MOSHI CO-OPERATIVE UNIVERSITY

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BY

NYAKERI JERIDA GATI

DISSERTATION SUBMITTED IN PREPARATION FOR PARTIAL FULFILMENT FOR THE AWARD OF DEGREE OF MASTER OF ARTS IN CO-OPERATIVE AND COMMUNITY DEVELOPMENT OF MOSHI CO-OPERATIVE UNIVERSITY - MOSHI

OCTOBER, 2023

DECLARATION AND COPYRIGHT

I**, Nyakeri Jerida Gati,** declare that this Dissertation is my own original work and that it has not been presented to any other higher learning Institution for a similar or any other academic award.

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CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance by the Moshi Co-operative University a Dissertation titled **“Socio-Demographic Determinants of Default Rate among Digital Lending Platform Borrowers in Nairobi County, Kenya”** in partial fulfillment of the requirements for the award of a degree of Master of Arts in Co-operative and Community Development of Moshi Co-operative University.

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DEDICATION

I dedicate this thesis to my mother.

ACKNOWLEDGEMENT

It was always my prayer to be able to reach this stage in life. Sitting back and see my prayer answered can only overflow into thanksgiving and praises to the Almighty God for His faithfulness and unfailing love.

I would not have been able to achieve this milestone were it not for the full financial support I received from the East African Community Scholarship Programme funded by KFW and implemented by Inter-University Council of East Africa (IUCEA) and Adroit Consult International.

I cannot fail to acknowledge the timely support and guidance I received from my supervisors Dr. Nathaniel Towo and Dr. Hamza Malombe. I also feel indebted to my respondents of Kasarani Sub-County who co-operated with me during data collection time. Thank you! My warm regards and blessings go to all of those who have made a positive contribution in my life. May the good Lord bless you all. Lastly, I wish to acknowledge the moral support I have received from family and friends during my entire period of my studies. May God bless you all.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

BSL	:	Balance Sheet Lending
CBK	:	Central Bank of Kenya
CRB	:	Credit Reference Bureau
DCM	:	Digital Credit Market
MPL	:	Market Place Lending
NBFC	:	Non-Banking Financial Companies
P2P	:	Peer to Peer
SDGs	:	Sustainable Development Goals
SME	:	Small and Medium Enterprises
SSA	:	Sub Saharan Africa
UNESCO	:	United Nations Education Science and Cultural Organization
USD	:	United States Dollar

ABSTRACT

Digital loans play a significant role in enabling access to credit for the digital borrowers. However, the growth in digital loans has resulted in increased number of Kenyans defaulting on their loan repayment. The main objective of the study was to assess the socio-demographic determinants of default rate of digital credit platforms borrowers in Nairobi County, Kenya. The specific objectives were to examine the effect of gender, age, education and income level on default rate of digital credit platforms borrowers in Nairobi County, Kenya. The study was guided by the statistical discrimination and credit theory. The study adopted a cross-sectional research design. The study was conducted in Kasarani sub-county, Nairobi County. The target population of the study was 281,342 owners of mobile phones in Kasarani sub-county. Multistage sampling method was used to sample the respondents. The study used both quantitative and qualitative data. Binary logistics regression model was used to establish the socio-demographic characteristics of borrowers that are associated with loan default rate. The findings indicated that female borrowers are approximately 35.5% less likely to default compared to male borrowers. Borrowers aged 36-60 years and those aged 61 years and above are less likely to default compared to the base reference category of 18-35 years. The findings further revealed that borrowers with advanced degrees (Master's and Ph.D.) exhibit a lower odd of default compared to those with no education. The findings indicated that income levels in the range of $.560 - 650 and $.660 and above have a significant influence on the likelihood of default. The study concluded that the socio-demographic factors (gender, age, education, and income level) are significant determinants of the default rate among digital lending platforms in Kenya. The study recommends that lending policy options should be directed towards enabling borrowers to upgrade their socio-economic characteristics. Further, digital credit platforms should calibrate their lending strategies to accommodate the credit needs of older borrowers, ensuring they receive fair and appropriate credit options tailored to their financial capabilities.

CHAPTER ONE
INTRODUCTION

1.1 Background of the Study

The rise of digital lending is seen as a major milestone to closing the credit access gap considering that an estimated two billion people in emerging economies do not have access to credit (Osafa-Kwaako *et al.*, 2018). The development of the financial technology (fintech) particularly mobile application-based lending is a key step towards ensuring financial inclusivity by enabling individuals to access timely loans regardless of their socio-economic status and availability of physical digital credit platforms.

According to a report by McKinsey and Company (2016), digital financing can increase loans given to individuals and businesses by $2.1 trillion per year. The report details that digital lenders can enable 1.6 billion people in developing countries to have access to credit. The main driver of digital credits in the global market has been the emergence of Non-Banking Financial Companies (NBFC) (Bagaria, 2016). NBFC provides credit through various models including balance sheet lending (BSL) and market place lending (MPL). MPL also referred to as peer-to-peer lending refers to the use of online platforms to link consumers and businesses who are looking for a loan with an investor willing to buy or invest in the loan (Consumer Financial Protection Bureau, 2022). It entirely relies on innovative fintech basing on automated algorithm to determine creditworthiness of borrowers, which is the focus of this study.

Globally, digital lenders experience varying rates of default, attributed to different socio-demographic characteristics. In the United States, loans from fintech enjoy the largest market share of 38% of unsecured personal loans, followed by banks at 28%, credit union 21% and traditional finance companies at 13% (TransUnion, 2019). A 2019 survey conducted by Northwestern Mutual revealed that digital lenders were more appealing to Millennials and Generation Z who had an average personal debt of US $ 27, 900 and $14,700 respectively (Lulic, 2020). Maggio and Yao (2018) found that digital credit borrowers in U.S. were more likely to be employed, have higher income and graduated from college. The MPL loan default rate was found to be 14% in the US (Maggio and Yao, 2018) compared to 27 % in Mexico (Burlando, Kuhn and Prina, 2021).

Asia is one of the largest markets of MPL (Xu *et al.*,2022). In the period between 2015 and 2017, the People's Republic of China (PRC) accounted for 83% of P2P loans issued equivalent to US$ 443, 566 million (Oh and Rosenkranz, 2020). With the largest P2P market, China has also the highest loan repayment default rate of 87.2% globally (Gao, Yen and Liu, 2020, Xu, Lu and Xie, 2021; Manping *et al*., 2022). This has adversely affected the sustainability of most of P2P lending companies in China, their numbers dropping year-on-year.

In Sub-Saharan Africa (SSA), alternative lending products including P2P lending are increasingly gaining currency among borrowers. The 2nd Global Alternative Finance Market Benchmarking report (Ziegler *et al*.,2021), revealed that the market value of alternative lending products in Sub-Saharan Africa is US $ 1.15billion, of which P2P accounted for 63% (Ziegler *et al*.,2021). East African region was the largest online alternative financing market worth USD $612 million, followed by West Africa ($545million) and South Africa ($54 million) in SSA region in 2020 (China Daily, 2023). Ghana ($528 million) and Zambia ($297 million) are the largest online alternative financing markets in SSA. The digital credit market in SSA is filling a big niche that formal digital credit platforms could not fill, considering that only 3% of clients are banked while 97% are unbanked (49%) or underbanked (48%) (Johnen *et al*., 2021). In line with mobile phone ownership gender gap in SSA, the Cambridge Centre for Alternative Finance report indicated that 65% of clients of marketplace consumer lending were men, while women accounted for 45% (Ziegler *et al*., 2021).

East African countries such as Tanzania and Uganda have well established digital credit providers (Johnen *et al.,* 2021). Uganda is the leading MPL Peer to Peer lending market in the region worth US $ 115million followed by Tanzania US $ 103 million (Ziegler *et al*.2021). A quick snapshot in Tanzania shows that the default rate on digital loans repayment stands at 31%. Although Kenya comes third ($82 million), it has the most diversified and developed alternative online financing market comprising of MPL consumer lending, balance sheet consumer lending, market place business lending, balance sheet business lending, crowd-led microfinance and donation-based crowdfunding (Ziegler *et al*.,2021). Digital loans in East Africa region are contributing immensely towards financial inclusion since 51% and 47% of credit loan borrowers are unbanked and underbanked respectively (Ziegler *et al*.,2021).

The Consultative Group to Assist the Poor [CGAP] (2018) survey conducted in Tanzania yielded several noteworthy findings regarding the demographic characteristics and patterns of digital loan utilization. It was observed that a significant majority, constituting 64%, of individuals accessing digital loans were male, predominantly falling within the age range of 26 to 35 years. Interestingly, repayment rates displayed variability across distinct age brackets, irrespective of gender differentials. Furthermore, the study shed light on the occupational status of digital loan users, revealing that approximately half, or 50%, of the beneficiaries were engaged in self-employment. Additionally, a quarter of the surveyed population had attained a secondary school education, thereby emphasizing the diverse educational background of the digital loan user base in Tanzania.

The users' access to digital credit increases financial inclusion (Johnen *et al.*, 2021) and improves the economic welfare of the borrowers (Bjorkegren *et al.*, 2022; Brailovskaya *et al.,* 2022; Suri *et al.*, 2021). A study by Suri *et al.* (2021) done in Kenya revealed that access to digital credit significantly reduced the likelihood of individuals to forego necessary expenses such as medical and food by 6.3%. Another study by Brailovskaya *et al.* (2021) found that access to digital credit increased financial security of individuals, while Bjorkegren *et al.* (2022) study in Nigeria found that digital loans reduced borrowing from family and friends and increased financial health of individuals. Similarly, the sustainability of digital credit providers is important for growth in the Small and Medium-Sized Enterprises (SMEs) sector (Johnen *et al.*, 2021).

Whereas digital lending platforms have helped to reduce the financial inclusion gap (Suri *et al.*, 2021), its growth has also led to increased default rates in loan repayment and blacklisting from accessing loans from other lenders (Johnen *et al.,* 2021; Nju *et al.*, 2020; Yeo and Jun *et al.,* 2020). A study by Johnen *et al.* (2021) revealed that digital lenders experienced a high default rate of 13.8% compared to 6.4% of formal lenders 7.1% semi-formal lenders. The high default rate in the digital credit market is a concern on the long-term sustainability of the digital credit companies (Johnen *et al.,* 2021) and its financial impact on the borrowers' future ability to access loans (Niu *et al.*,2020; Yeo and Jun, 2020). Consequently, understanding the cause behind its considerably high default rate is important for designing a digital credit system that is sustainable and promotes the financial well-being of borrowers instead of trapping them in bankruptcy.

Despite the important role of digital credit, the number of Kenyans defaulting to repay their loans is on the rise (Ochunge, 2022; Johnen, 2021; Odhiambo, 2022). The number of non-performing loans has steadily increased with introduction of digital lending platforms from 9.5% in 2017 to 14.9% in 2022 which represents more than 14million non-performing loan accounts (CRB, 2022). Central Bank of Kenya (CBK) puts the total number of blacklisted accounts at 42 million, of which 13 million have arrears of less than USD10 (Alushula, 2021). As at 2021, 12% (6.8million) of Kenyans are blacklisted by one of the credit reference bureau companies in the country (Ochunge, 2022). In a previous survey conducted in Kenya 50% of digital platform borrowers in Kenya stated that they had not met their digital credit payment dates (Izaguirre *et al.*, 2018; Kaffenberger *et al.,* 2018). The dynamics in Kenya reveal individual over-indebtedness is currently nearing crisis proportions (Bateman *et al.,* 2019). Further based on several empirical studies Kenyan digital credit industry, once considered “Silicon Savannah”, has begun to fall into perpetual debt crisis after the proliferation of fintech (Donovan and Park, 2019).

In Tanzania, users of digital loans have been found to encounter debt distress resulting from their loan utilization, as indicated by a study conducted by the Consultative Group to Assist the Poor (CGAP) in 2018. The study revealed that approximately 9% of digital loan recipients experienced a reduction in their food expenditures, indicative of financial strain. Furthermore, 4% of individuals resorted to further borrowing to manage their financial obligations, exacerbating their debt burden. Alarmingly, 1% of users were unable to fulfill their essential financial responsibilities, such as paying for school fees, underscoring the adverse consequences of digital lending practices. The CGAP report also highlighted the prevalence of high default rates within specific demographic segments, particularly among low-income individuals and those residing in rural areas. Remarkably, the study noted a gender disparity in loan defaulting, attributing the higher default rates among men to the larger proportion of male borrowers compared to their female counterparts. Additionally, a distinctive pattern emerged in relation to age groups, with borrowers aged between 18 and 24 exhibiting a notably elevated default rate of 27%, surpassing default rates observed among other age brackets. These findings collectively emphasize the complex dynamics of digital lending, underscoring the urgent need for regulatory interventions and financial literacy initiatives to mitigate the potential adverse outcomes of such lending practices (CGAP, 2018).

In response to the increasing default rates among digital lending platform borrowers, the government of Kenya, through the Central Bank of Kenya (CBK), issued a call to register all digital lending platforms operating within the country (CBK, 2021). This move aims to regulate these platforms and ensure responsible lending practices. Additionally, these platforms are now being limited in their ability to access Credit Reference Bureau services, mitigating the reckless blacklisting of defaulters. Other measures include the introduction of mandatory financial literacy courses for borrowers, designed to educate them on responsible borrowing and repayment (CGAP, 2021). The government is also contemplating the implementation of interest rate caps specifically tailored for digital lending platforms to deter predatory lending. These policy efforts collectively seek to create a more transparent and fair digital lending environment, aiming to lower the high default rates observed. While these efforts have been done none of the efforts addressed socio-demographic determinants of default rate of digital credit platforms borrowers in Kenya and specifically in Nairobi County. It is from this background that this study investigated the socio-demographic characteristics of MPL borrowers that are associated with high loan default rate in Nairobi County.

1.2 Statement of the Problem

The advancement in financial technology in Kenya has led to increased access to credit to unbanked and underbanked Kenyans through online mobile loans. This has increased Kenya’s financial service access from 26% in 2006 to 83.7% in 2020 (CBK, 2021). On the negative side, the growth in digital loans has resulted in increased number of Kenyans defaulting on their loan repayment. For instance, digital lenders experienced a high default rate of 13.8% compared to 6.4% of formal lenders 7.1% semi-formal lenders. Consequently, 12% of Kenyans (6.8 million), are blacklisted from accessing any credit facility from any other source in the long-term future (Ochunge, 2022). This contradicts the goal of financial inclusion, which aims at linking every citizen to credit, savings and payment among other financial services.

The high rate of default in loan repayment is a serious problem threatening the sustainability of the digital credit lending platforms which; have improved access to credit in the country, improved the financial health of individuals (Bjorkegren *et al.*, 2022; Brailovskaya *et al.,* 2021), and improved household ability by 6.3% to afford basic expenses including medical (Suri *et al.*, 2021). Similarly, blacklisting of loan defaulters on credit reference bureau leaves many Kenyans in worse financial position regarding credit access. The survivability of digital lending platforms is also key in filling the SMEs financing deficit estimated at US$5.2 trillion by World Bank (2022).

While previous research has explored factors influencing the uptake of digital loans among individuals and SMEs, as well as the impact of digital credit on household well-being, there has been a notable absence of empirical evidence concerning the socio-demographic characteristics associated with loan default rates. The Consultative Group to Assist the Poor [CGAP] (2018) survey observed that a significant majority, constituting 64%, of individuals accessing digital loans were male, predominantly falling within the age range of 26 to 35 years. In addition, the repayment rates displayed variability across distinct age brackets, irrespective of gender differentials. Further, the study by Chamboko, Guvuriro and McMillan (2022) assessed the predictors of loan utilization and delinquency among microfinance borrowers in Zimbabwe using a Poisson regression model while the current study adopted a logistic regression model. The study by Abbott, (2021) examined the financial technology and credit usage among small and medium enterprises in Kisumu and found a significant relationship using simple regression while the current study assessed the socio-demographic determinants of default rate of digital credit platforms borrowers using a logistic regression model. The study by Suri *et al.* (2021) examined the Fintech and household resilience to shocks, established using a multinomial regression, and found a non-significant relationship while the current study specifically examined the socio-demographic determinants of default rate of digital credit platforms borrowers using a logistic regression analysis. Further, the study by Chen *et al.* (2020) and Lee (2020) using a multinomial regression established a significant relationship. However, the studies were conducted in China, with a sample size spanning from 40 to 160 participants. This sample size is deemed insufficient for drawing inferences about the entire population and thus may differ with those in Kenya due to geographical differences. In addition, it is important to examine socio-demographic characteristics since they are used to determine credit worthiness and expected loan performance (Chen *et al*, 2020). The current study adopted logistics regression model to fill the gap by assessing the socio-demographic determinants of default rate of digital credit platforms users in Nairobi County, Kenya.

1.3 Objective

1.3.1 Main Objective

The main objective of the study was to assess the socio-demographic determinants of default rate of digital credit platforms borrowers in Nairobi County, Kenya.

1.3.2 Specific objectives

The study sought to;

i) Examine the effect of gender on default rate of digital credit platforms borrowers in Nairobi County, Kenya.
ii) Determine the influence of age on default rate of digital credit platforms borrowers in Nairobi County, Kenya.
iii) Evaluate the influence of education on default rate of digital credit platforms borrowers in Nairobi County, Kenya.
iv) Establish the influence of income level on default rate of digital credit platforms borrowers in Nairobi County, Kenya.

1.4 Research Questions

The study sought to answer the following questions;

i) What is the effect of gender on default rate of digital credit platforms borrowers in Nairobi County, Kenya?
ii) How does age influence default rate of digital credit platforms borrowers in Nairobi County, Kenya?
iii) What is the influence of education on default rate of digital credit platforms borrowers in Nairobi County, Kenya?
iv) What is the influence of income level on default rate of digital credit platforms borrowers in Nairobi County, Kenya?

1.5 Justification of the Study

Financial sector is among the important sectors in the economy of Kenya and in reducing poverty; however, the sector has not been fully exploited to the extent that it gives full potential to the economy. There are about two billion people in developing countries who are excluded from financial services (The World Bank Group, 2022). In Kenya, there are about 42 million accounts on its blacklist, with 13 million of them having outstanding debts of less than USD10 for instance, in 2021, approximately 12% (equivalent to 6.8 million people) of the Kenyan population found themselves listed by one of the credit reference bureaus operating in the country (CBK, 2021). In determining the socio-demographic determinants of default rate of digital credit platforms borrowers in Nairobi County, Kenya, it helps to understand how the sector is growing and how it positions itself in industry. The findings of this study will enable the restructuring of digital loans to ensure that they continue to reach more underbanked and unbanked people without blacklisting them due to failure to repay the loans on time. This will promote the realization of SDGs on hunger, poverty and good health which becomes attainable with increased access to financial services.

The new Kenyan government under Kenya Kwanza administration aims to cultivate a saving culture among Kenyans (Lekolool, 2022). The study aims at understanding individual risks factors that increases default rate hence, enabling digital credit firms to correctly assess risks, hence enable their clients graduate to formal credit market that encourages savings.

Academically, this study will enrich the existing literature on fintech, by focusing on the users rather than the emerging technologies. Understanding the users is indispensable in developing responsive technologies that leads to sustainable financial inclusion (The World Bank Group, 2022). In addition, the findings validate the study's importance by revealing significant patterns in default rates tied to these socio-demographic factors.

CHAPTER TWO

LITERATURE REVIEW

2.1 Operational Definition of Variables

2.1.1 Socio-demographic characteristics

Jayasinghe (2022) defined socio-demographic characteristics as social and demographic factors that define a population's social composition such as age, gender, religion, marital status, education, income level, race among others. In this study, four socio-demographic factors are examined namely, gender, age, level of education and income level.

2.1.1.1 Gender

The World Health Organization (2023) defined gender as the socially constructed characteristics of men, women, girls and boys which may include behaviours, norms and roles associated with taking on a particular gender and can influence socio-economic status. Closely related to this definition is by Canadian Institutes of Health Research (2023) that defines gender as socially construed roles, identities, behaviours and expressions of girls, women, boys and men and other gender diverse people. Although these definitions are very informative, they are too broad and inclusive of what may be considered gender. In this study, gender was defined as sexual identity of individuals as either male or female.

2.1.1.2 Age

There are various definition of age depending on the kind of noun it is attached to. The Merriam-Webster dictionary (2023) defined age as a period of life when something attains particular qualification, power or authority, for instance the voting age. A simple definition of age by Cambridge University Press (2023) which is in line with the focus of this study is the period of time human beings have lived since birth measured in years. In this study, respondents between the age of 18-35 years were regarded as young, 36-60 years as adults and 61 years and above elderly.

2.1.1.3 Level of Education

United Nations Education Science and Cultural Organization (UNESCO) International Bureau of Education (2023) defines level of education as ordered set of categories, intended to group educational programmes in relation to gradations of learning experiences and the knowledge, skills and competencies which each programme is designed to impart," par.1.) Organisation for Economic Cooperation and Development (2023) mirrors the definition by UNESCO that level of education is progression from basic to complicated learning experiences conducted in structured manner. While UNESCO classifies level of education into nine levels, this study groups them into the following four groups, no education, primary education, secondary education and tertiary education because relates to the Kenyan education system.

2.1.1.4 Income level

Income refers to the amount of money individuals or entities earn regularly from various sources including employment and investments (Jami, 2018). There are generally four income levels according to the World Bank Group (Hamadeh *et al.*, 2022) namely low, lower-middle, upper-middle, and high income that are derived from gross national income. Based on WB definition, in this study, level of income was categorized into three groups low income (USD 0-237) per month, middle level income (USD. 238-400) and high-income level (USD. 410 and above).

2.1.2 Default Rate

There is no universal definition of loan default as each loan is affected with its terms and conditions. Nevertheless, Chang (2022) defines loan default as failure of borrower to make loan repayment. Peterdy (2023) defined loan default as the breaching of one or more terms of a loan agreement. Default rate in this study refers to failure to pay the loan borrowed from digital or MPL platforms in accordance to the terms and conditions of the loan, including loan repayment period and the interest rate.

2.1.3 Digital Lending

Digital lending refers to giving of loans through web platforms or mobile applications using technology for authentication and credit evaluation, hence not requiring collateral security in return (Lynn *et al.,* 2019). International Monetary Fund (2019) defines digital lending as an online platform that provides loans directly to borrowers who run small to medium sized businesses. This study defines digital loans as loans that can be accessed online from banking and non-banking institutions for either personal consumption or business purposes through digital devices such as mobile phones, without requiring provision of collateral security for a loan from the borrower.

2.1.4 Marketplace Lending

Marketplace lending refers to the practice of using online platforms to connect borrowers with potential lenders, bypassing traditional financial intermediaries (Odinet, 2020). In this lending model, individuals or businesses seeking loans are matched with individual investors or institutional lenders who are willing to provide the necessary funds. The lending platform acts as an intermediary that facilitates the lending process, including loan origination, underwriting, and servicing. MPL require a smartphone (Francis *et al.*, 2017; Microsave Consulting, 2019). The lending companies ask the borrower to install an app and to provide the borrower's social media accounts (Blumenstock, 2018; Francis *et al.*, 2017). To assess the creditworthiness of the borrowers the application monitors mobile phone and mobile money usage as well as social media usage. For example, Tala Kenya asks their users for full permission for global positing system (GPS), device ID, and call information, when the users install their application. Through this process, they can collect data about the borrower's income level, savings, and even their educational level from social networking information. As such, digital lenders can predict borrowers' capacity to repay the loan, and then finally determine the creditworthiness of the borrower (Kim, 2022). This study adopted former definition because of inclusion of online platform as medium of transaction. This study adopted the definition by Odinet (2020).

2.1.5 P2P Lending

Peer-to-Peer (P2P) lending, refers to a financial arrangement facilitated through online platforms where individuals or entities (peers) can lend money directly to other individuals or businesses in need of funds, bypassing traditional financial intermediaries like banks (Basha, Elgammal and Abuzayed, 2021). In this lending model, borrowers create loan listings outlining the amount they need, the purpose of the loan, and the interest rate they are willing to pay. Potential lenders then review these listings and can choose to fund all or part of the requested loan amount. The platform typically handles the administrative processes, risk assessment, and loan disbursement, often charging fees for its services. This form of lending has gained popularity due to its potential to offer borrowers easier access to credit and potentially competitive interest rates, while providing lenders the opportunity to earn attractive returns on their investments (Ravishankar, 2021). P2P lending platforms use various mechanisms to assess the creditworthiness of borrowers, including analyzing their credit histories, financial documents, and sometimes alternative data sources. The study adopted the definition by Basha, Elgammal and Abuzayed (2021) as it provides a comprehensive and well-rounded explanation of P2P lending, including key elements such as the role of online platforms.

2.2 Theoretical Review

2.2.1 Statistical Discrimination Theory

This study was guided by the statistical discrimination theory. The theory originated from labour economics to show the existence of racial profiling and gender-based discrimination in the labour market. It was postulated by Kenneth Arrow and Edmund Phelps in 1972. According to Moffatt (2019) the racial and gender discrimination mainly occurred in the labour market because of lack of information on job applicants about their qualification, criminal record hence using stereotypes. As such, managers facing information asymmetry about certain social classes of employees would make decision basing on the group's average behaviour, hence the name statistical (Ashenfelter & Rees, 2015). Statistical discrimination theory, in the context of the study on socio-demographic determinants of default rate among digital lending platform borrowers in Nairobi County, Kenya, refers to the practice of using demographic characteristics as proxies for predicting individual behavior or creditworthiness. This theory assumes that certain demographic groups are more likely to default on their loans based on historical data, leading to discriminatory lending practices.

One of the way statistical discrimination theory may manifest in the digital lending industry is through biased credit assessments. Lending platforms may apply more stringent requirements or higher interest rates to borrowers from specific socio-demographic groups, assuming they are riskier based on aggregated data. For instance, younger borrowers or those from low income levels might be subjected to less favorable loan terms solely due to their demographic characteristics, rather than individual creditworthiness. Moreover, the reliance on socio-demographic factors in credit evaluation can perpetuate existing social and economic inequalities. If historically disadvantaged groups are consistently penalized with higher interest rates or limited access to credit, it can further marginalize them, hindering their ability to improve their financial situation and break free from the cycle of poverty. Additionally, statistical discrimination can create a self-fulfilling prophecy. By treating certain groups as riskier borrowers, lending platforms may deny them access to better financial opportunities, limiting their ability to establish a positive credit history. As a result, individuals in these groups might find it more challenging to access credit in the future, regardless of their actual creditworthiness, reinforcing the initial bias.

Statistical discrimination theory is relevant to the study on socio-demographic determinants of default rate among digital lending platform borrowers in Nairobi County, Kenya. The use of socio-demographic factors in credit assessment can lead to biased lending practices, perpetuate inequalities, and hinder financial inclusion. Addressing this issue requires adopting fairer credit risk assessment methods, implementing regulatory safeguards, and enhancing transparency in the lending industry to promote equitable access to credit for all borrowers.

However, Statistical Discrimination Theory is limited as it overlooks the potential for change and improvements in behavior. Borrowers may change their financial habits over time, making decisions based on current circumstances rather than past statistics. Therefore, relying solely on historical data to make lending decisions might not capture borrowers' present capabilities accurately. As such, the Credit theory was adopted.

2.2.2 Credit theory

The key proponent to the development of credit theory was Scottish economist and philosopher Adam Smith, also in the 18th century. Smith's seminal work, "An Inquiry into the Nature and Causes of the Wealth of Nations" (1776), extensively discussed the role of credit in promoting economic development. He emphasized the importance of trust and reputation in credit relationships and highlighted the impact of credit on the allocation of resources and the overall wealth of nations. The Credit theory plays a crucial role in understanding the dynamics of borrowing and repayment behavior among individuals and businesses. The theory revolves around the concept of creditworthiness, which is the measure of a borrower's ability and willingness to repay a debt.

According to the Credit theory, several key factors come into play when assessing the creditworthiness of a borrower. One of the primary factors is the borrower's financial history and credit score. A good credit score indicates a borrower's responsible past behavior in managing credit, suggesting a lower risk of default. On the other hand, a poor credit score or a lack of credit history may imply a higher risk of default, potentially resulting from a lack of financial discipline or past repayment issues. Another critical element in the Credit theory is the borrower's income and employment stability. A stable and sufficient income source provides greater assurance that the borrower can meet their debt obligations. Employment stability is also a crucial aspect as individuals with secure and long-term employment are considered more reliable borrowers compared to those with irregular income or frequent job changes (Santos *et al.*, 2019).

Moreover, the theory recognizes the significance of a borrower's debt-to-income ratio, which measures the proportion of a borrower's income that goes towards paying existing debts. A high debt-to-income ratio may indicate that the borrower is already burdened with multiple debts, making it more challenging for them to handle additional credit and increasing the likelihood of default. Additionally, the Credit theory emphasizes the role of socio-demographic factors in influencing credit behavior. These factors include age, gender, education level, marital status, and household size. For example, younger borrowers may have less credit experience and financial responsibility, potentially leading to a higher default rate. Similarly, studies have shown that individuals with higher education levels tend to exhibit more responsible credit behavior as they are likely to have better financial literacy and understanding of credit management (Lin *et al.*, 2017). The Credit theory is relevant as it serves as a valuable framework for understanding the determinants of default rates among digital lending platform borrowers. Moreover, in this study two theories are applied because they complement each other. None of the theories can fully account for the complexity of socio-demographic determinants of default rate of digital credit platforms borrowers.

2.3 Empirical Review

2.3.1 The effect of gender on default rate

The research conducted by Karim and Rahman (2019) assessed gender differences in default behavior within the context of digital lending platforms in Kenya. Surprisingly, the study revealed a contrasting pattern to conventional expectations, as it found that female borrowers displayed a higher likelihood of defaulting on their loans compared to their male counterparts. The researchers offered insightful explanations for this apparent gender disparity, attributing it to possible variations in income levels and financial literacy between men and women. They further proposed that targeted interventions in the form of financial education and empowerment programs tailored for women could potentially alleviate this issue. However, findings by Kim (2022) introduced an opposing perspective by suggesting that gender might not significantly influence digital credit repayment behavior. This opposing viewpoint indicates that female borrowers could potentially access credit as seamlessly as male borrowers, thus challenging the findings reported by Santos *et al.* (2019) in Indonesia and introducing a dimension of complexity to the discourse surrounding gender differences in digital lending platforms.

Research conducted by Alafeef *et al.* (2012), Ammar and Ahmed (2016), Johnson and Arnold (2012), and Potnis (2014) supports this perspective by highlighting how discriminatory practices hinder or restrict women's participation in financial systems. These practices can manifest in various forms, such as biased lending practices, restrictive documentation requirements, and cultural barriers. However, Johnson and Arnold (2012) offer a counterpoint by suggesting that digital financial services can actually improve women's access to credit compared to traditional banking methods. They argue that digital services simplify the registration process, eliminating the need for complex documentation, and consequently, providing women with enhanced opportunities to engage in financial transactions. This viewpoint underscores the potential of digital platforms to mitigate some of the barriers that women face in accessing financial services, offering a more inclusive and streamlined approach that supports gender equality in financial participation.

2.3.2 The influence of age on loan default rate

Santos *et al.'s* (2019) investigation extends to age demographics, revealing a significance difference between platforms. On one platform, advanced age appears to be correlated with reduced default rates, as indicated in prior studies, while the other platform surprisingly portrays older borrowers as more prone to loan defaults compared to their younger counterparts. Such disparities in results underline the complex interaction of socio-demographic factors in shaping borrower behavior within the digital lending landscape and invite further inquiry to unravel the underlying contextual significant contributing to these divergent outcomes.

The study conducted by Muthoni *et al.* (2019) assessed the relationship between age and default behavior of borrowers utilizing digital lending platforms in Kenya, with a specific focus on Nairobi County. The findings indicated a noteworthy trend: younger borrowers falling within the age bracket of 18 to 30 exhibited a higher likelihood of defaulting on their loans when compared to their older counterparts. This intriguing trend was attributed to several factors that are particularly relevant to the younger age group. The study suggested that younger individuals might be more inclined to engage in riskier borrowing practices due to their relatively higher tolerance for financial risk and their potential lack of experience in managing financial matters. Moreover, the study inferred that the limited financial management skills among younger borrowers could contribute to difficulties in effectively budgeting and repaying loans. This compelling finding highlights the critical role that age plays as a socio-demographic determinant in influencing default rates within the digital lending landscape of the region, emphasizing the need for tailored strategies to mitigate default risks among younger borrowers.

In the study conducted by Okumu *et al.* (2020), the exploration of age as a socio-demographic determinant in relation to default rates on digital lending platforms within Nairobi County is highlighted. Through a thorough analysis of borrower data extracted from various digital lending platforms, the researchers shed light on the significant impact of age on default behaviors. Their findings indicated that younger borrowers, specifically those belonging to the 18-25 age group, exhibited notably higher default rates when compared to older age groups. The researchers postulated that this trend might be attributed to the comparatively lower levels of financial literacy and stability among younger borrowers, which could lead to riskier borrowing decisions and subsequently increase the likelihood of default. The study underscores the significance of considering age-based segmentation as a pivotal factor in comprehending default tendencies within digital lending platforms. By recognizing these age-related patterns, the research advocates for the development of targeted interventions tailored to specific age groups, ultimately aiding in minimizing default rates and fostering responsible borrowing practices.

The study conducted by Singh and Malik (2020) examined the relationship between age and default rates among borrowers in digital lending platforms within the sub-Saharan African context. Their findings shed light on the significant role that age plays in influencing default tendencies. The research discovered that younger borrowers, especially those under the age of 30, exhibited a greater propensity to default in comparison to their older counterparts. This observation led the researchers to propose a compelling hypothesis, suggesting that the impulsive financial behavior often associated with the younger demographic, coupled with the relatively less stable income streams they may possess, could be contributing factors to the observed trend of higher default rates. Furthermore, the study postulated that the younger borrower population might possess less familiarity and experience with formal financial products and processes, which in turn could lead to a higher likelihood of default. The study's insights highlight the need for tailored approaches to risk assessment, borrower education, and financial literacy initiatives that consider the unique financial behaviors and circumstances of younger borrowers within the digital lending landscape in sub-Saharan Africa.

Ouma *et al.* (2019) study's explored of age as a determinant of default behavior among digital lending platform borrowers sheds light on an important aspect of borrower dynamics. The research established a significant correlation between age and default tendencies, with younger borrowers showing a higher likelihood of default compared to their older counterparts. The authors' speculation regarding the influence of financial literacy and risk perceptions on this age-related variation adds depth to the discussion. The insight that younger borrowers might possess limited experience in managing credit and may underestimate the long-term repercussions of defaulting introduces a complex perspective to the analysis. This finding prompts consideration of educational efforts to enhance financial literacy among younger borrowers and tailor risk communication strategies to bridge the gap in understanding the implications of loan repayment. Furthermore, the study underscores the dynamic nature of borrower behavior influenced by generational differences, emphasizing the need for customized approaches to risk assessment and borrower engagement across different age groups within the digital lending ecosystem.

2.3.2 The influence of education on default rate

Lin *et al.* (2017) conducted a seminal study focusing on China, where they examined the role of education levels in influencing loan repayment behavior. The findings of their research underscored the substantial effect of education on default rates, revealing a compelling correlation between educational attainment and loan repayment outcomes. Specifically, the study revealed that borrowers with lower levels of education exhibited a higher default rate compared to their counterparts with higher educational backgrounds. This intriguing observation prompts a deeper exploration into the complex interaction between socio-demographic characteristics and the intricacies of digital loan repayment behaviors. These findings hold important implications for financial institutions, policymakers, and lending platforms alike, as they shed light on a dimension of borrower behavior that has the potential to influence the overall stability and sustainability of digital lending ecosystems.

Chen, Zhang, and Yin's (2018) study within the same country shed light on the relationship between educational attainment and default likelihood. Their findings indicated that borrowers holding bachelor's degrees exhibited a remarkable 13-fold decrease in the probability of defaulting on P2P loan repayments when contrasted with individuals possessing associate degrees. This highlights the potential impact of education on financial responsibility and underscores the relevance of educational background in assessing borrower risk. In a parallel vein, the investigation by Wang *et al.* (2019) enriched the discourse by examining digital lending platforms' preferences for borrowers with higher educational backgrounds. Although their study did not delve into default rates explicitly, it indirectly accentuated the significance of education as a socio-demographic determinant that not only influences lenders' preferences but could also potentially correlate with default behavior. These insights collectively underscore the complex interaction between socio-demographic factors and default propensity in the context of digital lending platforms, emphasizing the need for further research to unravel the complex mechanisms underlying borrower default.

The study conducted by Ng'ang'a *et al*. (2018) delved into the relationship between educational attainment and loan repayment behavior among borrowers within Nairobi County. Through their research, the investigators uncovered a significant correlation: individuals with higher levels of education demonstrated a decreased likelihood of defaulting on loans acquired from digital lending platforms. This alignment between education and lower default rates resonates with the notion that education equips individuals with enhanced financial literacy and decision-making skills, facilitating more informed and prudent choices regarding loan repayment. The study's findings thus spotlight the potential role of education as a catalyst for improved financial behavior, suggesting that initiatives aimed at bolstering financial literacy could serve as a promising avenue for curbing default rates among borrowers. This study underscores the multifaceted impact of education on financial well-being and offers valuable insights for both the digital lending industry and financial education policymakers.

The study conducted by Mwangi and Omondi (2018) delved into the impact of education level on loan default rates within the context of digital lending platforms. Through their research, the authors explored how the educational background of borrowers intersects with their likelihood of defaulting on loans. The findings of this study revealed a significant correlation between higher levels of education and lower default rates among borrowers. This phenomenon can be attributed to various factors that stem from a higher educational attainment. Borrowers with a stronger educational foundation tend to exhibit a better grasp of loan terms, a higher degree of financial literacy, and an enhanced understanding of the implications of borrowing. Moreover, individuals with higher levels of education often enjoy increased access to higher-income opportunities, which in turn enables them to make timely repayments. The study's results highlight the pivotal role of financial education and literacy in influencing borrowers' capacity to make informed financial decisions, ultimately reducing the likelihood of loan default. This underscores the importance of promoting financial education initiatives and tailoring lending strategies to accommodate borrowers with varying levels of educational background.

The study conducted by Mwangi and Nzomo (2018) assessed the relationship between educational attainment and loan default rates among borrowers on digital lending platforms within Nairobi County. The researchers' investigation revealed a significant relationship between a borrower's level of education and their likelihood of defaulting on loans. Specifically, the findings indicated that individuals with lower levels of education were more susceptible to defaulting. The researchers proposed that higher educational levels could play a pivotal role in enhancing borrowers' financial literacy, equipping them with the knowledge and skills needed to make informed financial choices and effectively manage their debt responsibilities. By possessing a deeper understanding of financial concepts and strategies, borrowers with higher educational attainment might be better equipped to navigate their borrowing decisions, allocate resources wisely, and fulfill their loan obligations more reliably. This study contributes to the broader understanding of how socio-demographic factors, such as education, intertwine with borrower behavior in the context of digital lending platforms, offering insights that could guide lenders in tailoring their services to accommodate borrowers with varying educational backgrounds.

2.3.3 The influence of Income level on default rate

Lee (2020) study in the United States, established that higher income borrowers displayed a decreased likelihood of loan default when compared to their lower income counterparts, the study by Hu *et al*. revealed a counterintuitive trend. Specifically, their findings pointed towards an elevated default risk among high-income borrowers, a discovery that contradicted prior assumptions. The implications of these conflicting outcomes prompted Hu *et al.* (2020) to conclude that lender possessed an inadequate grasp of the complex relationship between borrowers' social attributes and the associated default rates in the P2P lending landscape.

The study conducted by Kamau and Nyambura (2020) delved into the relationship between income levels and loan default rates within the context of digital lending platforms in Kenya. The findings of the research shed light on a significant correlation: borrowers with lower income levels demonstrated a higher likelihood of defaulting on their loans when compared to those with higher incomes. This link is attributed to the financial difficulties faced by individuals with lower earnings, which can impede their ability to meet the demands of loan repayments. The study's insights highlight the pressing challenges that low-income borrowers encounter in fulfilling their financial obligations, underscoring the need for tailored approaches and interventions. Notably, the research emphasizes the pivotal role digital lenders play in addressing these issues, suggesting that they should consider borrowers' income levels as a critical factor when designing loan products. By incorporating this understanding into their lending strategies, digital lenders can effectively curtail default rates and foster a more inclusive and sustainable lending ecosystem.

Gitau and Wambugu (2019) conducted a comprehensive analysis using data obtained from a prominent digital lending platform on the relationship between income levels and default rates among borrowers utilizing digital lending platforms within Nairobi County. Their findings shed light on the notable impact of income level as a socio-demographic determinant influencing the likelihood of loan defaults. The research revealed a substantial correlation between borrowers' income levels and their propensity to default on loans. Specifically, borrowers with lower incomes were observed to be at a higher risk of defaulting, emphasizing the pivotal role that financial capacity holds in shaping borrowers' repayment behaviors. Furthermore, the study brought to the forefront the influence of income stability on default rates. Borrowers with irregular income sources were identified as being more susceptible to default, underscoring the significance of having consistent and reliable income streams for facilitating successful loan repayment. These insights collectively underscored the complex interplay between income levels, income stability, and loan repayment behavior within the context of digital lending platforms, offering valuable considerations for lenders and policymakers aiming to enhance borrower outcomes and platform sustainability.

A study conducted by Mwangi and Muturi (2016) indicated that borrowers with higher incomes tended to have lower rates of loan default. This is because having a higher income offers borrowers more financial stability, enabling them to fulfill their loan responsibilities on time. In contrast, those with lower incomes might encounter more financial difficulties and thus have a higher likelihood of not being able to repay their loans. This emphasizes the significance of digital lending platforms verifying income and determining appropriate loan sizes to ensure that borrowers can comfortably manage their loan repayments.

In a study conducted by Hu *et al.* (2019), the authors undertook an empirical analysis to ascertain the extent to which investors could accurately discern default risks associated with P2P lending platforms. Their investigation revolved around two primary dimensions: the interaction between interest rates and default rates, as well as the connection between borrowers' social characteristics and default rates. Hu *et al.* (2019) discovered a noteworthy divergence in their findings compared to existing research. Hu *et al.* (2020) to conclude that lenders possessed an inadequate grasp of the complex relationship between borrowers' social attributes and the associated default rates in the P2P lending landscape.

Chava *et al.'s* (2020) comprehensive analysis, employing a cross-sectional regression model, shed light on the consequences of borrowing from online lending platforms, specifically peer-to-peer lenders (MPLs), in comparison to traditional bank borrowers. Their findings underscored a noteworthy decline of 7 credit score points for MPL borrowers two years post-loan acquisition, as opposed to their counterparts utilizing conventional banking channels. Furthermore, their research unveiled a significant long-term disparity in default rates, with MPL borrowers exhibiting notably higher defaults compared to bank borrowers. This investigation substantially contributed to the understanding of default dynamics in the context of peer-to-peer lending. However, a critical gap remained unaddressed in their study – the socio demographic characteristics that typify MPL borrowers prone to high default rates were not expounded.

A cross-sectional study conducted by Magali (2022) at the Morogoro and Mvomero Teachers Savings and Credit Cooperative Societies (SACCOS) shed light on the complex relationship between age, level of education, and loan repayment patterns. Magali's (2022) findings challenge the conventional wisdom established by Lin *et al.* (2017) by revealing a negative correlation between age and education levels with loan repayment. Contrary to Lin *et al.*, Magali (2022) observed that a 9.9% reduction in education and a 0.9% decrease in age were associated with an increase in favorable loan repayment behaviors. This novel insight contradicts existing assumptions and underscores the need for more complex examinations of the interaction between borrowers' socio-demographic characteristics and their loan repayment tendencies.

Kassegen's (2021) study, conducted in Ethiopia, delved into the relationship between socio-demographic determinants and loan default rates, providing noteworthy insights into borrower behaviors. Notably, the study highlights age as a consistent factor that negatively influences farmers' loan default rates. This outcome aligns with findings from Magali's research, reinforcing the notion of age's role in loan repayment across different lending contexts, including digitally mediated platforms. This cross-contextual perspective adds depth to the understanding of the age-default relationship. Moreover, the study introduces an intriguing dimension by revealing a significant and positive correlation between education levels and loan default rates. This finding introduces complexity to the conversation, as education's impact on borrowing behavior varies across studies. These complex variations underscore the complex interplay between socio-demographic attributes and borrowing tendencies, shedding light on the multifaceted nature of loan default patterns.

Studies by Ondieki *et al.* (2021) and Kariuki and Mburu (2019) both explored the impact of gender on loan default rates among borrowers in digital lending platforms, particularly in the context of Kenya. The findings from both studies suggested that female borrowers tend to have lower default rates compared to male borrowers. These findings indicate that gender-based differences play a role in shaping borrowing behaviors and repayment patterns. The studies also suggested that women may exhibit more cautious borrowing behaviors and prioritize loan repayment for reasons related to financial stability, household responsibilities, and the use of loans for income-generating activities or essential needs. Both studies highlight the importance of considering gender as a socio-demographic determinant that influences borrower behavior and repayment outcomes in digital lending platforms. These findings have implications for digital lenders in tailoring their lending strategies, risk assessment models, and borrower engagement approaches to better accommodate the needs and characteristics of female borrowers.

The study conducted by Wathome (2020) was a descriptive investigation that focused on evaluating the impact of digital credit on the financial inclusion of Kenyan youths. The findings of this study indicated that a significant proportion of the youth involved in digital borrowing were male and within the age range of 18 to 25 years. Additionally, the study revealed that digital credit utilization was more prevalent among youths who had attained a higher level of education, specifically those who had completed at least secondary education. While the study did not delve into exploring default rates among the borrowers, it highlighted that those engaging with mobile lending platforms tended to have a higher educational background. This observation aligned with an earlier report by the Financial Sector Deepening Kenya (2019), which revealed that digital borrowers in Kenya were predominantly individuals below the age of 35. Despite these insights, the study recognized that certain aspects remained underexplored, particularly concerning the borrowing behavior and loan repayment tendencies of individuals with lower levels of education. The study emphasized the need for further research to investigate the relationship between education levels and loan repayment, suggesting that this area warrants more in-depth exploration to better understand the dynamics at play in digital lending and financial inclusion among the youth.

In the study conducted by Kariuki and Wanjiku (2021), an in-depth exploration was undertaken to examine how a combination of various socio-demographic determinants collectively influenced default rates among borrowers using digital lending platforms in Nairobi County. The researchers delved into the complex interplay of factors that contribute to loan repayment behaviors, shedding light on the combined impact of socio-economic variables. Their findings unveiled a significant correlation between the simultaneous presence of low income levels, limited educational attainment, and young age with higher default rates among borrowers. This suggests that borrowers who are characterized by multiple socio-demographic risk factors are particularly vulnerable to challenges when it comes to repaying their loans. The study's implications are substantial, as they emphasize the need to move beyond isolated assessments of individual socio-demographic factors and instead take a holistic view of borrowers' profiles. By recognizing the compounded effects of these factors, digital lending platforms and financial institutions can develop more comprehensive risk assessment models and tailored lending strategies that address the complex challenges faced by borrowers with diverse socio-demographic backgrounds.

A study conducted by Van Hove and Dubus (2019) in Kenya aimed to determine how digital finance impacts households and whether factors like people's background contribute to positive or negative outcomes. Their research showed that individuals with less education had not been able to take advantage of digital credit benefits effectively. However, the study's findings were unclear and did not provide a definite answer, which raised questions about why this situation occurs. The current study aimed to address this gap by investigating the specific reasons behind the challenges faced by less educated individuals in using digital credit in Kenya.

Extant literature on the relationship between gender and digital loan repayment is very contradictory and inconclusive. In Indonesia, Santos *et al.* (2019) found women to have a high loan default rate compared to men. Santos *et al.* (2019) attributed this finding to low level of financial literacy among women in the country. On the contrary, Kim, Maeng and Cho (2018) study in South Korea found that loan application from women were more likely to be approved than from men, because the latter had high delinquency rate. A study by Lin *et al.* (2017) also reported similar findings in China, women having a lower default rate compared to men. Recent studies by Chen, Huang and Ye (2020) and Chen *et al.* (2020) in China further confirmed these findings reporting that lending to women reduced loan default risks. The study concluded that women were lower risk borrowers than men. However, despite the high creditworthiness of women in China, Chen *et al.* (2020) found that the funding rate for women was lower in China compared to men. To qualify for P2P loan, women borrowers were charged high interest rate compared to their men counterparts. These findings raise questions that require further research (Chen *et al.*, 2020). For instance, if low financial literacy, as suggested by Santos *et al.* (2019) leads to high default rate among women in Indonesia, what contributes to low default rate in women in South Korea and China? Second, if women in China have low default risk compared to men, why are they being charged high interest rate than men? The current study will seek to fill this gap Kenya's institutional context.

2.4 Research Gaps

The existing research on the relationship between age and education levels in relation to default rates among digital lending platform borrowers presents varying and\sometimes contradictory findings. Studies like Magali (2022) and Kassegen (2021) suggest a negative correlation between age and default rates, with older borrowers exhibiting lower default rates. However, Singh and Malik (2020) argue that younger borrowers, particularly those in the 18-25 age group, are more likely to default. Similarly, educational attainment's impact on default rates varies.

The role of gender as a socio-demographic determinant of default rates remains inconclusive. Some studies, such as Karim and Rahman (2019), suggest that female borrowers are more likely to default, while others like Kim (2022) find no significant gender-based differences in digital credit repayment behavior. Understanding why these gender-based differences exist and whether they hold true in Kenya's context is crucial. Moreover, examining how gender influences not only default behavior but also access to credit, interest rates, and financial behavior patterns could offer a more comprehensive understanding of the gender dynamics in digital lending platforms.

Research consistently highlights the relationship between income level and default rates. Gitau and Wambugu (2019) and Kamau and Nyambura (2020) both suggest that borrowers with lower incomes are more prone to default, as they might face financial strain and challenges in meeting repayment obligations. However, the complex interaction between income variability, stability, and its impact on default rates warrants further investigation. A deeper exploration of how digital lending platforms can design loan products that cater to borrowers with different income levels and patterns could provide valuable insights.

Few studies, such as Kariuki and Wanjiku (2021), have explored the combined effects of multiple socio-demographic factors on default rates. Their findings underscore the significance of considering age, education, and income collectively. However, the reasons behind these combined effects remain unexplored. Investigating how these factors interact and compound risk, especially among vulnerable borrower segments, can provide actionable insights for designing more targeted risk assessment and mitigation strategies.

Several studies, including Mwangi and Nzomo (2018), Mwangi and Muturi (2016), and Ondieki *et al.* (2021), highlight the role of education and financial literacy in shaping borrower behavior. However, the mechanisms through which education impacts financial behavior and how financial literacy interventions can effectively mitigate default rates require more exploration. Understanding how education and financial literacy initiatives can empower borrowers to make informed decisions, manage their loans, and avoid defaulting is a significant research gap.

The findings from the literature are mostly contradictory and inconclusive except for level of education. For instance, women were found to have high default rate in Indonesia (Santos *et al.*, 2019), yet in China and South Korea, they had the lowest default rate (Chen *et al.,* 2020; Kim *et al.,* 2018). Further confusing is the fact that MPL lenders charged high interest rate on women than men, implying that they were regarded as high-risk borrowers in China (Chen *et al.,* 2018). These contradicting results create an empirical research gap that can be filled through further research. Most of the previous studies were based on secondary data collected directly from P2P lending platforms and did not include any primary qualitative data collected directly from digital loan borrowers. Lee (2020) recognized this limitation stating that failure to collect primary data from borrowers made it difficult to consider other psychological factors about borrowers' personalities which may affect loan default rate. The study sought to fill this methodological research gap by using survey questionnaire to collect primary data directly from digital loan borrowers hence expanding on variables that affect digital loan repayment.

While the relationship between socio-demographic characteristics of P2P borrowers and loan repayment has been extensively studied in developed and emerging economies such as China (Chen *et al.,* 2020; Wang *et al.,* 2019), South Korea (Kim *et al.,*2018) and United States (Lee, 2020), similar studies are few in developing SSA countries like Kenya. The existing contextual differences in terms of economic power, financial literacy levels particularly among women, and unemployment among highly educated youths, makes the findings in developed countries less generalizable to developing countries like Kenya. Consequently, this study seeks to fill this contextual research gap by carrying out a similar study in Kenya.

2.5 Conceptual Framework

The statistical discrimination theory argues that in absence of information, preferential decisions can be made basing on group's average behaviour. In addition, credit theory revolves around the concept of creditworthiness, which is the measure of a borrower's ability and willingness to repay a debt. Premised on these theories, this study attempts to conceptualize that loan default rate of digital loan borrowers can be predicted basing on their socio-demographic characteristics namely, gender, age, education level, and level of income. Thus, this study conceptualizes that these socio-demographic characteristics affect loan default rate. For example, young borrowers may have higher default rates, this might be due to lack of understanding on implication of defaulting but also misuse the fund as in most cases they take the loan without any purpose. The opposite is also true. This is demonstrated in the figure 1.

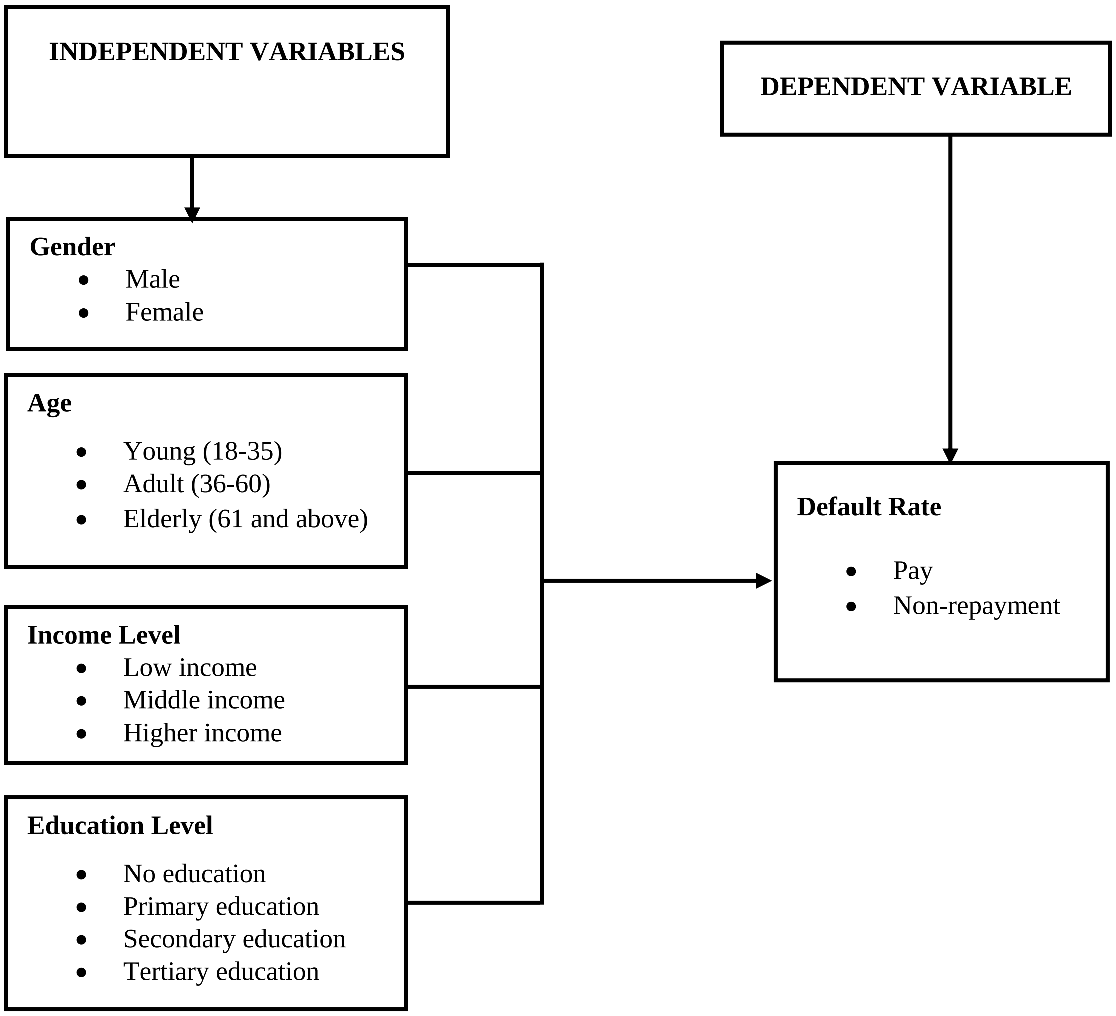

Figure 1: Conceptual Framework on Socio-demographic characteristics and Loan default rate of online loan borrowers.

CHAPTER THREE
METHODOLOGY

3.1 Research Design

The study adopted a cross-sectional research design to facilitate collection of data at a single point in time. The cross-sectional design is a research methodology commonly used in social sciences to gather data from a single point in time to understand the characteristics of a population or phenomenon (Spector, 2019; Ngugi, 2022; Alushula, 2022). In this design, data is collected from a diverse group of participants, allowing researchers to draw conclusions about a specific population at a specific moment. It provides a snapshot of the population's characteristics and relationships among variables at that particular time (Wang & Cheng, 2020).

The study used a mixed method approach where parallel quantitative and qualitative analysis was conducted. This enabled triangulation of the results and findings. To conduct this study, the first step involved planning and organizing the research process. After establishing the research objectives and questions, scheduling field visits and interactions with digital lending platform borrowers in Nairobi County was undertaken. Over a three-month period, engagement with respondents occurred through surveys and online questionnaires, depending on their accessibility and preferences. These interactions allowed for data collection on various socio-demographic factors such as age, gender, educational background, and income level, alongside loan repayment behavior and any defaults experienced.

During these field visits, engagement with respondents from diverse backgrounds took place, involving conversations to gather information on socio-demographic characteristics and experiences with digital lending platforms. Ensuring that the sample was representative of the digital borrowing population in Nairobi County was a priority. This data collection process involved active listening, open-ended questions, and structured surveys to gather comprehensive information. The cross-sectional design enabled capturing a snapshot of borrowers' characteristics and default behaviors during a specific timeframe, contributing to a better understanding of the socio-demographic determinants of loan defaults in the digital lending landscape of Nairobi County.

3.2 Geographical Coverage

The study was conducted in Kasarani sub-county, Nairobi County. The sub county had a dynamic population comprising of the youths, adults, senior adults, low and middle-income earners from both genders (Kenya National Bureau of Statistics [KNBS], 2019), providing a representative population of the entire Nairobi County. Kasarani sub-county was chosen because of higher percentage of a population who own a mobile phone hence able to access the digital loans. According to a 2021 report on the state of digital lending in Kenya (Reelanalytics, 2021), 210,010 (66%) of dwellers in Kasarani sub-county are subscribed to mobile loan apps. The sub-county had five wards as shown in Figure 2.

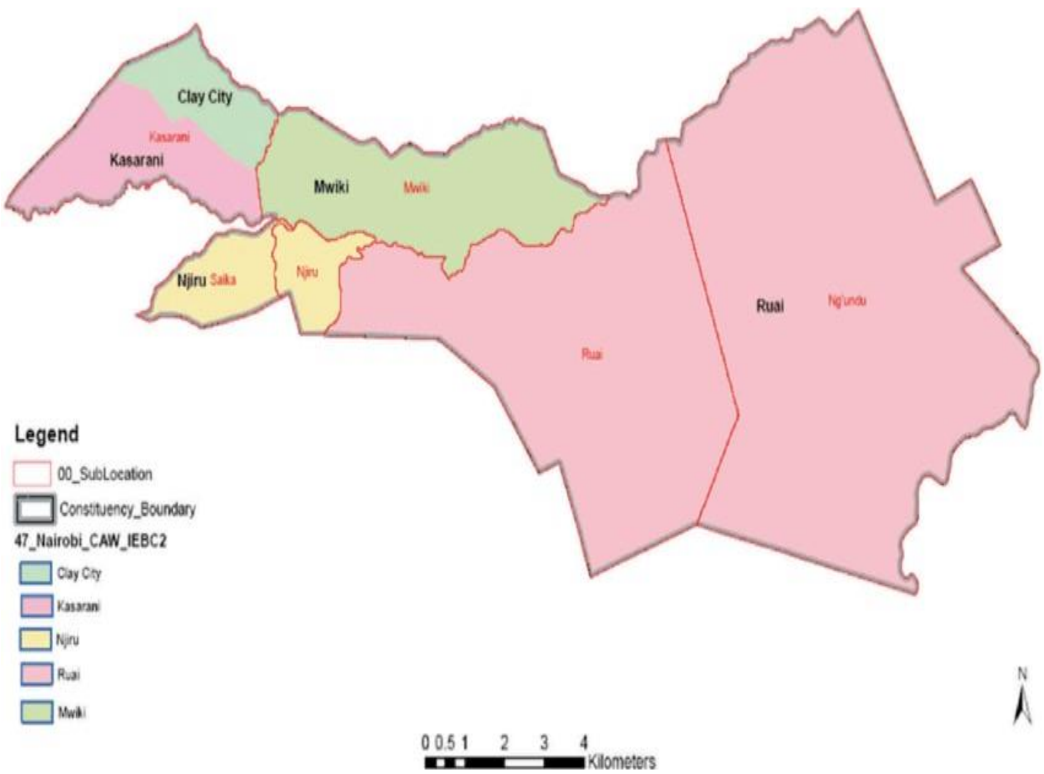

Figure 2: Map of Kasarani showing the study site

Source: Kenya National Bureau of Statistics (2019)

3.3 Target Population

The target population of the study was 281,342 owners of mobile phones in Kasarani sub-county spread across the five wards namely Ruai, Njiru, Kasarani, Mwiki and Clay City (Appendix III) that have attained the age of majority according (KNBS, 2019). Selection of people who have reached the age of majority are typically considered adults, and they often have more mature financial behaviors and experiences compared to younger individuals. Furthermore, they are likely to borrow money from financial institutions, making them a valuable source of reliable information for research on financial behavior, credit usage, and borrowing habits.

3.4 Sample and Sampling Technique

3.4.1 Sample Size

Yamane formula was applied to determine the sample size because the population size was known. The formula was also used by Magali (2022); Muthoni *et al.* (2019) and Ng'ang'a *et al.* (2018). Thus, applying Yamane formula, the sample size of the study was 400 respondents.

Yamane formula $n = \frac{N}{1+N(\varepsilon)^2}$

Whereas n = sample size, N = Population size, ε = margin of error

$$n = \frac{281342}{1 + 281342(0.05)^2} = 399.43 \text{ respondents}$$

Thus, the sample size was 400 respondents.

3.4.2 Sampling Technique

The research utilized a multistage sampling method to select respondents for the study. Multistage sampling is a complex sampling technique that involves dividing a large population into smaller, more manageable groups or stages, and then selecting samples from each of these stages (Sedgwick, 2015). This method is often used when it is difficult or impractical to collect data from the entire population. The multistage sampling process typically involves several stages, each with its own sampling method (Acharya, Prakash, Saxena, and Nigam, 2013). In the first stage, all five wards were purposely chosen as the primary sampling units. In the second stage, two hamlets/villages were randomly selected from each ward using a list obtained from the chief's office. At the third stage, a proportionate random sampling technique was employed to allocate 40 respondents to each selected hamlet. Subsequently, in the fourth stage, purposive sampling was employed to select 40 respondents from each hamlet.

In the second stage, after the hamlets/villages were randomly selected, 40 respondents were allocated to each of these chosen hamlets proportionally based on their population. This allowed for a representative sample from each hamlet. In the fourth stage, respondents were purposively chosen from within these hamlets. The purposive sampling aimed to ensure that the chosen respondents had used digital loans for at least two years, which increased the likelihood of including individuals who may have experienced non-repayment. Further, in the process of data collection, potential respondents were identified by standing at locations like M-pesa outlets, shops, and trading centers. This approach allowed individuals who came to these locations for services to be approached. By using this method, individuals who were active users of digital lending platforms could be interacted with and selected.

3.5 Data Collection

3.5.1 Types of Data

The study used quantitative and qualitative data to conduct the study. Quantitative included open ended questions while qualitative data included interview guide. Quantitative data was collected through closed-ended questions. Quantitative data was used because the study was focusing on answering the question on what (Albers, 2017) causes non-repayment of the loan rather than why loan default occurs. Moreover, qualitative research allows for effective data collection from participants, especially when primary data is involved (Padros & Johnson, 2020).

3.5.2 Sources of Data

The study used both primary and secondary sources of data. The use of primary sources of data increased the reliability of the collected data since the data was collected directly from respondents, for specific objectives of this study. Secondary data was obtained from one of the leading P2P platforms in the country having been in operation for more than five years. In addition, secondary data from a leading digital lending company that was used to collaborate the study findings that were obtained the primary data. The secondary data was derived from a sample of 210 borrowers from a digital lending company in Kenya.

3.6 Data Collection Instruments

3.6.1 Questionnaire Survey

Data was collected using a structured survey questionnaire. The questionnaire contained closed and open-ended questions. The first section contained the socio demographic while the second section presented questions on digital loan default. The questionnaire was researcher administered and collected immediately after filling to increase return rate given that some of the respondents were mobile.

The researcher administered questionnaires (Appendix I) in persons to respondents who were owners of mobile phones in Kasarani sub-county, who have benefitted from P2P lenders. Some respondents filled the questionnaires immediately in the presence of the data collector while others requested to fill them later. A follow up was done on the pending questionnaires weekly for up to a month until they were completed.

3.6.2 Key Informant Interviews

The study conducted five key informant interviews (KIIs) (Appendix II) with three officers involved with three screening digital loan applicants and two loan account officers in the lending companies. The KIIs sought to understand what the officer's thought were some of the risky socio-demographic attributes on loan repayment. The use of interview as data collection technique stems from the need to collect detailed data which cannot be obtained through other methods of data collection (Bartram, 2019).

3.7 Validity and Reliability

The survey questionnaire was subjected to content validity tests to ensure that the instruments have enough number of items to measure the required subject (Creswell, 2016). An evaluation was conducted to enhance the quality of the study by addressing poorly phrased or objectives that deviated from the intended focus. The supervisors, played a pivotal role in this assessment. Each statement within the study objectives underwent thorough scrutiny to ensure its content validity and alignment with the research's intended goals. Their guidance and input were instrumental in shaping the objectives to accurately represent the research's scope and objectives, ensuring a coherent and purposeful direction for the study. Content validity was then tested using a content validity index (CVI) as recommended by Amin (2005) and should be above 0.5 as recommended. This was done by dividing the number of valid questions (12) by the total number of questions in questionnaire (15) leading to CVI of 0.8, which was above the recommended minimum 0.5.

As recommended by Creswell (2016) that the sample size of pilot study should always be greater than the number of items in the questionnaire, a pilot study involving 22 respondents was conducted. Cronbach Alpha coefficient was used to test internal consistency of the questionnaire, where if a value above 0.7 as recommended by

Creswell (2016) is obtained then the question is not modified. The pilot results indicated that the categories had a Cronbach Alpha of above 0.7 and thus was reliable.

Table 1: Reliability Outputs

Categories	Cronbach Alpha	N of items	Comment
Gender	0.722	2	Acceptable
Level of education	0.776	6	Acceptable
Income level	0.825	6	Highly acceptable
Age	0.883	3	Highly acceptable
Frequency of borrowing	0.760	5	Acceptable
Amount borrowed	0.767	5	Acceptable
Types of loan	0.717	2	Acceptable
Period of borrowing	0.728	4	Acceptable
Overall	0.772		

3.8 Data Analysis

This study used a mixed method approach in data analysis, to enable the analysis of both qualitative and quantitative data that was collected (Creswell, 2014; Morse and Niehaus, 2016). Quantitative included open ended questions while qualitative data included interview guide. Quantitative data was collected through closed-ended questions.

3.8.1 Descriptive

Descriptive analysis was carried out to generate frequency and percentage, hence giving statistical meaning to the raw data. The study employed descriptive statistics to comprehensively analyze various socio-demographic factors and borrowing patterns among the digital lending platform borrowers. Descriptive statistics were utilized to reveal insights into the distribution and central tendencies of variables such as gender, level of education, income level, and age (Kaliyadan and Kulkarni, 2019). Through frequency counts and percentages, the study outlined the prevalence of different gender categories, educational backgrounds, income ranges, and age groups within the borrower population. Additionally, descriptive statistics illuminated the frequency of borrowing instances, providing an overview of how often borrowers engaged with digital loans.

3.8.2 Binary Regression Analysis

Binary logistics regression model was used to establish the socio-demographic characteristics of borrowers that are associated with loan default rate. The probability can take two values, default (BDR = 0) or non-default (BDR =1). Let Pi represent the probability that the borrower will not default, then the probability that the borrower will default is given as 1- Pi. Since we do not observe Pi, but the outcome BDR=1, if borrower will not default and BDR = 0 if borrower will default.

The model was chosen because the dependent variable was binary in nature involving only two options (Sakarani and Bourgie, 2016), payment of loan or non-payment. The assumptions tests that were conducted included sample size, outliers and multicollinearity.

The outcome variable of this study was loan default rate and was fitted in the binary logistics model. The variable was categorized into a binary response namely borrowers who have paid their loans coded as 1 and those who have defaulted coded as 0. Consequently, the independent variables (gender, age, education level, and income level) and the outcome variable was fitted into the following binary logistics equation then we have the following:

$$\Pr(BDR_i = 1) = P_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

$$\Pr(BDR_i = 0) = 1 - P_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$$

$$Logit(P_i) = \alpha + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \varepsilon_0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3$$

Where:

Logit (Pi) = Y= dependent variable and represents the probability of borrowers paying their loan, coded as 1 for pay and 0 for default.

α = intercept

$\beta_{1-}\beta_5$= Regression coefficients

X_1 = Gender,

X_2 = Age

X_3 = Educational level

$X_{4=}$ Income level

ε_o= stochastic error term.

Table 2: Operational Definition of Variables and their measurement levels

Variables	Definition	Measurement	Instrument
Gender	Male, Female	Nominal scale	Questionnaire
Age	Youth, adult, elderly	Interval scale	Questionnaire
Education level	Not educated, primary education, secondary education, tertiary education	Ordinal scale	Questionnaire
Income level	Lower income, middle income, upper income	Ordinal scale Scale	Questionnaire
Loan default rate	Payment or Non-payment of digital loan	Binary: 1= Yes, 0= No	Questionnaire

3.8.3 Content analysis

Content analysis involves a systematic and rigorous process of identifying, categorizing, and interpreting patterns within textual or verbal data to extract meaningful insights and uncover underlying themes (Hsieh and Shannon, 2005). First interviews were transcribed into word document. Then from these transcriptions' key themes, concepts or phrases related to social-demographic (age, gender, education and income level) and default rate of digital credit platforms borrowers were identified. This was done to organise the information into common themes that emerged in response to dealing with specific items. These themes were organised into a coherent category which summarised key results. Qualitative information was then integrated with the quantitative information to provide a meaningful study conclusion. The summary of the content analysis is as shown in Appendix IV. The coding is as shown in Table 3.

Table 3: Interview Coding

Category	Code	Total
Digital Loan Officers	DLO (I-V)	5
Respondents (Open ended questions on Loan Default Rate)	RSP (I-V)	5

3.9 Assumptions of Regression Results

The binary regression assumptions of the study were sample size, outliers and multicollinearity.

3.9.1 Sample Size

Sample size is an important consideration when conducting binary logistic regression. Having a larger sample size is beneficial as it increases the likelihood of capturing the true underlying relationships between variables and reduces the risk of obtaining spurious or unstable results. A larger sample size allows for more precise estimates of regression coefficients and enhances the generalizability of findings. A common rule of thumb is to have at least 10 to 20 observations for each predictor variable in your model (Alderdice, Harrison, Henderson and Quigley, 2019). This helps ensure that the model has enough degrees of freedom to estimate coefficients accurately. The study had 387 observations, which was adequate for the sample size.

3.9.2 Outliers

The study utilised the box plot method to assess outliers. The findings depicted in Figure 3, revealing that the residuals exhibit no outliers and depicted a normal distribution.

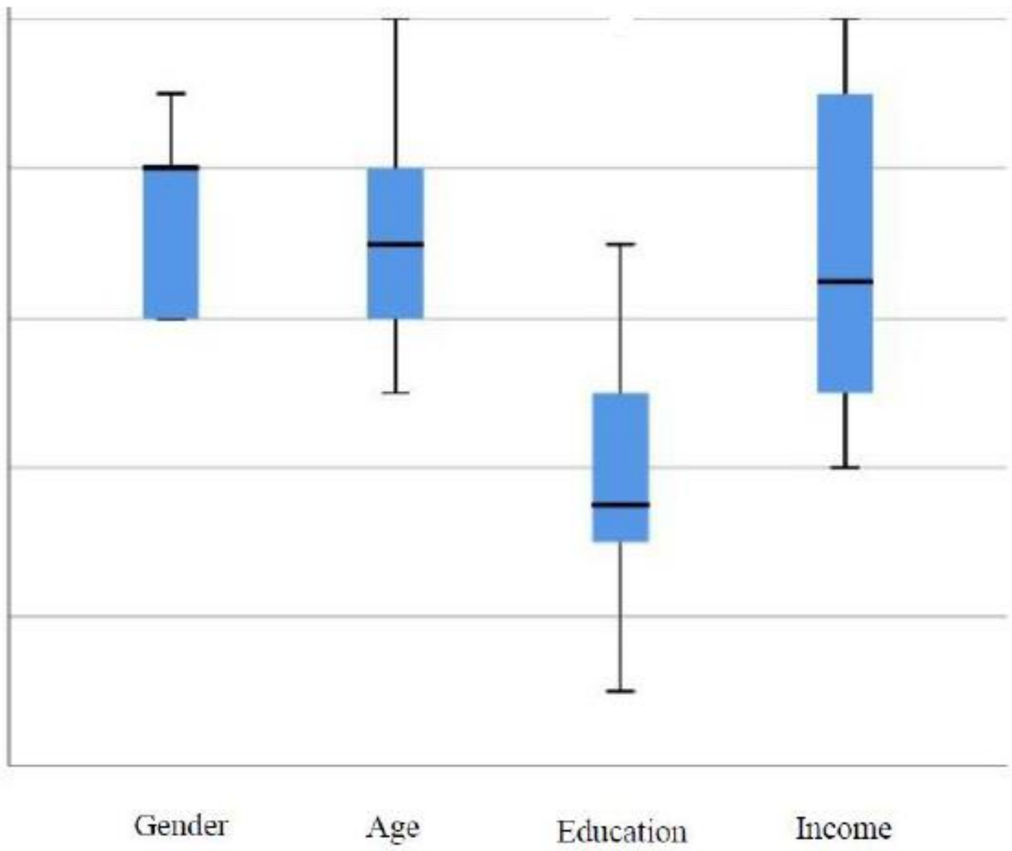

Figure 3: Box plots

The box plots illustrating age, gender, education level, and income level appear to depict normal distributions, as the central tendencies of each distribution are approximately symmetrically aligned with their respective medians, while the whiskers of the boxes extend proportionally in both directions, indicative of consistent dispersion. This suggests that the data points for these variables are relatively evenly distributed around their mean values, reinforcing the notion of normality within the dataset for these key demographic factors (Smiti, 2020).

3.9.3 Multicollinearity Test

Multicollinearity is a statistical phenomenon that occurs when two or more independent variables in a regression model are highly correlated, making it challenging to discern their individual effects on the dependent variable (Shrestha, 2020). Multicollinearity test is a crucial analytical step to ensure the reliability and validity of your regression analysis (Kim, 2019). A Variance Inflation Factor (VIF) of 1 signifies no significant correlation between the variable and others, making it suitable for inclusion in the model. VIF values between 1 and 5 suggest acceptable levels of multicollinearity, implying that the variable's variance is mildly affected by correlation. However, VIF values above 5 indicate a moderate to high degree of multicollinearity, potentially leading to instability in regression coefficients. Particularly, VIF values exceeding 10 signal substantial multicollinearity that can jeopardize coefficient interpretation. Careful consideration is crucial when variables exhibit high VIF values, as they might need addressing through techniques like variable removal or transformation to ensure robust and reliable regression results. The results in Table 4 indicated that the VIF values were between 2 and 4 and thus the data did not suffer from Multicollinearity.

Table 4: Multicollinearity Outputs

Variables	VIF
Types of loan	3.70
Period of borrowing	3.21
Amount borrowed	2.92
Age	2.75
Income level	2.62
Level of education	2.60
Frequency of borrowing	2.53
Gender	2.03

3.10 Ethical Considerations

In conducting research on the socio-demographic determinants of default rates among digital lending platform borrowers in Nairobi County, Kenya, the study adhered to strict ethical guidelines to ensure fairness, accuracy, and respect for all participants. The study sought authorization from Moshi Co-Operative University (Appendix V), NACOSTI (Appendix VI) and from the study area. Personal data was collected with informed consent, and confidentiality was maintained by anonymizing the data to protect individuals' identities. The research did not discriminate based on gender, or economic status, and aimed to be as inclusive as possible to obtain a comprehensive understanding of the community. Additionally, the study was transparent in its objectives, methods, and intended use of findings, ensuring that participants were fully aware of how their information would be used. By taking these steps, the research aimed to uphold the principles of integrity, respect, and social responsibility.

CHAPTER FOUR

4.0 FINDINGS AND DISCUSSIONS

This chapter presents the study findings, analyses, and accompanying discussions. It is basically divided into three sections, which entail the demographic description of the unit of observation, the findings of the study, and the statistical model results. In this study, there are four demographic characteristics that represent the independent variables in the study: age, gender, employment status, income level, and education.

4.1 Response rate

The study administered 400 questionnaires to the owners of mobile phones in five wards namely Ruai, Njiru, Kasarani, Mwiki and Clay City in Kasarani Sub County. Out of the 400 questionnaires issued, 387 were returned, having been fully filled, translating to 96.75 % response rate. A response rate above 50% was considered adequate for representativeness of this study (Nayak &Nayaran, 2019). In addition, all the 5 digital loan officers responded to the interview guide translating to 100%. This is also supported by Alderdice, Harrison, Henderson, and Quigley (2019) that a higher response rate is usually desirable since it ensures good representation of the population and the effectiveness of the data collection instrument.

Table 5: Response Rate

Category	Respondents	Digital Loan Officers
Filled	387	5
Not Filled	13	0
Administered	400	5
Response Rate	97%	100%

4.2 Demographic Characteristics of Respondents

The study focused on four major demographic characteristics which Chen *et al*. (2020) emphasized are used to determine credit worthiness and expected loan performance. These are gender, age, education and income level. The respondents were asked to indicate on the questionnaire their age, gender, level of education, and income level. In addition, secondary data from a leading digital lending company that was used to corroborate the study findings. The secondary data was derived from a sample of 210 borrowers from a digital lending company in Kenya.

4.2.1 Gender

Out of the 387 respondents who participated in the study, 216 (55.8%) were male while 171 (44.2%) were female (see table 6). As such, it implied that male borrowers dominate the digital credit space. The secondary data indicated that 117 are male, representing 55.7% of the total, while 93 are female, making up 44.3%. This gender distribution may be important for the lending company to consider when developing marketing strategies and tailoring loan products to specific target groups. This finding concurs with a report about digital credit in Kenya that revealed digital borrowers are more likely to be male (Gubbins and Totolo, 2018).

4.2.2 Age

Majority of the respondents were between the age group of 18-35 years constituting 230 (59.6%) of the respondents, these were followed by respondents within the age bracket of 36-60 representing 123 (31.9%) respondents. Lastly, there were 33 (8.5%) respondents within the age range of 61 years and above. Using the secondary data, majority of borrowers, 57%, fall within the 18-35 years age bracket, while 43% are between 36 and 60 years old. There is also a smaller group, comprising 16 borrowers, who are above 61 years of age. This age distribution may inform the lending company's decisions regarding loan terms and conditions, as different age groups may have varying financial needs and repayment capabilities. These findings demonstrate that most users of digital lending platforms are youthful between the age of 18-35, as such, reinforcing the findings of an earlier report which revealed that digital borrowers were predominantly below 35 years, accounting for 62% of borrowers in Kenya, (Financial Sector Deepening Kenya, 2019).

4.2.3 Education Level

In terms of the level of education attained, the results indicated that majority of the respondents had a Bachelor’s degree as represented by 134 (34.6%) of the respondents. This was closely followed by respondents with secondary education represented by 119 (30.7%) of the respondents. Respondents having attained no education and Master’s degree constituted of 29 (7.5%) and 21 (5.4%) of the respondents respectively. Lastly there was only 1 (0.3) PhD respondent. Using the secondary data, the highest number of borrowers have completed secondary education (39%), followed closely by those with a Bachelor's degree (35%). Smaller percentages hold primary education (22%), Master's degrees (3%), and even a few with a Doctor of Philosophy (1%). Education level is relevant in terms of tailoring communication and loan offerings to cater to the needs of borrowers from various educational backgrounds. These findings are similar to an earlier study that found 38.5% of digital borrowers held college certificate while 31.7% had acquired University education, consequently, the findings implied that advancement in education plays a vital role in influencing the use of digital credit (Wathome, 2020).

4.2.4 Employment status

The distribution of respondent's employment status revealed that out of the 387 respondents, 124 (32.0%) reported unemployment, while 71 (18.3%) respondents represented public sector employment rate and a significant number of respondents 191 (49.4%) represented private sector employment rate. This is as per the Financial Sector Deepening Kenya (2019) report on the rising unemployment especially among the youths. While unemployment is a significant issue, the private sector seems to offer the most job opportunities, with public sector employment also making up a smaller but notable percentage of employment.

4.2.5 Income level

Respondents were asked to identify their monthly income level. The findings showed that out of the 387 respondents, 170 (43.9%), fell within the income range of 0-$237. There were 94 (24.3%) respondents in the income bracket between $238 and $350. 48 (12.4%) respondents were earning between $360 and $450, 44 (11.4%) respondents between $460 and $550, 12 (3.1%) between $560 and $650, and lastly 19 (4.9%) respondents revealed they were earning $660 and above. The secondary data indicated that on income distribution, 42% of borrowers earn an income ranging from 0-$237, while 23% fall into the $238 to $350 income range. Understanding borrowers' income levels can help the lending company determine suitable loan amounts and repayment terms that align with their financial capabilities. The findings concur with Trends and Insights for Africa report [TIFA], (2023) which revealed that 38% of Kenyans did not have a monthly income. The implication is a major income inequality.

Table 6: Demographic information of respondents

Variable	Response	Frequency (n=387)	Percentage (%)
Gender	Male	216	55.8
	Female	171	44.2
	Total	**387**	**100.0**
Age			
	18- 35 years	230	59.6
	36 to 60 years	123	31.9
	Above 61 years	33	8.5
	Total	**387**	**100.0**
Employment Status			
	No	124	32.0
	Yes (Public Sector)	71	18.3
	Yes (Private Sector)	191	49.4
	Total	**386**	**99.7**
Education Level			
	No Education	96	25.5
	Primary education	139	37.0
	Secondary education	126	33.5
	Bachelor's degree	15	4.0
	Master's degree	21	5.4
	PhD	1	0.3
	Total	**387**	**100.0**
Monthly Income Level			
	$0-237	170	43.9
	$238-350	94	24.3
	$360-450	48	12.4
	$460-550	44	11.4
	$560-650	12	3.1
	$660 and above	19	4.9
	Total	**387**	**100**

4.2 Digital Borrowing practices

The section provides information on frequency of borrowing, borrowing duration, amount borrowed and type of loan by the borrowers from the digital lending companies.

4.2.1 Frequency of Borrowing

In terms of frequency of borrowing, majority of respondents 95 (24.5%) said, they borrowed once every week. This continuous borrowing trend can be linked to the aggressive marketing and need of money by digital credit lenders. Borrowers are tempted to borrow money constantly because there is no limit to the number of times they can borrow, consequently making the borrowers even more burdened with repayments.

A total of 67 (17.3%) of respondents reported borrowing every two weeks. A significant percentage of respondents 92 (23.8%) also indicated that they borrowed once each month, indicating a consistent borrowing tendency. Additionally, 84 (21.7%)

respondents reported borrowing once in three months basis. Lastly, few respondents 49 (12.7%) said they borrowed once a year, which indicates a less regular borrowing pattern compared to the other groups. These findings surpass those of a recent study that found out only 6% of Kenyans had taken a digital loan in a month (Nzisa and Kithandi, 2023).

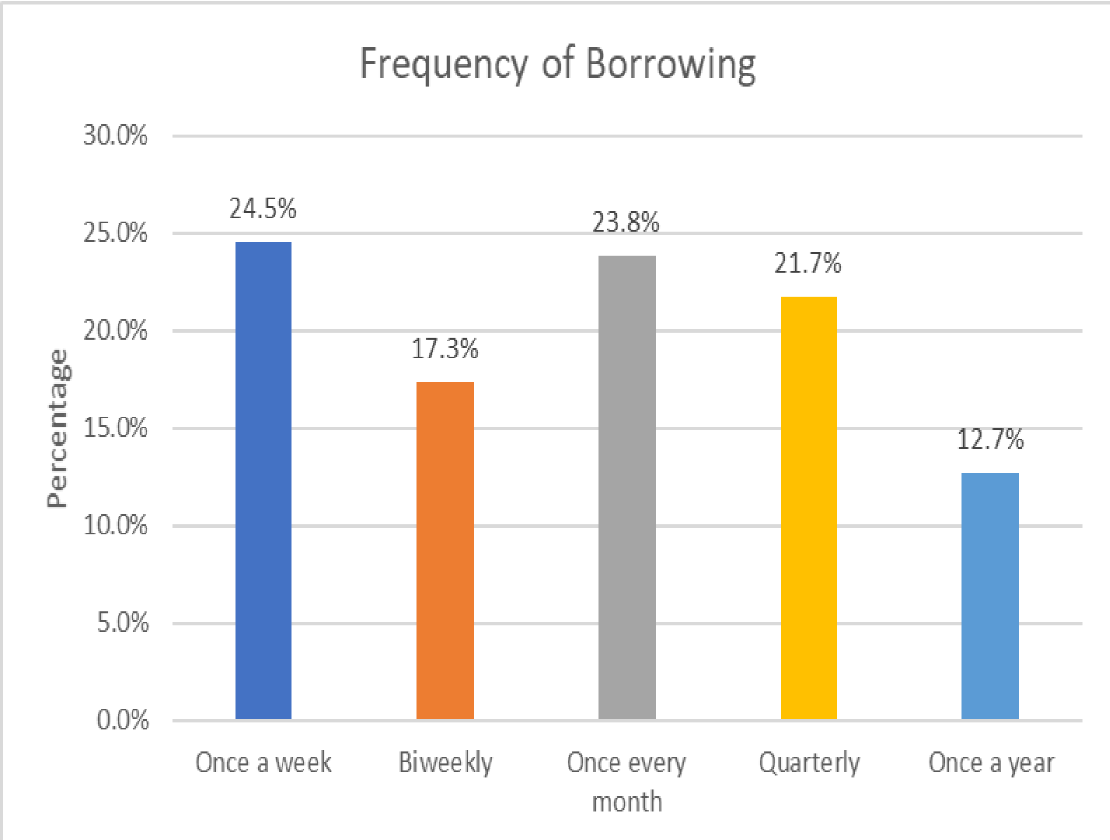

Figure 4: Frequency of Borrowing

On borrowing duration, the respondents were asked to indicate how long they have been borrowing. The findings revealed that majority 169 (43.7%) of respondents, had borrowed money for more than a year. While 113 (29.2%) reported they had borrowed in the last one year, 66 (17.1%) reported borrowing in the last six months. Lastly, 39 (10.1%) revealed borrowing in the last three months. This is as indicated by Ochunge, (2022) and Odhiambo (2022) on the borrowing of digital loans and that despite the important role of digital credit, the number of Kenyans defaulting to repay their loans is on the rise. When borrowers frequently turn to digital loans, it can indicate financial instability or a reliance on credit to meet daily expenses. This heightened borrowing frequency, without corresponding increases in income or financial stability, can lead to an increased risk of default.

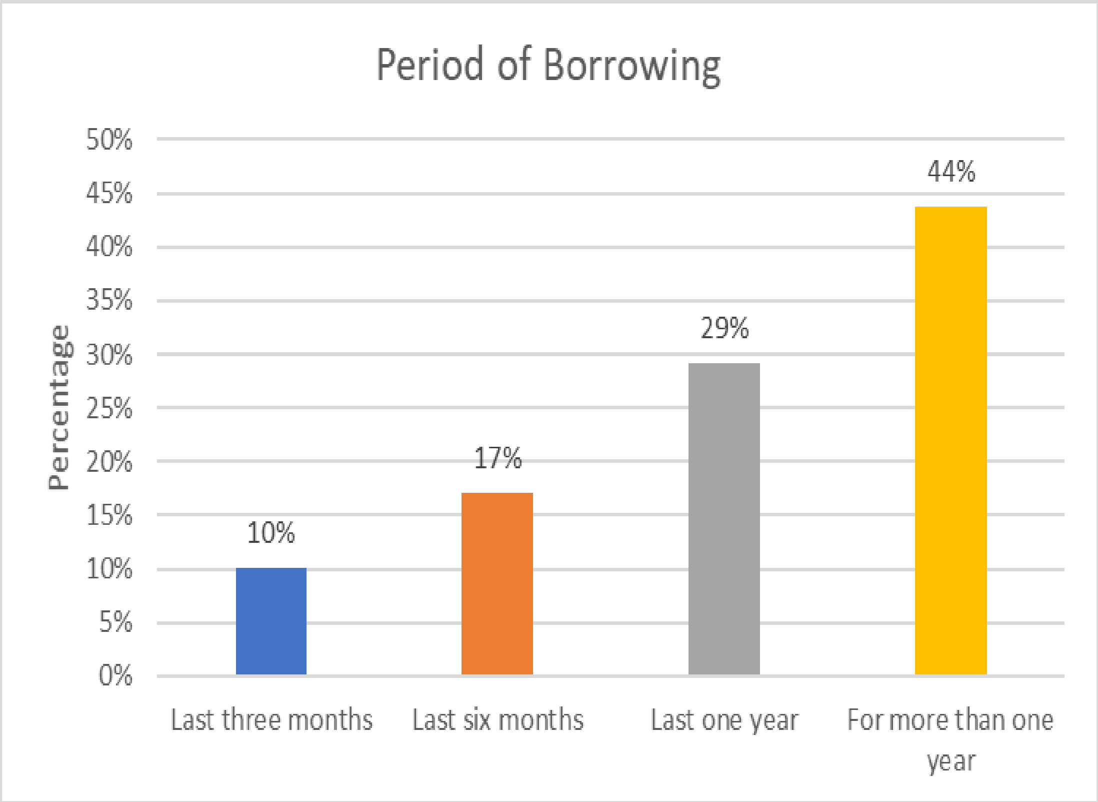

Figure 5: Borrowing Duration

4.2.2 Amount Borrowed

The study also asked respondents to identify the average amount of money borrowed from digital companies. Respondents were found to be borrowing varied amounts. 79 (20.4%) of the respondents took out loans between $5 and $10, while 89 (23.0%) borrowed between $10 and $20. Furthermore, 62 (16.0%) borrowed between $36 and $45, while 77 (19.9%) borrowed between $210 and $350. Lastly, 80 (20.7%) respondents, reported to have borrowed $460 and above. In addition, the secondary data indicated under the distribution of loan amounts borrowed by customers, the majority of borrowers have borrowed amounts ranging from $50 to $200, accounting for 61% of the total. Loan amount is relevant for the digital lending company to design loan products that cater to the most popular loan amounts and to assess the risk associated with higher loan amounts.

The findings, closely corroborates those of earlier studies which revealed that the most common borrowed amount ranged between $20 and $100 (FSD Kenya, 2019).

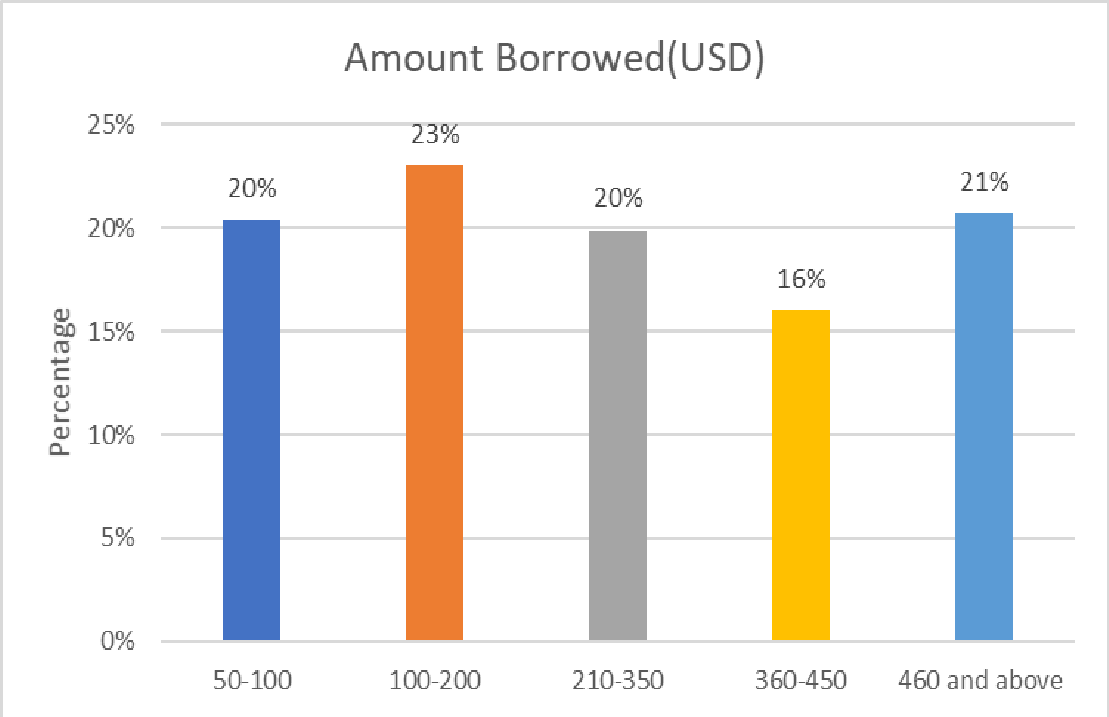

Figure 6: Amount Borrowed

4.2.3 Type of Loan

Out of the 387 respondents 295 (76.2%) respondents took personal loans, while only 89 (23.0%) took business loans. The findings revealed that personal loans were the most dominant type of loan. The result positively correlates with a report by GeoPoll (2023) which found that majority of the digital borrowers taking out loans were doing so for personal use, with 66.5% stating they had taken out personal loans, and 33.5% using loans for business. Similarly, Peer to Peer lending companies often issue smaller loans that are tailored for personal consumption rather than business, therefore, most borrowers use the loan to cater for their daily expenses like food and other emergencies. Access to digital credit in Kenya significantly reduced the likelihood of individuals to forego necessary expenses such as medical and food by 6.3% (Suri *et al.*, 2021).

4.3 Loan Delays in Digital Lending

The section provides information on default, number of loan default and reasons for default by the borrowers from the digital lending companies.

4.3.1 Loan Default

Respondents were asked to indicate whether they defaulted on loan repayment. While 215 (55.6%) of the respondents admitted to having defaulted/delayed payments on their loans. In contrast, 172 (44.4%) reported they had not defaulted. The findings suggest that a significant number of respondents had defaulted on a loan. The results closely resonate with a previous survey by CGAP (2018) which revealed that 50% of digital borrowers in Kenya defaulted their loan repayment. Additionally, the ease of accessing credit attracts borrowers in urgent need of loan product with limited ability to repay the loan. At least one out of every five borrowers had trouble repaying their loans (CBK, 2019).

4.3.2 Number of Loan Default

In terms of the number of loans defaulted, the respondents were asked to indicate the number of loans defaulted. Among the borrowers, 170 (43.9%) had not defaulted any loan. Additionally, 83 (21.4%) respondents defaulted once, while 37 (9.6%) respondents had defaulted twice. 97 (25.1%) said they had defaulted more than two loans. The findings suggest that most borrowers had multiple defaults, which implied multiple borrowing from different lending companies thus making it difficult to repay on time and consequently, borrowers being overburdened by loan repayment. In addition, the issuance of digital loans without collateral makes them vulnerable to lenders, as such, a vicious cycle of debt that becomes inevitable to break among borrowers (Predatory Lending, 2019; Mwaniki, 2022).

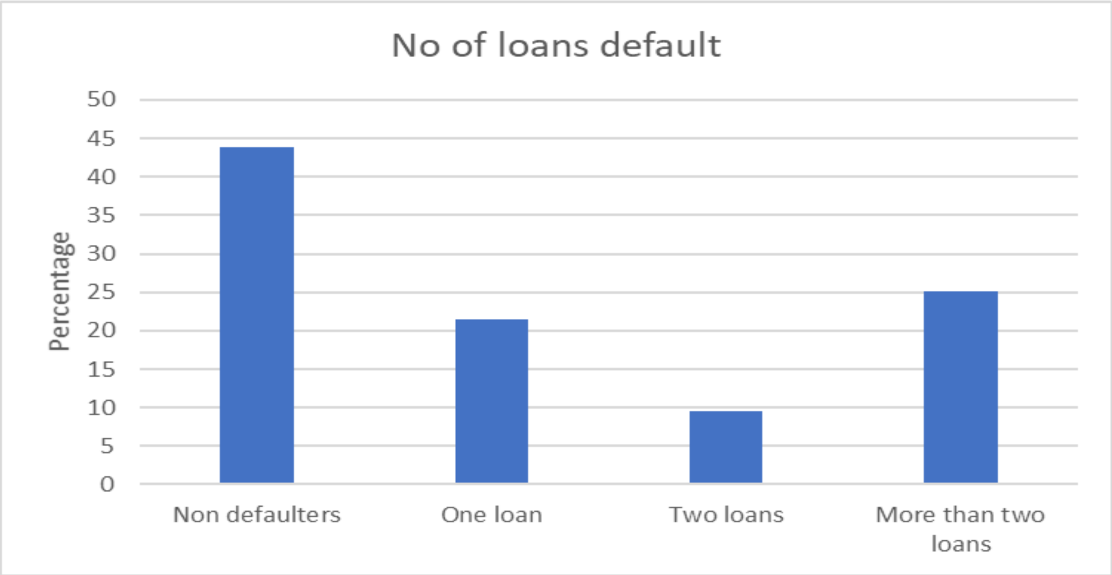

Figure 7: Number of Loan Default

4.3.3 Reasons for Default

Respondents were asked to indicate the reasons for loan default. Among those who defaulted, the most dominating reason cited was financial hardship by 82 (21.2%) of the respondents. This was followed by high interest rate, accounting for 64 (16.5%) of the defaults. This finding indicated that high interest rate was a leading cause of default. A total of 60 (15.5%) were attributed to a short repayment period. Digital loans design limit borrowers to short repayment periods, with the most common duration being 30 days. A smaller percentage 11 (2.8%) reported having no intention of repaying their loans. While lending companies make credit easily accessible, the borrowers are however left with the burden of repayment that result from perceived high interest rate that are charged and other underlying issues. Carnegie Endowment for International Peace [CEFIP], (2023) also reached the same conclusion that high interest rates make it more difficult for low-income borrowers to repay loans.

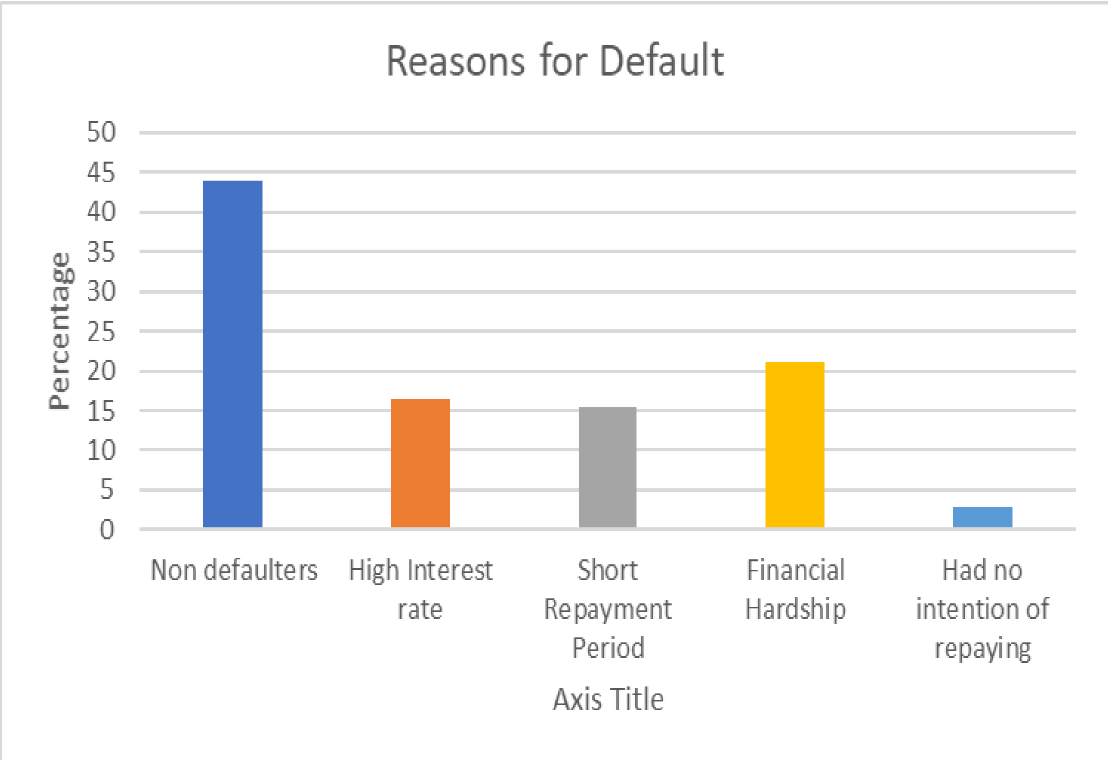

Figure 8: Reasons for Default

4.4 Effect of Gender on Default Rate of Digital Credit Platforms Borrowers

The first objective aimed to predict the probability of an event occurring (e.g., defaulting on a loan) based on the values of the independent variable (e.g., gender). The outputs are as shown in Table 7.

Table 7: Binary Logistic Outputs for Gender on Default Rate of Digital Credit Platforms Borrowers

Omnibus Tests of Model Coefficients			
	Chi-square	Df	Sig.
Step	24.620	1	.000
Block	24.620	1	.000
Model	24.620	1	.000

Model Summary		
-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
507.088[a]	.062	.083

Hosmer and Lemeshow Test		
Chi-square	Df	Sig.
.000	0	0.40

Variables in the Equation	**Exp(B)**	**B**	**S.E.**	**Wald**	**df**	**Sig.**	**95% C.I. for EXP(B)**	
							Lower	Upper
Female	-0.355	-1.036	0.212	23.878	1	**0.000**	0.234	0.538
Constant	1.408	0.342	0.155	4.87	1	0.027		

Base reference; Male

The omnibus tests evaluate the overall significance of the model coefficients. The chi-square value of 24.620 with 1 degree of freedom (df) and a significance level of .000 ($p < .001$) indicates that the model's predictor variable(s) significantly contribute to predicting the dependent variable (e.g., loan default). This means that the model is statistically significant and can help differentiate between defaulted and non-defaulted cases. The -2 Log likelihood value (507.088) is a measure of model fit. Lower values indicate a better fit to the data. However, its absolute value does not give much interpretative insight on its own. Cox and Snell R Square (.062) and Nagelkerke R Square (.083) are measures of the model's goodness of fit. They indicate the proportion of variance explained by the model. In this case, the model explains approximately 6.2% (Cox & Snell) to 8.3% (Nagelkerke) of the variance in the dependent variable (e.g., loan default). The Hosmer and Lemeshow test chi-square value is 0.40 with 0 degrees of freedom (df), indicating that the model fits the data well.

The logistic regression equation includes one predictor variable, which is "Female" (gender). The Exp(B) column represents the odds ratio for the variable, indicating how the odds of the event (e.g., loan default) change with a one-unit change in the predictor variable. The coefficient of -1.036 suggests that being female is associated with a lower odds of defaulting on a loan compared to being male. The odds ratio (Exp (B) = -0.355) indicates that females have approximately 0.355 times (or 35.5%) lower odds of defaulting compared to males. The p-value (0.000) indicates that this effect is statistically significant. The binary logistic regression analysis reveals that gender has a significant effect on the default rate of borrowers using digital credit platforms. Female borrowers are approximately 35.5% less likely to default compared to male borrowers. To add on that, a digital loan officer (DLO-I) from a digital credit platform responded that;

> *"……we have found a link between gender and default rates among borrowers. The female borrowers exhibit lower default patterns, indicating that gender does play a decisive role in determining loan repayment behavior."* (Digital loan officer-DLO-I, 3rd June, 2023)

Another digital loan officer (DLO-II) from a digital credit platform was asked if they observed any differences in default rates between male and female borrowers and the response was that;

> *"Yes, from my experience, we have observed some differences in default rates between male and female borrowers on our digital lending platform. Female borrowers, especially those in certain age groups, tend to have more irregular or informal sources of income, which can make it challenging for them to meet loan repayment obligations consistently*." (Digital loan officer- DLO-II, 6th June, 2023)

This is in contrast with Santos *et al.* (2019) who found women to have a high loan default rate compared to men. Santos *et al.* (2019) attributed this finding to low level of financial literacy among women in the country. On the contrary, Kim, Maeng and Cho (2018) study found that loan application from women were more likely to be approved than from men, because the latter had high delinquency rate. A study by Lin *et al.* (2017) also reported similar findings that women having a lower default rate compared to men. Chen, Huang and Ye (2020) and Chen *et al.* (2020) further confirmed these findings reporting that lending to women reduced loan default risks. The study concluded that women were lower risk borrowers than men. However, despite the high creditworthiness of women, Chen *et al.,* (2020) found that the funding rate for women was lower compared to men. To qualify for P2P loan, women borrowers were charged high interest rate compared to their men counterparts. The findings highlight the presence of gender-related factors influencing default rates, with female borrowers demonstrating a lower likelihood of default compared to males. This supports discrimination theory, suggesting that gender-based discrimination may manifest in the credit ecosystem, leading to differential treatment and outcomes for male and female borrowers (Ashenfelter & Rees, 2015).

4.5 Influence of Age on Default Rate of Digital Credit Platforms Borrowers

The second objective was to investigate the influence of age on the default rate of borrowers using digital credit platforms. The binary logistic outputs provided here offer valuable insights into how age influences the likelihood of default among borrowers, with the base reference for age being 18-35 years. The outputs are as shown in Table 8.

Table 8: Binary Logistic Outputs for Age on Default Rate of Digital Credit Platforms Borrowers

Omnibus Tests of Model Coefficients

	Chi-square	Df	Sig.
Step	31.309	2	.000
Block	31.309	2	.000
Model	31.309	2	.000

Model Summary

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
500.399[a]	.078	.104

Hosmer and Lemeshow Test

Chi-square	Df	Sig.
.000	1	1.000

Variables in the Equation

	Exp(B)	**B**	**S.E.**	**Wald**	**df**	**Sig.**	**95% C.I. for EXP(B) Lower**	**Upper**
AGE								
36-60years	-0.140	-1.967	0.448	19.284	1	**0.000**	0.058	0.337
61 years and above	-0.322	-1.133	0.463	5.994	1	**0.014**	0.130	0.798
Constant	3.714	1.312	0.426	9.496	1	0.002		

Base reference;18-35years

The Omnibus Tests of Model Coefficients. The chi-square test statistics indicate that the model is statistically significant ($p < 0.001$). This suggests that the age variable has a significant on the default rate of borrowers in digital credit platforms. The Model Summary shows the goodness-of-fit statistics for the logistic regression model. The -2 Log likelihood value indicates the overall fit of the model, and in this case, it is 500.399a. The Cox & Snell R Square and Nagelkerke R Square measures, which range from 0 to 1, are 0.078 and 0.104, respectively. These measures provide information about the proportion of variance in the dependent variable (default rate) that can be explained by the independent variables (age). The values obtained here suggest that age explains approximately 7.8% to 10.4% of the variation in the default rate among borrowers. To assess the goodness-of-fit further, the Hosmer and Lemeshow Test was conducted. The test assessed whether the observed and predicted default rates match well. The test statistic is 0.000, and the associated p-value is 1.000, indicating a good fit of the model.

The logistic regression coefficients (B) provided information about the direction and strength of the relationship between the independent variable (age) and the log-odds of default. The Exp (B) values are the exponentiated coefficients and represent the odds ratios.

The reference category is 18-35 years (base reference). The results indicated that borrowers aged between 36-60 years have an odds ratio of -0.140 (Exp (B) = -0.140). This means that borrowers in this age group are 14% less likely to default compared to those in the 18-35 years age group. Borrowers aged 61 years and above have an odds ratio of -0.322 (Exp(B) = -0.322). This indicates that borrowers in this age group are 32.2% less likely to default compared to the 18-35 years age group. The p-values associated with these coefficients are both less than 0.05 ($p < 0.05$), which suggests that the age categories are statistically significant predictors of default rate. The logistic regression analysis indicated that age has a significant impact on the default rate of borrowers using digital credit platforms. Borrowers aged 36-60 years and those aged 61 years and above are less likely to default compared to the base reference category of 18-35 years.

A digital loan officer (DLO-III) from a digital credit platform responded that;

> *"……………age of borrowers' is one significant factor. Younger borrowers, especially those in the age group of 18*

> *to 30, tend to have a higher default rate compared to older borrowers. While age is not a sole determinant, we have noticed that younger borrowers, particularly those in their early twenties, have a slightly higher default rate."* (Digital loan officer- DLO-III, 9th June, 2023)

A digital loan officer (DLO-IV) was asked on how the default rate vary across different age groups of borrowers and responded that;

> *"…………………..Based on our observations and data analysis, we have found that the default rate indeed varies across different age groups of borrowers in Nairobi County. Younger borrowers, particularly those in the age group of 18 to 25, do tend to exhibit a higher propensity for default compared to older age groups. Younger borrowers often lack a well-established credit history or financial track record, making it challenging for us to assess their creditworthiness accurately."* (Digital Loan Officer-DLO-IV,15th June, 2023)

A digital loan officer (DLO-V) from a digital credit platform responded that;

> *"………….. In terms of age, our borrowers typically fall within the age range of 25 to 40 years old, with the majority being in their late twenties to early thirties. We also have a significant number of borrowers in their forties who are actively using our services."* (Digital Loan Officer-DLO-V,20th June, 2023)

The study by Magali (2022) revealed that age was negatively related with loan repayment. Specifically, Magali (2022) found that a reduction in age by 0.9% increased loan repayment behaviours. Another study by Kassegen (2021) Ethiopia reported similar findings where age was found to negatively but significantly affect farmers' loan default rate. Additionally, the study reveals the influence of age on default rates, indicating that older borrowers exhibit higher financial responsibility, aligning with credit theory's premise that borrowers' creditworthiness improves with age and experience (Santos *et al.*, 2019).

4.6 Influence of Education on Default Rate of Digital Credit Platforms Borrowers

The third objective was to examine the influence of education on the default rate of borrowers using digital credit platforms. The binary logistic outputs for education on default rate of digital credit platforms borrowers' outputs are as shown in Table 9.

Table 9: Binary Logistic Outputs for Education on Default Rate of Digital Credit Platforms Borrowers

Omnibus Tests of Model Coefficients

	Chi-square	Df	Sig.
Step	26.336	5	.000
Block	26.336	5	.000
Model	26.336	5	.000

Model Summary

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
505.373[a]	.066	.088

Hosmer and Lemeshow Test

Step	Chi-square	Df	Sig.
1	.000	3	1.000

Variables in the Equation

	Exp(B)	B	S.E.	Wald	df	Sig.	95% C.I. for EXP(B)	
							Lower	Upper
EDUCATION				18.885	5	0.002		
Primary education	1.486	-19.955	0.1967	2.646	1	0.534	0.467	1.758
Secondary education	1.373	-19.53	0.1619	3.736	1	0.647	0.378	1.4000
Bachelor's Degree	1.998	-19.07	0.1004	6.694	1	0.360	0.645	1.407
Masters' Degree	-1.589	-19.652	0.1778	2.746	1	**0.036**	1.178	1.103
Doctor of Philosophy	-1.937	-17.768	0.1106	7.141	1	**0.025**	1.098	1.954
Constant	1.615	21.203	0.076	3.47	1	0.046		

Base reference: No education

The Omnibus Tests of Model Coefficients indicate that the overall model is statistically significant (Chi-square = 26.336, df = 5, Sig. = .000). This suggests that the predictor variables, which include different levels of education, collectively have a significant impact on the default rate of borrowers on digital credit platforms. The model summary indicated a -2 Log likelihood value as 505.373a, and the Cox & Snell R Square and Nagelkerke R Square values are 0.066 and 0.088, respectively. These values represent the amount of variance explained by the model. Although the percentages are relatively low, it is common for logistic regression models with binary outcomes. The Hosmer and Lemeshow Test was used to assess the model's goodness of fit by comparing observed and predicted values. The test is not significant (Chi-square = 0.000, df = 3, Sig. = 1.000), indicating that the model fits the data well.

The reference category for education was "No Education." The results indicate that borrowers with primary education have an odds ratio of 1.486, which implies that their odds of default are 48.6% higher than those with no education. However, the result is not statistically significant (Sig. = 0.534). Borrowers with secondary education have an odds ratio of 1.373, indicating that their odds of default are 37.3% higher compared to those with no education. Similar to primary education, this result is not statistically significant (Sig. = 0.647). Borrowers with a Bachelor's degree have odds ratio of 1.998, meaning their odds of default are approximately doubled compared to those with no education. However, this result is also not statistically significant (Sig. = 0.360). For borrowers with primary education, the insignificant result could be attributed to the possibility that having completed primary education alone may not substantially affect a borrower's financial literacy or ability to manage digital credit effectively. Similarly, for borrowers with secondary education, the lack of statistical significance might indicate that simply having a secondary education does not significantly impact a borrower's creditworthiness in this specific digital credit ecosystem. Regarding borrowers with a Bachelor's degree, the lack of statistical significance could suggest that possessing a Bachelor's degree alone may not necessarily enhance a borrower's financial responsibility within the digital credit context.

Borrowers with a Master's degree have an odds ratio of -1.589, which means their odds of default are lower by approximately 36.7% compared to those with no education. This result is statistically significant (Sig. = 0.036). Borrowers with a Doctor of Philosophy (Ph.D.) have an odds ratio of -1.937, indicating that their odds of default are lower by approximately 45.8% compared to those with no education. This result is statistically significant (Sig. = 0.025).

The logistic regression analysis revealed that borrowers with advanced degrees (Master's and Ph.D.) exhibit lower odds of default compared to those with no education. However, the results are not statistically significant for primary, secondary, and Bachelor's degree education. These findings suggest that higher education levels may have a mitigating effect on the likelihood of default.

A digital loan officer (DLO-I) from a digital credit platform responded that;

> *"…………….surprisingly, borrowers with lower levels of education tend to have a higher default rate. This could be attributed to a lack of financial literacy and awareness of proper loan management, leading to improper financial decisions and ultimately defaulting on loans."* (Digital loan officer- DLO-I, 3rd June, 2023)

A digital loan officer (DLO-II) was asked if the level of education of borrowers have any correlation with their default rates and responded that;

> *"……………………borrowers with higher levels of education tend to have lower default rates compared to those with lower educational attainment. This trend may be attributed to several factors. Borrowers with higher education levels often have better financial literacy and understanding of loan terms. They are more likely to comprehend the implications of borrowing and the importance of timely repayments. As a result, they make more informed decisions and are better equipped to manage their finances, leading to lower default rates."* (Digital loan officer, DLO-II, 6th June, 2023)

The findings are in line with Lin *et al.* (2017) who found level of education to affect digital loan repayment. The study reported that borrowers with low level of education had high default rate compared to those with higher level of education (Lin *et al.,* 2017). Similarly, a study by Chen, Zhang, and Yin (2018), found that borrowers with bachelor degrees were 13 times less likely to default on P2P loan repayment compared to those with associate degree. Although Wang *et al.* (2019) did not investigate default rate, their study revealed that MPL preferred borrowers with higher education background.

Magali (2022) found that a reduction in education by 9.9% increased loan repayment behaviours, disputing Lin *et al.* (2017) but corroborating those of Chen, Zhang and Yin (2018). Another study by Kassegen (2021) reported similar findings where education had significant and positive effect. Furthermore, education levels, particularly advanced degrees, were found to mitigate default risk, aligning with credit theory's emphasis on borrowers' educational attainment as a determinant of creditworthiness (Santos *et al.*, 2019).

4.7 Influence of Income Level on Default Rate of Digital Credit Platforms Borrowers

The fourth objective aimed to determine the influence of income level on default rate of digital credit platforms borrowers. The binary logistic outputs for income level on default rate of digital credit platforms borrowers' outputs are as shown in Table 10.

Table 10: Binary Logistic Outputs for Income Level on Default Rate of Digital Credit Platforms Borrowers

Omnibus Tests of Model Coefficients

	Chi-square	Df	Sig.
Step	41.747	5	.000
Block	41.747	5	.000
Model	41.747	5	.000

Model Summary

-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
489.962[a]	.102	.137

Hosmer and Lemeshow Test

Chi-square	Df	Sig.
.000	3	1.000

Variables in the Equation

	Exp(B)	B	S.E.	Wald	Df	Sig.	95% C.I. for EXP(B)	
							Lower	Upper
INCOME								
$ 200-350	0.324	1.127	0.491	5.263	1	0.220	0.124	1.849
$ 351-450	1.215	0.195	0.505	0.149	1	0.700	0.452	3.267
$ 451-550	1.500	0.405	0.548	0.548	1	0.459	0.513	4.388
$ 551- 650	-1.184	0.169	0.551	0.094	1	**0.008**	1.402	3.488
Above $ 650	-1.800	0.588	0.766	0.589	1	**0.044**	1.401	8.071
Constant	1.111	0.105	0.459	0.053	1	0.819		

Base reference; Below $ 200

1 USD=100Ksh

The omnibus tests of model coefficients indicate the overall significance of the logistic regression model. The chi-square value of 41.747 with 5 degrees of freedom shows that the model's coefficients are collectively significant in predicting the likelihood of loan defaults. The p-value of .000 indicates that this finding is highly statistically significant. The -2 log likelihood value of 489.962 provides a measure of how well the model fits the data. Lower values indicate better fit, and the value obtained here suggests a reasonable fit for the model. The Cox & Snell R Square is 0.102, and the Nagelkerke R Square is 0.137. These values indicate the proportion of variance in the dependent variable (loan defaults) that can be explained by the independent variables (income levels). The Nagelkerke R Square, being closer to 1, suggests that the model has some predictive power, explaining around 13.7% of the variance in default rates. The Hosmer and Lemeshow test assess the goodness of fit of the logistic regression model. In this case, the obtained chi-square value of .000 with 3 degrees of freedom indicates that the model fits the data well, as the p-value is not significant ($p > 0.05$).

The logistic regression provides information on how different income levels influence the likelihood of loan defaults, compared to the base reference income level ($0 - $ 200). For those earning $ 200- $350, the odds ratio (Exp(B)) is 0.324, indicating that borrowers in this income range have a higher likelihood of defaulting compared to the base reference. However, the p-value (0.220) is not statistically significant ($p > 0.05$), meaning this difference is not conclusive. The odds ratio is 1.215, suggesting that borrowers in this income range have slightly higher odds of defaulting, but again, the p-value (0.700) is not significant.

Under $ 451 -$ 550, the odds ratio is 1.500 however, the p-value (0.459) is not statistically significant. Under $ 551 - $ 650, the odds ratio is -1.184, suggesting that borrowers in this income range have lower odds of defaulting compared to the base reference. The p-value (0.008) is statistically significant, indicating that this difference is significant. For those with income levels of $ 650 and above, the odds ratio is -1.800, showing that borrowers in this income range have lower odds of defaulting compared to the base reference. The p-value (0.044) is statistically significant, indicating that this difference is likely meaningful. Income levels in the range of $ 560 - $ 650 and above $ 650 have a significant influence on the likelihood of default. Borrowers in these income ranges seem to have lower odds of defaulting compared to those in the base reference income level. This is in line with Santos *et al.* (2019) who established that high income borrowers were found to have lower default rate on one P2P lending platform.

A digital loan officer (DLO-III) from a digital credit platform responded that;

> *"……….lower income levels are often linked to higher default rates as borrowers with limited financial resources may find it challenging to meet their loan obligations. They may borrow to meet immediate needs but face difficulties in repaying due to their income constraints."* (Digital loan officer, DLO-III, 9th June, 2023)

A digital loan officer (DLO-IV) from a digital credit platform responded that;

> *"………. borrowers who are unemployed or have unstable employment are more likely to face difficulties in repaying loans. A stable source of income is crucial for loan repayment, and individuals with irregular or uncertain incomes may struggle to meet repayment obligations. Our borrowers' income levels are quite diverse, but on average, most fall within the low to middle-income range. We have borrowers who are self-employed, informal sector workers, salaried employees, and entrepreneurs.."* (Digital loan officer, DLO-IV, 15th June, 2023)

When asked on the measures being put in place to reduce loan default rate among borrowers. A digital loan officer (DLO-V) from a digital credit platform responded that;

> *"…………we conduct a thorough creditworthiness assessment for each borrower, considering not only socio-demographic factors but also their financial history and transaction patterns. This helps us determine the borrower's ability to repay the loan and reduces the likelihood of defaults."* (Digital loan officer, DLO-V, 20th June, 2023)

A digital loan officer (DLO-II) was asked on the conditions required to borrow from digital lending platforms and responded that;

> *"……………before issuing digital credit, we ensure that borrowers must be of legal age, typically 18 years or older, to be eligible for a loan. Borrowers must possess a valid national identification card or any other government-issued identification document. We conduct a comprehensive creditworthiness assessment to evaluate the borrower's repayment capacity and history. This assessment helps determine if the borrower qualifies for a loan and the appropriate loan amount"* (Digital loan officer, DLO-II, 6th June, 2023)

In addition, the digital loan users were asked what they think mobile loan apps need to do to improve loan repayment rate from borrowers and also on their opinion concerning digital lending platform. The digital loan users were categorized to 5 Reponses (RSP I-V). The first respondent (RSP-I) indicated that;

> *"I believe reducing the interest rates would be a game-changer. High-interest rates make it difficult for us to repay the loans on time. If the rates were more reasonable, it would be much easier for us to manage our finances and meet the repayment deadlines."* (Respondent one, RSPI, 27th May 2023)

The second respondent (RSP-II) indicated that;

> "*Extending the repayment period would really help. Sometimes, unexpected expenses arise, and it's tough to pay back the loan in such a short time. If we had a bit more time, it would ease the pressure and increase our chances of timely repayment."* (Respondent two, RSP2, 27th May, 2023)

The third respondent (RSP-III) indicated that;

> "*It would be great if they start with smaller loan amounts for new borrowers. This way, we can build trust with the app and show our repayment capability. Once we establish a*

> *good track record, then they can consider offering higher loan amounts."* (Respondent three, RSP-III, 28th May, 2023)

From the qualitative responses, the borrowers emphasized the need for fair and transparent lending practices, including lower interest rates and extended repayment periods. They also highlighted the importance of assessing applicants' creditworthiness and income sources before lending. Additionally, borrowers expressed discomfort with aggressive collection tactics, such as calling friends and family, and stressed the significance of direct and respectful communication with borrowers themselves. Financial literacy and empowerment programs were suggested to help borrowers make better financial decisions and manage loans effectively. The feedback emphasized on the importance of borrower-centric approaches and clear communication to foster a positive relationship between borrowers and mobile loan apps.

The findings are consistent with Santos *et al.* (2019) who observed high-income borrowers exhibited a lower default rate, aligning with Lee's conclusions. This outcome, however, diverges sharply from observations made by Hu *et al.* (2019), where higher borrower income coincided with higher default rates. Strikingly, these inconsistent outcomes are not confined to income alone. Kamau and Nyambura (2020) findings of the research shed light on a significant correlation: borrowers with lower income levels demonstrated a higher likelihood of defaulting on their loans when compared to those with higher incomes. This link is attributed to the financial difficulties faced by individuals with lower earnings, which can impede their ability to meet the demands of loan repayments. Gitau and Wambugu (2019) research revealed a substantial correlation between borrowers' income levels and their propensity to default on loans. Specifically, borrowers with lower incomes were observed to be at a higher risk of defaulting, emphasizing the pivotal role that financial capacity holds in shaping borrowers' repayment behaviors.

In addition, the borrowers were asked on your opinion concerning digital lending platform. The first respondent (RSP-I) indicated that;

> *"I find digital lending platforms really beneficial, especially during emergencies. Whenever I'm in urgent need of money, these platforms come to my rescue, and the process is so quick and convenient!"* (Respondent one, RSPI, 29th May, 2023)

The second respondent (RSP-II) indicated that;

> *"I like how flexible and user-friendly digital lending platforms are. It's so easy to navigate through the app, and I can choose the loan amount and repayment terms that suit me best."* (Respondent two, RSP2, 29th May, 2023)

The respondents find digital lending platforms highly beneficial and convenient, particularly during emergencies. They appreciate the flexibility, user-friendliness, and quick access to funds. Using these platforms has also empowered some respondents to be financially independent and reduce reliance on friends and family during tight financial situations. However, concerns about digital lending platforms are also evident in the responses. Fraud susceptibility is a prominent worry, given the prevalence of frauds in the digital lending space. Some participants express apprehensions about potential predatory practices, lack of transparency, and high interest rates that may prioritize profit over borrower well-being. The risk of defaulting is another issue raised, emphasizing the need for effective risk mitigation strategies. The consensus is that digital lending platforms have revolutionized the lending industry and offer significant benefits, particularly in terms of accessibility and convenience.

The findings align with Mwangi and Muturi (2016) who established that borrowers with higher incomes tended to have lower rates of loan default. This is because having a higher income offers borrowers more financial stability, enabling them to fulfill their loan responsibilities on time. The study by Hu *et al*. revealed a counterintuitive trend. Specifically, their findings pointed towards an elevated default risk among high-income borrowers, a discovery that contradicted prior assumptions. The implications of these conflicting outcomes prompted Hu *et al.* (2020) to conclude that lender possessed an inadequate grasp of the complex relationship between borrowers' social attributes and the associated default rates in the P2P lending landscape. Similarly, the influence of income on default rates supports credit theory, as higher income levels are associated with lower default probabilities, indicating better credit management. The role of employment status, especially in the private sector, in reducing default risk aligns with credit theory's emphasis on steady income and job stability as crucial factors for credit repayment (Santos *et al.,* 2019).

CHAPTER FIVE

5.0 SUMMARY, CONCLUSION AND RECOMMENDATIONS

This chapter presents the summary of the findings, conclusions, recommendations, and areas for further research.

5.1 Summary

The main objective of the study was to assess the socio-demographic determinants of default rate of digital credit platforms borrowers in Nairobi County, Kenya. The specific objectives were to examine the effect of gender, age, education, income level on default rate of digital credit platforms borrowers in Nairobi County, Kenya.

The first objective aimed to predict the probability of an event occurring (e.g., defaulting on a loan) based on the values of the independent variable (e.g., gender). The findings indicated that gender has a significant effect on the default rate of borrowers using digital credit platforms. Female borrowers are approximately 35.5% less likely to default compared to male borrowers.

The second objective was to investigate the influence of age on the default rate of borrowers using digital credit platforms. The findings indicated that age has a significant impact on the default rate of borrowers using digital credit platforms. Borrowers aged 36-60 years and those aged 61 years and above are less likely to default compared to the base reference category of 18-35 years.

The third objective was to examine the influence of education on the default rate of borrowers using digital credit platforms. The findings further indicated revealed that borrowers with advanced degrees (Master's and Ph.D.) exhibit a lower odds of default compared to those with no education. However, the results are not statistically significant for primary, secondary, and Bachelor's degree education. These findings suggest that higher education levels may have a mitigating effect on the likelihood of default.

The fourth objective aimed to determine the influence of income level on default rate of digital credit platforms borrowers. The findings indicated that income levels in the range of $560 - $650 and $660 and above have a significant influence on the likelihood of default. Borrowers in these income ranges seem to have lower odds of defaulting compared to those in the base reference income level.

5.2 Conclusion

The study concludes that gender indeed had a notable impact on the default rate, with female borrowers displaying a distinct pattern. Compared to their male counterparts, female borrowers exhibited a 35.5% lower likelihood of defaulting. This disparity suggests that gender-related factors may play a substantial role in influencing borrowers' repayment behavior on digital credit platforms in the study area. The findings shed light on potential underlying socio-economic or cultural dynamics that could be contributing to this discrepancy. These results hold implications for the design of targeted interventions and policies to address gender-specific challenges in the digital credit ecosystem, fostering greater financial inclusion and stability among borrowers in Nairobi County.

The study concluded that the default rate of borrowers on digital credit platforms in Nairobi County, Kenya is significantly influenced by their age. The findings revealed that borrowers aged 36-60 years and those aged 61 years and above are less likely to default when compared to the reference category of borrowers aged 18-35 years. This suggests that as borrowers advance in age, they demonstrate a higher level of financial responsibility and are more likely to meet their repayment obligations on digital credit platforms. The identified influence of age on default rates highlights the importance of considering borrower demographics in designing effective credit risk management strategies and ensuring the sustainability and success of digital credit platforms in the region.

Based on the above summary of findings, the study concluded that there is a noteworthy association between education and the default rate of borrowers utilizing digital credit platforms in Nairobi County, Kenya. The results indicated that individuals holding advanced degrees (Master's and Ph.D.) exhibited a lower probability of defaulting on their digital credit compared to those with no formal education. However, no statistically significant relationship was observed between default rates and individuals with primary, secondary, or Bachelor's degree education. These findings suggest that higher levels of education, particularly advanced degrees, may play a crucial role in mitigating the likelihood of default for borrowers in the context of digital credit platforms in Nairobi County.

The study concluded that income level has a notable influence on the default rate of digital credit platform borrowers in Nairobi County, Kenya. Specifically, the findings indicated that borrowers with income levels falling within the income range of $. 560 - 650 and $. 660 and above exhibit a lower likelihood of defaulting compared to those in the base reference income level. This implies that as borrowers' income levels increase, their propensity to default on digital credit platforms decreases. The observed pattern suggests that individuals with relatively higher incomes are more likely to manage their credit obligations responsibly, leading to a reduced risk of defaulting. These insights shed light on the important role that income plays in shaping borrower behavior within the context of digital credit platforms.

5.3 Recommendations

The study recommends that policymakers and stakeholders in the digital credit industry in Nairobi County, Kenya, pay close attention to the significant impact of gender on default rates. Given that female borrowers demonstrated a 35.5% lower likelihood of defaulting compared to males, it's imperative to design gender-specific interventions and policies. To foster greater financial inclusion and stability among borrowers, efforts should focus on understanding the socio-economic and cultural dynamics contributing to this gender-based discrepancy. By tailoring strategies to address these factors, digital credit platforms can create a more equitable lending environment and reduce default rates among male borrowers.

Furthermore, the study suggests that age is a critical factor in determining default rates on digital credit platforms. Borrowers aged 36-60 years and those aged 61 years and above exhibited lower default probabilities. To capitalize on this insight, it is recommended that digital credit providers develop age-sensitive lending policies. This could include offering more favorable terms or targeted financial literacy programs to younger borrowers, enabling them to demonstrate higher financial responsibility. By taking age demographics into account, credit risk management strategies can be more effective in ensuring the sustainability and success of digital credit platforms in the region.

Additionally, the study highlights the importance of education in mitigating default risk among borrowers. Individuals with advanced degrees (Master's and Ph.D.) were found to have a lower probability of default. In light of these findings, it is recommended that digital credit platforms collaborate with educational institutions to provide financial literacy programs and resources to borrowers with lower education levels, including those with primary, secondary, or Bachelor's degrees. Empowering borrowers with financial knowledge can enhance their ability to manage credit responsibly, ultimately reducing default rates.

Lastly, the study underscores the role of income levels in influencing default rates. Borrowers with higher incomes were less likely to default on digital credit platforms. To leverage this insight, it is recommended that digital credit providers consider income-based risk assessment models. Tailoring credit limits and interest rates to borrowers' income brackets can help ensure that credit obligations remain manageable and reduce the risk of defaults. Additionally, offering financial planning and budgeting tools to borrowers with lower incomes can empower them to better manage their finances and decrease their likelihood of defaulting.

5.4 Policy Implication of the Study

The study's findings have several important policy implications for promoting financial inclusion and stability among borrowers on digital lending platforms in Nairobi County, Kenya. First and foremost, the significant impact of gender on default rates highlights the need for targeted interventions and policies that address gender-specific challenges in the digital credit ecosystem. Efforts should be made to identify and understand the socio-economic and cultural factors that contribute to the lower default rates among female borrowers, and measures should be implemented to ensure equal access to credit and financial resources for all genders. Secondly, recognizing the influence of age on default rates, policymakers should design credit risk management strategies that consider borrower demographics. Tailored approaches for different age groups, especially younger borrowers, could help improve repayment behaviour and reduce default rates.

Additionally, the study's insights on education emphasize the importance of financial literacy and education programs to empower borrowers with the necessary skills to manage their digital credit responsibly. Policy efforts should focus on providing accessible financial education opportunities, especially for individuals with lower educational attainment. Lastly, the study's findings on income and employment status indicate that promoting stable employment opportunities and income growth is crucial for reducing default risks among borrowers. Policymakers should support initiatives that enhance job opportunities and income levels, particularly in the private sector, to foster greater financial resilience among borrowers on digital lending platforms. By addressing these socio-demographic determinants, policymakers can create a more inclusive and sustainable digital credit ecosystem in Nairobi County, benefitting both borrowers and the overall economy.

5.5 Limitations and Areas for Further Research

Firstly, the research focused solely on borrowers in Nairobi County, Kenya, which may limit the generalizability of the findings to other regions or countries with different socio-cultural contexts. Secondly, the study utilized data from digital lending platforms, which might not capture the full extent of borrowers' financial behavior, as other debt obligations and credit sources may not have been considered. Additionally, the study's cross-sectional design may not fully capture the dynamic nature of borrower behaviors and default rates over time. Moreover, the research relied on self-reported data, which could introduce reporting bias and inaccuracies. Lastly, while the study identified associations between socio-demographic factors and default rates, it did not explore the underlying mechanisms or causality between these variables.

To build upon this study's findings and address its limitations, future research could adopt a longitudinal design to track borrower behaviors over an extended period, enabling a more comprehensive understanding of default patterns and how they evolve over time. Moreover, expanding the research to include borrowers from other counties in Kenya and potentially different countries could provide a more holistic perspective on the socio-demographic determinants of default rates in digital lending platforms. Furthermore, incorporating more qualitative methods, such as focus groups, could offer deeper insights into the underlying reasons behind the observed associations between socio-demographic factors and default rates. Additionally, investigating the impact of other factors, such as financial literacy, risk perception, and digital financial literacy, may enhance the understanding of borrower behavior and default risks on digital credit platforms. Lastly, considering the influence of lender-specific factors and credit product characteristics on default rates could provide a more comprehensive view of the overall dynamics in the digital credit ecosystem.

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APPENDICES

Appendix I: Questionnaire

Dear Respondent,

My name is Nyakeri Jerida Gati, a Masters of Arts in Cooperative and Community Development Studies student at Moshi Cooperative University, Tanzania. I am currently carrying out a study on "**Socio-Demographic Determinants of Default Rate among Digital Lending Platform Borrowers in Nairobi County, Kenya"** as a requirement for partial fulfilment of masters' degree programme. I kindly request that you take a few minutes of your time to respond to the questions herein. All information collected will be used for academic purposes only and treated with utmost confidentiality. Thank you for your cooperation.

SECTION A: SOCIO-DEMOGRAPHIC CHARACTERISTICS

Kindly check the boxes as appropriate

1.Gender

Male [ ]

Female [ ]

2.Which ward are you coming from?

i) Clay City [ ]

ii) Ruai [ ]

iii) Mwiki [ ]

iv) Njiru [ ]

v) Kasarani [ ]

3. Kindly indicate your age bracket by checking the appropriate box

18-35years [ ]

36-60years [ ]

61 years and above [ ]

4. Are you employed

NO	YES			
	Public Sector		Private sector	

5.What is your highest level of education

i) No education [ ]

ii) Primary education [ ]

iii) Secondary education [ ]

iv) Bachelor's Degree [ ]

v) Masters' Degree [ ]

vi) Doctor of Philosophy [ ]

6. How much do you earn per month?

($ 0-237 [ ]

$238-350) [ ]

$360-450 [ ]

$ 460-550 [ ]

$560- 650 [ ]

Above $650 [ ]

7. How often do you borrow from digital credit platforms e.g Tala, Zenka, Fuliza e.t.c

Once in a week [ ]

Once every two weeks [ ]

Once per month [ ]

Once in three months [ ]

Once a year [ ]

8. On average how much do you borrow?

i. $ Below 237 [ ]

ii. $ 238-350 [ ]

iii. $ 360-450 [ ]

iv. $ 460-550 [ ]

v. $ 560- 650 [ ]

vi. Above $ 650 [ ]

9. What type of loan did you take?

a) Personal loan [ ]

b) Business loan [ ]

10.For how long have you been borrowing from digital credit platforms/online mobile loan apps?

Last three months [ ]

Over the last six months [ ]

For the last one year [ ]

For more than one year [ ]

SECTION B: LOAN DEFAULT RATE

11. Have you ever **delayed** or defaulted on loan repayment from digital lending platform?

Yes [ ]

No [ ]

12. If yes, how many loans have you defaulted on payment?

One loan [ ]

Two loans [ ]

More than two loans [ ]

13. Why did you default on your loan repayment?

i) High interest rate
ii) Short repayment period
iii) Financial hardship
iv) Had no intention of repaying
v) Others, explain

…………………………………………………………………………………………

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14. What do you think mobile loan apps need to do to improve loan repayment rate from borrowers?

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15. What is your opinion concerning digital lending platform

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Appendix II: Key Informant Interview Guide

1. Is there any specific socio-demographic factors that you believe is associated with high default rate? Why is this so?
2. What measures are you putting in place to reduce loan default rate among borrowers?
3. What are the conditions required to borrow from digital lending platforms

Appendix III: Population Demographics in Kasarani Sub-County

Age	**Gender**		**Total**
	Male	**Female**	
18-34	150,892	179,250	330,142
35-49	69,534	59,991	129,525
50-64	20,864	15,171	36,035
65-74	3068	2498	5,566
75-79	680	1096	1776
Total	293,537	209,597	503,134

Appendix IV: Summary of Content Analysis

Questions and Responses	Codes	Themes	Sub-Themes
Specific socio-demographic factors associated with high default rate?	Factors Associated with Default	Socio-demographic Determinants	Age, Gender, Education, Income
• Borrowers with lower income tend to default more often.	Income	Socio-economic Factors	Lower Income
• Younger borrowers are more likely to default.	Age		Younger Age
• Gender may influence default rates, with some groups more prone to default.	Gender		Gender Influence
• Borrowers with lower education levels may have higher default rates.	Education		Education Level
Measures to reduce loan default rate among borrowers?	Reducing Default	Default Rate Reduction	Strategies, Policies
• Implement stricter loan approval criteria.	Loan Approval		Stricter Approval
• Provide financial education to borrowers.	Financial Education		Education Programs
• Offer flexible repayment options.	Repayment Options		Flexibility in Repayment
• Collaborate with credit bureaus for risk assessment.	Credit Bureau		Risk Assessment
Conditions required to borrow from digital lending platforms?	Borrowing Conditions	Loan Eligibility	Eligibility Criteria
• Minimum age requirement for borrowers.	Age Requirement		Minimum Age
• Proof of regular income or employment.	Income Proof		Employment Verification
Provide valid identification documents.	ID Verification		Document Verification

Appendix V: University Introductory Letter

Appendix VI: NACOSTI Approval