successfully may falter when given more substantial credit.

The moderating role of loan size is similarly evident in its interaction with loan characteristics. The positive and significant interaction indicates that the effect of unfavorable loan features is more evident when the loan size increases. For instance, short repayment timelines or high interest rates become more burdensome and detrimental to repayment when applied to larger

loan amounts. Youth borrowers may find themselves overwhelmed not only by the structure of the loan but by the financial pressure that accompanies higher loan values, leading to an increased likelihood of default.

Lastly, the interaction between lender characteristics and loan size is also positive and statistically significant. This relationship highlights that institutional weaknesses or inefficiencies—such as inadequate borrower risk assessment, lack of personalized loan terms, or automated and impersonal lending processes—can have a greater negative effect when the credit amounts involved are larger. In such cases, the risk of default rises not only because of borrower limitations or poor loan design, but also because institutional oversight fails to account for the increased risk posed by higher loan values. Lenders who apply a “one-size-fits-all” approach to credit may inadvertently contribute to rising default rates among youth when issuing larger loans without corresponding support or risk mitigation strategies.

In tandem with the findings of this study, (Featherstone et al., 2006) opines that the loan size can change the effect of the borrower, loan and lender characteristics on the probability of default. The loan size could impact the borrower’s perception of risk related to default such that if the loan size is small, they could consider default as opposed to when the size is large where there are more severe consequences of default. Additionally, the loan size could influence the impact of loan characteristics on credit default like loan purpose where a borrower could easily divert a small loan and use it for the purpose it was not intended for as compared to a large loan whose structure and repayment is more rigid. The loan size will also enable us to distinguish the default risks related to the micro digital loans and those of larger amounts.

5.4 Conclusions

5.4.1 Effect of Borrower Characteristics on the Probability of Default

The study concludes that borrower characteristics serve as critical predictors of the probability of default on digital credit facilities among youth in Nairobi County. Specifically, traits such as unstable income sources, low financial literacy levels, lack of formal employment, and high borrowing rate substantially increased the loan default likelihood. These findings affirm the presence of borrower-level risks that are often under-assessed by digital lenders due to minimal customer profiling processes. The results underscore the relevance of the Adverse Selection Theory, as youth borrowers often possess private information about their ability to repay, which is not adequately captured by the lenders’ current assessment mechanisms. Therefore,

addressing borrower-level risks through enhanced screening, education, and financial inclusion policies is critical to reducing default rates.

5.4.2 Effect of Loan Characteristics on the Probability of Default

The study concludes that loan characteristics like short loan repayment periods, high rates of interest, and limited grace periods significantly contribute to the probability of default. These structural features create repayment burdens that are disproportionate to the financial capacity of many youth borrowers, leading to elevated default levels. The findings support the Financial Intermediation theory through the notion that poor alignment between loan terms and borrower circumstances increases financial stress and non-compliance with repayment schedules. This implies that loan product design plays a fundamental role in determining credit outcomes. Consequently, lenders need to develop more flexible, affordable, and borrower-responsive credit products if they intend to sustainably serve the youth segment and reduce non-performing loan rates.

5.4.3 Effect of Lender Characteristics on the Probability of Default

The study concludes that lender characteristics exert a positive influence on the likelihood of default like the borrower and loan characteristics. Practices such as limited due diligence, over-reliance on automated scoring models, poor customer engagement, and lack of financial guidance propelled the rate of default. These results highlight a gap in lender accountability and a lack of tailored risk management frameworks suitable for the youth market. The findings reinforce the importance of the intermediary role emphasized in Financial Intermediation Theory, whereby lenders are expected to minimize risk through effective screening, information processing, and post-loan monitoring. It is therefore imperative for digital credit providers and banks to strengthen their credit assessment and customer relationship processes to reduce credit default risks.

5.4.4 Moderating Effect of Loan Size

The loan size significantly moderates the association between borrower, loan and lender characteristics and the probability of default among youth in Nairobi County as illustrated by the findings of the study. Specifically, the analysis revealed that as loan amounts increase, the mitigating effect of positive borrower traits—such as stable income or employment—on default risk weakens, thereby exposing even low-risk borrowers to higher default likelihood. Additionally, the risk associated with lenient lender practices, such as minimal due diligence or fast-tracked approvals, intensifies with larger loan sizes, amplifying the overall probability

of default. This illustrates that loan size not only influences default directly but also shapes how borrower and lender factors interact to affect repayment behaviour. Therefore, integrating loan size into credit risk assessment models is essential for improving predictive accuracy and ensuring that loan approvals, particularly for higher amounts, are matched with appropriate borrower profiles and stricter lending.

5.5 Study Contributions

This study adds to theory in several meaningful ways—conceptually, empirically, contextually, and theoretically. Conceptually, the study enriches the comprehensiveness of digital credit default by proposing a multidimensional framework that integrates borrower, loan, and lender characteristics as critical determinants. This integrated approach moves beyond conventional single-lens studies and demonstrates that default is not merely a borrower issue, but also a consequence of lending design and institutional practices.

Empirically, the study provides robust statistical evidence using probit regression to quantify the influence of these three dimensions on the default probability. The results offer concrete marginal effects that expand current literature, especially in the under-explored context of youth digital borrowing in emerging economies. These findings support and extend the Adverse Selection Theory by empirically validating the existence of information asymmetry in the digital credit market. Furthermore, the study bolsters Financial Intermediation Theory by showing that poor lender practices significantly increase default probability, thereby emphasizing the intermediary's responsibility in screening and monitoring. Contextually, the study fills a crucial population gap by narrowing down on Kenyan youth borrowers—an underserved and high-risk demographic in the digital lending space. Previous studies have rarely disaggregated default predictors by demographic segments or localized economic factors. As such, the study provides a grounded understanding of digital credit operations within Nairobi's unique financial and socio-economic context, thus offering a foundation for future research in similar urban, low-to-middle income settings.

This study contributes considerably to policy formulation and refinement. Firstly, the findings indicate a strong need for regulatory bodies such as CBK to establish comprehensive digital lending policies that mandate more rigorous borrower assessment mechanisms and transparency in loan terms. The study supports the formulation of a "Digital Lending Risk Assessment Policy" that would require both banks and Digital Credit Providers (DCPs) to incorporate alternative data and financial literacy scores in credit scoring models.

Secondly, the study highlights the inadequacy of current consumer protection policies. It recommends an extension of existing Consumer Protection Regulations to include clauses that prohibit exploitative interest rates and compel lenders to disclose all loan terms in an accessible format. The results indicate a vital need for specialized financial accessibility standards within national frameworks to protect young clients from the risks of unsupervised lending. Additionally, the investigation supports the integration of compulsory financial education modules into broader government programs designed to empower the youth population. These would aim to enhance the financial decision-making capacity of young people and reduce behavioural default due to ignorance or misjudgement. In this way, the study provides a concrete policy roadmap toward sustainable digital credit governance in Kenya.

The study offers practical insights for financial market players, digital lenders, and credit policy implementers. Managers in both banks and DCPs should adopt data-driven risk segmentation strategies that go beyond credit scores and factor in borrower behaviour, income patterns, and historical loan usage. The results strongly advocate for the adoption of flexible loan design models—including income-aligned repayment schedules and interest rate caps tailored to young borrowers with variable incomes. Additionally, lenders are advised to improve their post-loan engagement practices, including setting up repayment reminder systems, offering grace periods, and providing financial advisory support through mobile platforms. These practices can mitigate behavioural default and enhance customer loyalty.

The findings also imply that the current performance metrics used by digital lenders—often focused solely on loan uptake—should be recalibrated to include loan recovery rates and default ratios by demographic segments. Such recalibration will promote responsible lending and help institutions avoid unsustainable portfolio expansion. Finally, lenders should avoid practices such as predatory lending, opaque loan terms, and overreliance on automation in loan approvals. Instead, they should adopt human-centred risk assessment methods that combine fintech efficiency with ethical lending standards. In doing so, the study encourages a shift toward inclusive, sustainable, and responsible digital financial services.

5.6 Recommendations

Grounded on the results of the study, contributions, and implications of this study, various key recommendations are proposed to guide future research, inform practice among digital credit providers, and influence policy development to enhance the sustainability and effectiveness of digital lending systems for youth in Nairobi County.

5.6.1 Recommendations to Researchers/Academicians/Scholars

This study reveals the multifaceted nature of digital loan default, suggesting the need for further research in three critical directions. First, scholars should undertake a longitudinal approach to observe how borrower behaviour and default patterns develop over time, predominantly in response to changes in economic conditions or digital lending regulations. Second, future research should explore alternative and behavioural data sources like psychometric tests, mobile phone and social media—as predictive tools for creditworthiness, given the limitations of traditional scoring models for youth borrowers. Additionally, comparative studies across counties or countries can help contextualize the findings within different regulatory, cultural, or economic environments. Such comparative work would be vital in determining whether the observed predictors of default are universally applicable or context specific. Researchers should also consider expanding the theoretical frameworks by integrating behavioural economics and fintech innovation theories to further understand the digital borrowing landscape.

5.6.2 Recommendations to Credit Providers

Credit providers, including banks and DCPs, must refine their credit assessment models by incorporating broader borrower profiling metrics such as income consistency, digital footprints, and education levels. The study shows that poor borrower evaluation and rigid loan terms contribute significantly to default risk; therefore, lenders should adopt risk-adjusted pricing and flexible repayment plans, especially for young borrowers with fluctuating incomes.

Credit providers are also urged to invest in financial literacy and borrower education programs, possibly bundled within mobile applications or delivered through SMS campaigns. These initiatives can improve financial decision-making and reduce behavioural defaults. Moreover, customer engagement must go beyond loan disbursement—regular check-ins, proactive repayment support, and restructuring options can enhance repayment rates and reduce delinquencies. Lastly, digital lenders should implement robust data protection measures and ensure transparent communication of loan terms, as trust and information clarity were found to affect repayment behaviour. Institutions that prioritize ethical lending will not only improve performance but also build stronger, long-term customer relationships.

5.6.3 Recommendations to Government/Policy Makers

Policy makers, particularly the CBK and the Ministry of ICT and Youth Affairs, are encouraged to develop a national digital credit regulation framework that specifically targets

youth borrowers. This framework should mandate transparency in lending terms, require real-time credit data sharing across institutions, and prohibit exploitative interest rates that disproportionately affect young, financially vulnerable individuals.

There is also a pressing need to integrate financial awareness into the national education and youth-targeted empowerment programs. A financially literate youth population will not only reduce default rates but also support broader economic inclusion objectives. Furthermore, regulators should consider introducing a Digital Borrower Registry that allows lenders to assess credit behaviour across platforms, thereby reducing information asymmetry and strengthening risk-based lending. Policies should also promote innovation in alternative credit scoring methods using non-traditional data, ensuring that youth with limited credit histories are not excluded from the formal credit ecosystem.

5.7 Study Limitations

Albeit the thorough approach adopted in this study, a number of limitations must be acknowledged. These limitations do not undercut the results of the study but rather indicate areas where caution should be employed in interpretation of the results and where future studies can build upon this research.

This study was geographically limited to Nairobi County, which, while economically vibrant and digitally advanced, may not represent the experiences of youth in other counties across Kenya. Nairobi's unique access to digital infrastructure and financial services may have influenced the findings, thus limiting the generalizability of results to rural or underserved urban areas with different socio-economic dynamics.

Although the sample size was statistically adequate for the target population and ensured broad representation through stratified sampling, it may still not encompass all the borrower's experiences. Certain subgroups within the youth population—like the informal sector workers, students, or disabled individuals—may have been underrepresented, potentially affecting the robustness of some conclusions.

The study applied a cross-sectional, exploratory research design that identifies associations but limits the ability to infer causality. The lack of longitudinal data means we cannot determine how borrower, lender, or loan characteristics might influence default risk over time or how the relationships are altered in varying economic and regulatory environments.

The use of probit regression, while effective for identifying significant predictors of binary outcomes, may not fully capture complex or nonlinear relationships between variables. Advanced machine learning techniques or time-series models could potentially provide deeper insights, particularly in the advancing digital finance landscape.

While the study focused on key factors—borrower, loan, and lender characteristics—it did not incorporate macroeconomic variables (such as inflation, unemployment rates) or behavioural factors (like spending habits or psychological traits), which have been shown in other studies to significantly influence credit risk. Including these could have enriched the analysis and provided a more holistic view of default risk among youth.

5.8 Suggested Areas for Future Research

An expansion of the geographical scope to include other counties across Kenya beyond Nairobi should be considered by future studies—particularly underserved urban areas and rural ones where access to digital financial services, economic opportunities, and financial literacy levels may differ significantly. This would provide comparative insights and enhance the generalizability of the findings across diverse socio-economic and geographic contexts.

Subsequent studies should aim to increase the sample size to include a larger and more varied group of youth borrowers. A bigger sample would allow for more granular subgroup analyses (e.g., by income level, education status, or employment sector), thereby improving the accuracy and depth of the findings and enhancing representativeness.

Given that a cross-sectional exploratory design was applied in this study, future research could adopt a longitudinal design to track borrower behaviour over time. This would allow for causal inference and a better understanding of how borrower, loan, and lender characteristics evolve and influence default probabilities in the medium to long term.

While probit regression provided robust estimates, future researchers should consider complementing or replacing it with advanced analytical systems such as machine learning algorithms like neural networks and decision trees. These methods can model complex, nonlinear relationships and potentially advance the forecasted accuracy of default models in the digital lending context.

Future studies should incorporate additional variables to capture macroeconomic, psychological, and behavioural dimensions influencing credit default. For example, incorporating factors such as financial literacy, borrower attitude toward debt, employment

stability, inflation, or broader economic trends could provide a more holistic understanding of the default phenomenon. Additionally, including lender-side data such as risk-scoring algorithms and underwriting practices would offer further insights into systemic contributors to default.

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APPENDICES

Appendix I: Questionnaire

Section A: Borrower characteristics

1. Select your gender
 - Male
 - Female
2. Select your marital status
 - Single
 - Married
 - Divorced/Separated
 - Widowed
3. Select your age bracket
 - 18-25
 - 26-30
 - 31-35
4. Select your highest level of education
 - No formal education
 - Primary
 - Secondary
 - Tertiary (College/University)
5. Do you currently have an outstanding student loan?
 - Yes
 - No
6. What is your occupation?
 - Employed
 - Self-employed
 - Un-employed
7. If employed or self-employed, select your monthly income below
 - 0- 20,000
 - 21,000- 50,000
 - >50,000
8. Did you take a student loan to facilitate your higher education?
 - Yes
 - No

Section B: Loan characteristics

9. For the digital loan that you have ever borrowed, were you aware of the interest rate and other charges levied on the loan?
 - Yes
 - No
10. To what extent do the following factors influence you in taking a digital loan?

Factor	Strongly agree	Agree	Neutral	Disagree	Strongly Disagree
Interest rate					
Bank charges					
Loan Tenure					

11. If you have ever borrowed a digital loan, please select the loan repayment period within which you had to pay back the loan

- 1 month
- 2-3 months
- 4-5 months
- 6-12 months
- Over 12 months

12. What was the purpose of borrowing the loan? Select all that apply

- For my personal business
- For meeting day to day needs like food
- For paying school fees
- For buying airtime
- For a big home improvement purchase like electronics and furniture
- For paying medical bills
- For paying off other debts that were due at the time
- For betting
- For buying a car
- Other, please specify...

13. Please indicate the range of the digital loan amount that you have borrowed

- Less than Ksh. 1000
- Ksh. 1,000- Ksh. 5,000
- Ksh. 5,001- Ksh. 10,000
- Ksh. 10,001- Ksh. 50,000
- Ksh. 50,001- Ksh. 100,000
- Ksh. 100,001- Ksh. 1,000,000

Section C: Lender Characteristics

14. Which of these digital lenders have you borrowed from?

- M-Shwari
- KCB Mpesa
- Eazzy Banking
- M-Coop Cash
- Timiza
- Branch
- Tala
- Other, please specify....

15. Based on the response on 14 above, what attracted you to this lender? Select all that apply

- Loan approval process

- Loan limit amount
 - Interest rate and other applicable fees
 - Loan repayment period
 - Other, please specify.....
16. Select the appropriate mode of payment that you used to pay back the loan
- Standing order
 - Cash deposits
 - Checkoff
 - Mobile Money
17. How long did it take before you received the digital loan?
- 24 hours
 - 36 hours
 - 48 hours
 - Above 48 hours

Section D: Probability of default

18. Please select the type of loan that you have ever borrowed from the options below
- Digital loan from a digital credit provider
 - Digital loan from a bank
 - Both above
19. Between a digital loan from a digital credit provider like Tala and Branch and that from a bank, which one would you prefer to borrow?
- Digital credit provider
 - Bank
20. Based on the response above, indicate the reason you prefer that type of loan compared to other credit providers

Reason	Strongly agree	Agree	Neutral	Disagree	Strongly Disagree
The loan approval process is not complicated					
The loan is disbursed to my account fast					
The loan repayment process is convenient					
I get access to the loan amount I want					
I am not charged hefty fees to					

access the loan					
I trust this credit provider more than others in the industry					

21. Have you ever defaulted on a loan?

- Yes
- No

22. If yes, please select the loan in default from the categories below

- Digital loan from a bank
- Digital loan from a digital credit provider
- Both above



Appendix II: Ethical Approval



22nd April 2025

Ms Mururu Brenda,
brenda.mururu@strathmore.edu

Dear Ms Mururu,

RE: The Determinants of Probability of Default for Digital Credit Facilities by Youth in Nairobi County

This is to inform you that SU-ISERC has reviewed and approved your above SU- Masters proposal. Your application reference number is SU-ISERC2854/25. The approval period is from 22nd April 2025 to 21st April 2026.

This approval is subject to compliance with the following requirements:

- i Only approved documents including (informed consents, study instruments, MTA) will be used.
- ii All changes including (amendments, deviations, and violations) are submitted for review and approval by SU-ISERC.
- iii Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to SU-ISERC within 72 hours of notification.
- iv Any changes anticipated or otherwise that may increase the risks or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to SU-ISERC within 72 hours.
- v Clearance for the export of biological specimens must be obtained from relevant institutions.
- vi Submission of a request for renewal of approval at least 60 days prior to the expiry of the approval period. Attach a comprehensive progress report to support the renewal.
- vii Submission of an executive summary report within 90 days of completion of the study to SU-ISERC.

Before commencing your study, you will be expected to obtain a research license from National Commission for Science, Technology, and Innovation (NACOSTI) <https://research-portal.nacosti.go.ke/> and obtain other clearances needed.

Yours sincerely,

Mr Ambrose Rachier,
Chairperson; SU-ISERC

Appendix III: NACOSTI Research Permit

 REPUBLIC OF KENYA	 NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION
RefNo: 212645	Date of Issue: 10/May/2025
RESEARCH LICENSE	
	
This is to Certify that Ms. Brenda Mururu of Strathmore University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nairobi on the topic: The Determinants of Probability of Default For Digital Credit Facilities by Youth in Nairobi County for the period ending : 10/May/2026.	
License No: NACOSTI/P/25/4173294	
212645	<i>[Signature]</i>
Applicant Identification Number	Deputy Director
NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION	
Verification QR Code	
	
NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.	
See overleaf for conditions	

Appendix IV: Participation Information and Consent Form

PARTICIPATION INFORMATION AND CONSENT FORM

THE DETERMINANTS OF PROBABILITY OF DEFAULT FOR DIGITAL CREDIT FACILITIES BY YOUTH IN NAIROBI COUNTY

SECTION 1: INFORMATION SHEET

Investigator: Brenda Mururu

Institutional affiliation: Strathmore Business School (SBS)

SECTION 2: INFORMATION SHEET–THE STUDY

2.1 : Why is this study being carried out?

This study is being carried out to investigate the determinants of probability of default for digital credit facilities by youth in Nairobi County. This shall be done by evaluating the characteristics of borrowers, loans and lenders for digital credit. This study will inform the pricing of future digital loans by digital credit lenders and enable them to have more effective digital lending policies in place for youth seeking digital credit

2.2 : Do I have to take part?

No. Taking part in this study is entirely optional and the decision rests only with you. If you decide to take part, you will be asked to complete a questionnaire to get information on your credit history. If you are not able to answer all the questions successfully the first time, you may be asked to sit through another informational session after which you may be asked to answer the questions a second time. You are free to decline to take part in the study from this study at any time without giving any reasons.

2.3 : Who is eligible to take part in this study?

- Youth aged between 18 -35 who have borrowed digital credit facilities from banks
- Youth aged between 18 -35 who have borrowed digital credit facilities from independent Digital Credit Providers
- Youth aged between 18-35 who have borrowed digital credit facilities from both banks and Digital Credit Providers

2.4 : Who is not eligible to take part in this study?

- Youth who have never borrowed digital credit facilities
- People aged below 18 years and above 35 years who have borrowed digital credit facilities

2.5 : What will taking part in this study involve for me?

You will be approached in person and requested to take part in the study. If you are satisfied that you fully understand the goals behind this study, you will be asked to sign the informed consent form (this form) and then taken through a questionnaire to complete.

2.6 : Are there any risks or dangers in taking part in this study?

There are no risks in taking part in this study. All the information you provide will be treated as confidential and will not be used in any way without your express permission.

2.7 : Are there any benefits of taking part in this study?

The information will be used to improve financial inclusion for youth by enabling more credit worthy youth borrowers to access finance. It will also be used to improve the credit lending policies by digital lenders.

2.8 : What will happen to me if I refuse to take part in this study?

Participation in this study is entirely voluntary. Even if you decide to take part at first but later change your mind, you are free to withdraw at any time without explanation.

2.9 : Who will have access to my information during this research?

All research records will be stored in securely locked cabinets. That information may be transcribed into our database but this will be sufficiently encrypted and password protected. Only the people who are closely concerned with this study will have access to your information. All your information will be kept confidential.

2.10 : Who can I contact in case I have further questions?

You can contact me, Brenda Mururu at SBS, or by e-mail brenda.mururu@strathmore.edu. You can also contact my supervisor, Dr. Moses Nyang'u, at the Strathmore Business School, Nairobi, or by e-mail mnyangu@strathmore.edu

If you want to ask someone independent anything about this research please contact:

The Secretary–Strathmore University Institutional Ethics Review Board, P. O. BOX 59857, 00200, Nairobi, email ethicsreview@strathmore.edu Tel number: +254 703 034418

I, _____, have had the study explained to me. I have understood all that I have read and have had explained to me and had my questions answered satisfactorily. I understand that I can change my mind at any stage.

Please tick the boxes that apply to you;

Participation in the research study

☐

I AGREE to take part in this research

☐

DON'T AGREE to take part in this research

Storage of information on the completed questionnaire

☐

I AGREE to have my completed questionnaire stored for future data analysis

☐

DON'T AGREE to have my completed questionnaire stored for future data analysis

Participant's Signature:

Date: ____/____/____

DD / MM / YEAR

Participant's Name:

(Please print name)

Time: ____/____

HR / MN

I, _____ (Name of person taking consent) certify that I have followed the SOP for this study and have explained the study information to the study participant named above, and that s/he has understood the nature and the purpose of the study and consents to the participation in the study. S/he has been given opportunity to ask questions which have been answered satisfactorily.

Investigator's Signature:

Date: ____/____/____

DD / MM / YEAR

Investigator's Name:

(Please print name)

Time: ____/____

HR / MN