DIGITAL CREDIT REVOLUTION AND CUSTOMER OVER-INDEBTEDNESS IN THE INFORMAL ECONOMY IN NAIROBI KENYA

KIPLAGAT K. VICTOR

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DECLARATION

This PhD thesis is my original work. It has not been previously, in its entirety or in part, been presented to any other University for the purpose of award of any degree.

Signed: Date: **30th November 2023**

KIPLAGAT K. VICTOR

Reg. No. D80/99587/2015

APPROVAL BY SUPERVISORS

This PhD thesis has been submitted to the University with our approval as the University supervisors.

Signed: Date: **30th November 2023**

Prof. Kate Litondo

Associate Professor

Department of Management Science and Project Planning

Faculty of Business and Management Sciences

University of Nairobi

Signed: Date: **30th November 2023**

Prof. XN Iraki

Associate Professor

Department of Management Science and Project Planning

Faculty of Business and Management Sciences

University of Nairobi

DEDICATION

I dedicate this PhD thesis to my mother Betty Kiplagat for supporting me through my entire journey in life. Her raising me in a godly way and ensuring I got everything I needed when I couldn't stand on my own, made the whole difference in whom I am today. Her many prayers have seen me this far. As a single parent, she struggled through thick and thin to put food on the table and to see me go through school seamlessly. For all I am today, I owe it all to her and God.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS AND ACRONYMS

ATM – Automated Teller Machine

CAK – Communication Authority of Kenya

CBK – Central Bank of Kenya

CRB – Credit Reference Bureaus

DFS – Digital Financial Services

DIT – Diffusion of Innovation Theory

FDIC – Federal Deposit Insurance Corporation

FDIP - Financial and Digital Inclusion Project

FinTech – Financial Technology

FSD – Financial Service Deepening

FY – Financial Year

GDP – Gross Domestic Product

HF – Housing Finance

ICT – Information Communication Technology

IEA – Institute of Economic Affairs

IT – Information Technology

IS – Information Systems

KCB – Kenya Commercial Bank

KNBS – Kenya National Bureaus of Statistics

MLE – Maximum Likelihood Estimation

NFC – Near Field Communication

OLS – Ordinary Least Squares

POS – Point of Sale Terminal

PPS – Probability Proportional to Size

SACCO – Savings and Credit Cooperatives

SME – Small and Micro Enterprises

TAM – Technology Adoption Model

TRA – Theory of Reasoned Action

UTAUT – Unified Theory of Acceptance and Use of Technology

OPERATIONAL DEFINITION OF KEY TERMS

Digital Credit Revolution – It is the rapid growth of the digital credit providers (lenders) through a process of remotely credit scoring a borrower and availing quick loans through a mobile money platform.

Customer Over-Indebtness – It is a situation where a customer borrows more loans than they can repay. Their household income is not enough to enable them settle all their loan obligations within the required time.

Customer Characteristics – These are personal descriptive traits, behavior that are commonly included in a customer profile.

Regulatory Controls – These are the laws that control the digital lending industry.

Culture – This is the customer's behavior, beliefs and orientation. This research looks at customer's culture towards digital credit and the adoption of technology in the access of credit services.

Informal Economy – Also popularly known as the *Jua Kali* Sector of the economy in Kenya. It comprises mainly of small-scale traders (both professionals and non-professionals) who are often not licensed and operate outside of the realm of the regulated entities.

ABSTRACT

The researcher set out to evaluate the relationship between digital credit revolution and customer over-indebtedness within the informal economy in Nairobi Kenya. From literature, it is evident that Kenya is witnessing a rapid expansion of short-term digital lenders (credit revolution) mainly driven by a segment of youthful users. This proliferation has led to many people borrowing more loans than they can repay (over-indebted). Guided by literature, the researcher identified five main constructs to be studied, mapped out a conceptual framework and identified the key hypotheses to be tested. The study used survey research design. Stratified sampling was used to obtain the 389 respondents who were digital loan users in the informal sector. Pearson correlation coefficient was used to determine the correlations of variables while Binary Logit Analysis Model, Linear Probability Model and Linear Regression Model were used in the hypothesis testing. Wald test and the F-test statistic were used to determine the significance of each construct. Data analysis was done using SPSS version 25. The findings solidified the propositions of the three theories that were relied on in the study: Diffusion of Innovation Theory (DIT), Theory of Reasoned Action (TRA) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These theories were key in researcher's understanding of respondents technology adoption behaviors, modelling key constructs of the study, showcasing the degree of respondent's perceived risk and identifying the most relevant determinants to be tested within each construct. The study findings showed that the respondents did not bother about the costs or the repercussions of excessive borrowing but ease of access and convenience were the main drivers on their usage. This was consistent with the postulates of the UTAUT theory. The correlation analysis showed that respondents who had taken digital loans in the recent past (within 30 days), those who did not have bank accounts, and those who confirmed to have taken digital loans just because it was accessible, all had positive and significant correlation to over-indebtedness. Those who feared getting into debt and are risk averse, had significant and negative correlation to customer over indebtedness. Academic qualification, family status and average monthly income all had positive significant correlation to customer over-indebtedness. In all the four hypotheses of the study, the null hypotheses were rejected. The research findings confirmed that there was significant effect of digital credit revolution on customer over-indebtedness. Customer characteristics and regulatory controls came out as strong control variables that significantly altered the predictive nature of the models when introduced hence these control variables needed to be held constant for more accurate results. Using both test models, all the five determinants of digital credit revolution were significant on predicting customer over-indebtedness but only one factor remained significant once the control variables were introduced. Culture was used as an instrumental variable. From regulatory perspective, the researcher concluded that there was need to re-look the role of regulation in curbing customer over-indebtedness. The study findings showed that most over-indebted respondents had good understanding of the digital loans landscape, understood the laws regulating lending and knew the consequences of defaulting. Most borrowed just because the loans were available. The researcher concluded that introducing punitive terms and even charging high interest rates could not deter this population from borrowing excessively. Training programs on prudent financial behavior and financial empowerment would help. The findings can be used by policy makers, key among them the managers of the newly launched Hustler Fund in Kenya and the office of the Data Commissioner. Since hustler fund targets the same population of this study, the findings contribute significantly to the body of knowledge required by the drafters. For the digital credit providers who are struggling with huge default rates, this research found out that the respondents who confirmed to have access to flexible repayment terms had significant negative correlation to over indebtedness - this could be one of the major strategies that the struggling lenders could use to increase their repayment rates.

CHAPTER ONE: INTRODUCTION

1.1 Background of the Study

Technology has significantly changed every aspect of life and business in the last 10 years; enabling economies to leapfrog decades of traditional industrial development (Singh, 2018). The global economic recession and the financial crisis of 2008 that led to joblessness, also triggered a substantial growth of global household indebtedness, increased competition in financial markets resulting to a lot of innovations and inventions to solve financial problems (D'Alessio & Lezzi, 2010). Digital transformation trends are shaping the banking processes, revamping the operating models, and driving usage of internet and mobile channels (Kaffenberger, Erduardo & Soursourian, 2018). The business world today has increased the use of cashless money and every institution is moving towards a cashless economy (Financial Service Deepening (FSD) Report, 2018). New technologies like blockchain are shaping the new digital products being released in the word and this does not exclude the cryptocurrencies such as bitcoin and Ethereum, though Africa is still lagging behind in terms of adaptability of the block chain technology. See Appendix 3.

With the enabling technology, the world has witnessed the rapid expansion of short-term digital lenders mainly driven by a segment of youthful users who often are not bothered by the pricing of these loans (Kaffenberger et al., 2018). This proliferation has led to many getting over-indebted. Schicks (2011) defines indebtedness as the accumulation of debts by a customer to a level that they cannot sustain its repayment. According to a study done by FSD in 2016, they found out that the majority of those who were taking digital loans were the youthful generation, proving that there was a significant relationship between customer characteristic and over-indebtedness (Persson, 2010). The absence of regulatory controls in Kenya too could have propelled the massive rush by the mobile application lenders to register the companies and operate in the market (Kombe & Wafula, 2015). As indicated by Biscaye, Callaway, Greenaway, Lunchick-Seymour and McDonald (2017), culture which is also defined as the customer behavior, believes and attitudes is an important factor to having a successful digital transformation and was important to establish in the study, what has been its role in the digital credit revolution that has been witnessed.

The digital credit revolution currently being witnessed in Kenya has a strong theoretical foundation that is discussed in detail in the next chapter. The access to digital credit and the actual use of funds depends on; varied individual decisions, the trust on the product, customer mobile savviness and the quality of the service provided (Kaffenberger et al., 2018). Southey (2011) summarizes the aspects in the three theories that anchored the study herein. These are Theory of Reasoned Action (TRA), Diffusion of Innovations Theory (DIT) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These theories were used to provide a frame of reference that provided a front for the study concept. TRA is used in this study since it takes into consideration a premise that customers are rational and can reflect upon the possible outcomes of their decisions before actioning on a particular idea. DIT has been used since the research sought to determine whether the variables under the study are the critical factors in the adoption of digital credit as a new technology. UTAUT focused on the adoption and use of technology in business entities across several areas of operations. It synthesizes eight other models that focus on technology acceptance and use, which came in handy in this research. All the three theories provided a very strong theoretic foundation to this study.

In Kenya, digital credit revolution can be traced back to the launch of M-Shwari in 2012, a product of Commercial Bank of Africa and M-Pesa, which offers a savings product on the phone and gives access to the mobile loans. Three leading banks in Kenya (Equity Bank, Kenya Commercial Bank (KCB) and Co-operative Bank) then followed suite. According to a KCB Investor Report of 2019, the amounts disbursed have been rising with KCB disbursing over Kshs 212 billion in Financial Year 2019. It was then followed by a wave of many non-bank institutions and fintechs that are doing lending business through the phone. Almost all banks and micro-finance institutions then followed suite including traditional foreign banks like Barclays Bank of Kenya, Standard Chartered and Ecobank (Totolo, 2018). It is estimated by year 2019, there were over 150 mobile lenders in Kenya offering digital credit with banks being the leading lenders such as KCB Mpesa, Mshwari, Tala, Branch, Okolea, Timiza, and HF Whizz. This is even after Central Bank of Kenya (CBK) introduced the regulations to limit the new registrations in 2021.

With the readily available loans flooding the Kenyan market, majority of the youth, especially those within informal economy have successfully borrowed or attempted to access these loans. Nairobi has the largest concentration of the informal economy operators in Kenya and that is why the research choose it as the context and the scope of the study. At first, this phenomenon projected a strong case on financial inclusion and easy access to capital, but with time it mutated to a nightmare with many struggling to pay back the very expensive loans leading to cases of over-indebtedness. According to the 2017 report by the Institute for Economic Affairs (IEA), youth between 18 and 35 years comprised over 60% of those working in the informal economy and accounted for over 83% of employment in Kenya. The researcher had hypothesized that this could be the group that is worst affected by customer over-indebtedness. Late repayment of digital loans is widespread, with FSD (2018) showing that up to 47% of digital borrowers in Kenya, majority of them in informal sector, reported repaying their loans late ending up being listed in the credit reference bureaus (CRBs).

1.1.1. Digital Credit Revolution

Kaffenberger et al., (2018) define digital credit revolution as the rapid expansion of short-term digital lenders in a market mainly driven by a segment of youthful active users who often are not bothered by the pricing of these loans. Digital transformation has democratized digital credit application making it instant, automated, and easily accessed remotely within a short time for both low and middle-income earners (FSD, 2018). Bigger populations in the informal economy including women, the rural poor and persons with disability that traditionally were excluded in the financial system have now gotten a chance due to the widespread of mobile money accounts. The growing number of digital credit providers, which was one of the constructs under this study, is now providing them easy access to digital credit. Digital credit has facilitated financial inclusion for the unbanked and the under banked. It has solved perennial problems where a lot of documentation was needed by banks before one is given a loan, requirements of collateral that may not be available to the poor, slow response to credit requests, inadequate product design, and a lot of inconveniences of traveling to the branch and the risk of carrying cash.

The digital credit has countered all the risks of handling cash by making everything available to clients via the phone. It has demonstrated financial access by offering credit even to the invisible clients who may not meet the bank requirements for a loan (Forest & Rose, 2015). Digital credit is different from the normal loan since it is instant, taking few seconds for one to get the money. It is automated in the sense that the borrowers' credit worthiness is analyzed using the data picked from the phone or information available online, money received through mobile money transfer. The entire process is remote and the interaction between the borrower and the lender is on a digital platform and they do not need to know one another (Biscaye, et al., 2017). The innovations around the robust risk analytical tools and robust credit scoring engines have made it easy for real time analysis of customer's credit worthiness. The financial technology companies (fintechs) are enabling a lot of borrowings on digital platforms though they are faced with a lot of challenges of low repayments and defaults, lack of transparency to the consumer, lack of proper monitoring tools and the potential consumer protection legal challenges. These key challenges formed the basis of operationalizing this construct.

With the digital inclusion, a lot still needs to be done to get the real economic and social impact of digital revolution reach the users (Totolo, 2018). Access to financial solutions is a bridge out of poverty for both banked and unbanked population. The introduction of Information Technology (IT) systems in the banking sector has facilitated revolution that has seen many banks grow their customer base. These systems cumulatively referred to as digital financial services (DFS), provide a range of services to the consumers delivered through the digital platforms like mobile phones, the internet, chip-enabled devices, tablets, and the electrically enabled cards (Abbasi & Weigand 2017).

Fintechs are leading in the development of new technology that is revolutionizing the way customers access and use financial services. Financial players including banks and telecommunication companies have transformed their strategies by mirroring consumer behavior. As a result, there has been a roll out of bank led digital financial products by the leading banks in Kenya, including M-Shwari by NCBA Bank, KCB-Mpesa by KCB Bank, Equity's Eazzy, M-Coop Cash by Cooperative Bank and HF Whizz by HFC Bank. The next phase of digitization has been the proliferation of digital lenders offering loans through the mobile phone, mainly apps. Overall, it is estimated that there are over 100 mobile apps in Kenya offering consumer and small business loans, and this is set to grow as consumers continue to adopt faster, more convenient, and increasingly efficient ways of borrowing (Francis, Blumenstock & Robinison 2017). Many of these mobile loan apps have been created mainly due to increasing demand and the huge mobile phone penetration in Kenya and shown by the Communication Authority of Kenya (CAK) Annual Report, 2017. While it is convenient for the customer, mobile lending resulted into to high default rates for the banks and other financial providers due high risks associated with it (AFI, 2017). With these growing number of loan providers, the researcher intended to establish whether there is a correlation to the increasing over-indebtedness and CRB listings that are on the rise.

1.1.2: Customer Over-Indebtedness

Schicks (2011) defines indebtedness as the accumulation of debts by a customer to a level that they cannot sustain its repayment. According to a report by FSD in 2018, 35% of digital borrowers were found to have borrowed from several digital loan providers. As much as digital credit revolution has increased the financial inclusion, it has also come with risks to both the consumer and the provider. Customers reported shame from harassment from the loan provider and well being listed on Credit Reference Bureaus (CRBs). Some reported being insulted, profiled and loosing their belongings to the lenders (Totolo, 2018).

A study conducted on household indebtedness by D'Alessio and Lezzi (2010) notes that financial indebtedness is a result of poor financial decisions, lack of transparency on the terms and conditions, borrower's inability to manage one's finance and often low or lack of financial literacy. Digital transformation also come with challenges which may include changing technologies and change in customer expectation towards the products and services provided to them (Dasho, Meka, Sharko and Baholli, 2016). Digital credit is characterized by automated loan decisions and processing of the loan through mobile phones. With automation, customers have found themselves borrowing more than they can repay hence the researcher operationalized this variable by finding out the number of loans the respondents have, how frequently they accessed these loans and whether they repaid on time.

Often, small loans are short term and more expensive compared to normal loans; and customer relations, repayment and loan collections are managed remotely (Hwang & Tellez 2016). This transformation has come with threats to customers including the risk-based pricing, lack of transparency, poor information disclosure on the interest rates, high charges and other hidden fees which are not clearly communicated on time to the clients (Njoroge, 2017). Many digital loan consumers have been faced with loan defaulting challenges due to unclear terms and lack of transparency on the part of the lender on interest rates and repayment periods (Kaffenberger et al., 2018). The researcher also tried to establish whether these challenges have contributed to over-indebtedness.

Mobile banking and mobile wallet are experiencing high rate of growth especially in Kenya which is good for both financial institutions and their clients. The financial institutions are growing their number and their profits while the consumers have been facilitated with financial inclusion. To ensure that these technological advancements become a blessing and not a curse in the long run, measures need to be put in place to ensure digital and the fintech loans that are enabled by these technologies are well controlled. The vices on consumer data exposure and harassment should be mitigated while ensuring that customers also do not get over-indebted.

1.1.3 Customer Characteristics

Customer characteristic is defined as the customer's demographics and personal characteristics that guide or stimulate the motivation of a consumer to act in a specific manner (Persson, 2010). Kenya is leading worldwide in the growth and usage of mobile money due to the robust M-Pesa infrastructure that has supported mobile payments. The researcher did confirm that there are specific character traits of Kenyans that makes them stand out in these sectors including the presence of large youthful population that is mobile-savvy.

According to a study done by FSD in 2016, they found out that there is a significant effect of individual socio-economic, personal, and behavioral characteristics on digital credit behavior. They explored the effect of a range of factors on the probability that mobile phone owners use digital credit. Their model predicted that there is a 29.1 percent probability (referred to as the base probability) that a mobile phone owner uses digital credit in Kenya. They also compared adults with some level of tertiary education versus individuals that have at most completed primary education; they found out that the primary level individuals are 14.6 percent less likely to use digital credit. As a comparison to these previous findings, the researcher operationalized these variables in this study by testing education levels, age, mobile savviness as well as family status and identifying their effect on the main constructs of the study.

In this research, the researcher attempts to establish and identify the main characteristics of the respondents and check whether the presence of those characteristics has a control for effect (needs to be held constant) on main relationship between digital credit revolution and customer over-indebtedness and the relationship between culture and digital credit revolution.

1.1.4 Culture

Culture can be defined as the customer behavior, beliefs, and attitudes (Kaffenberger et al., 2018). Due to consumers behavioral change, every business must think of how to conveniently serve the customers with their changing needs and preferences. This includes how financial institutions interact with customers every day to avoid being edged out competitively by fintechs who leverage on technology to offer quick and convenient financial services to their customers. Biscaye et al., (2017) indicate that culture is an important factor to having a successful digital transformation. Any organization that changes their technologies, processes and structures but does not address the human element will not have a lasting change. It is paramount for business leaders to focus on culture even as they lay long-term strategies for the sustainability of the business (Gefen, 2017).

In this research, the five key indicators of culture (consumer trust, financial discipline, risk taking tendencies, guilt conscience and the consumer beliefs and attitudes) were the focus as guided by the Hofstede and Hofstede (2005) and elaborately discussed in Chapter 2. These determinants are consumer trust on the digital credit platforms to maintain high levels of data confidentiality. Gefen

(2017) describes trust as the confidence a person has on something based on previous experiences and interactions. The research results showed that trust construct was statistically significant and influenced positively the adoption and use of mobile banking services in Malaysia. Concerning financial discipline as a culture, this can be defined as living and spending within your means and the prudent management of cash flow while risk taking culture addresses a consumer's belief that ignores the potential negative outcomes from the use of digital credit.

In this study, the researcher attempted to find out the relationship between the culture of financial indiscipline and customer over-indebtedness which has been discussed elaborately in chapter 5. On consumers belief and attitudes, researcher established that different countries/ societies have different values and traditions. This could explain why international firms like Tala and Branch did not start their mobile lending businesses from any other part of the world but in Kenya.

1.1.5. Regulatory Controls

Regulation can be defined as the set of laws governing a country or an entity (Claessens & Suarez, 2010). Governments across the world use instruments of law to govern how citizens of that country interact and relate to one another.

Digital credit involves access of funds through digital channels and poses a special risk of customers being exploited, elements of fraud, identity theft, predatory lending, and lack of price transparency. Some micro-finance institutions and fintechs that have recently come up are literally exploiting unsuspecting customers. Though new laws regulating the digital credit services offered by these institutions in Kenya have been enacted in 2021, most customers within the population of this study are not aware of these regulations and many lenders though unregistered formally with CBK, continue to operate. To operationalize this variable in the study, the researcher attempted to establish whether the absence of and/or lack of strict compliance of these regulations, has contributed to customer over-indebtedness. Kombe and Wafula (2015) concluded that huge presence of digital lenders coupled with many desperate borrowers had led to the potentially dangerous exploitation of those who are genuinely in need and this requires strict enforcement of the regulation governing digital credit provision to avoid more harm.

Article 46 of Kenyan Constitution (2010) gives provisions on protection of customer rights in Kenya. It explicitly states that the consumer has a right to quality products and services, safety, reasonable interest rates, entitled to the protection of their health and to access to all relevant information in regards to specific goods and services. However, from the research findings, these aspects have not been fully enforced through the relevant Acts of Parliament. The researcher attempted to answer the question whether the absence of and/ or lack of strict compliance to the regulatory laws could have contributed/ had an effect on the digital credit revolution currently witnessed and the resultant customer over-indebtedness.

1.1.6. The Informal Economy in Nairobi, Kenya

Informal Economy is widely known as the *Jua Kali* Sector in Kenya. *Jua Kali* simply means hot sun. World Bank Report (2016) lists out the players within the informal economy as follows: *Boda boda* riders, traders of shoes and clothes (both second-hand and new); traders of cereals and groceries; food kiosks; water kiosks owners; small retailers; small manufacturing and production of home supplies. These players are mainly concentrated in cities with Nairobi carrying the largest population. Refer to Appendix 10 on the graphical representation of the informal economy operators.

The informal economy plays a very key developmental role in Kenya. Institute for Economic Affairs (IEA) Report (2017) indicated that this sector accounted for over 83% of employment in Kenya. The operators of the informal economy (owners of these enterprises) are mainly in the urban areas, that is why the researcher picked the largest city in Kenya, the Nairobi, to analyze the phenomenon under the study. IEA Report also showed that over 60% of the operators working in this sector are the youth between ages of 18 to 35 years. This group needs day-to-day or short-term capital to run their enterprises and often do not have the collateral required by the mainstream long-term lenders hence become an easy target for the digital lenders who are quick to issue loans within minutes and without collateral. Unfortunately, these easily accessible loans (including those offered by the banks and registered micro finance institutions) come with high costs and long-term ramifications including over-indebtedness and loan defaults leading to being blacklisted on CRB and denied future access to loans.

In 2022, Kenyan government rolled out *hustler fund* aimed at enabling the informal economy players to access cheap loans as capital for their businesses. Research will need to be done in future to establish the sustainability of the fund, whether the fund did indeed meet the needs of the informal sector players and whether the fund led to reduction of customer over-indebtedness earlier witnessed in the population of study.

1.2 Research Problem

The Kenya's Vision 2030 emphasizes financial inclusion as a major pillar in the development of the economy by opening the access of financial services to the unbanked population (Kenya Vision 2030, 2007). Advancements in the financial technology have made it easier for clients to access loans through the phone leading to the digital credit revolution being witnessed (Ryan, Trumbull & Tufano, 2010). More than 100 million loan transactions are done annually in Kenya using the mobile phones (FSD, 2018). Technology has created many avenues for borrowers to easily access credit, the resultant over-indebtedness and the widespread CRB listing is where the main problem lies, with this research attempting to solve this new challenge. Late repayment of digital loans is widespread, with FSD (2018) showing that up to 47% of digital borrowers in Kenya, especially those in the informal sector, reported repaying their loans late ending up being listed in the credit reference bureaus (CRBs) and subsequently being cut off from accessing credit for the next 7 years.

Most of the borrowers listed on the CRB are from the informal sector, and once negatively listed, it will limit their future access to other loans. The Kenyan informal sector is large, employing over 83% of all the working citizens, with 60% of that group being within the youth bracket (Institute for Economic Affairs Report, 2017). The demand for quick loans as a source of capital for the informal economy operators is high (World Bank Report, 2016). With limited options on the source of capital, due to lack of credit collaterals, most of them end up borrowing the highly priced loans from the digital lenders. Although research has been done within this context of the informal economy, the researcher discovered that there still existed some gaps.

The study by Omwansa and Waema (2014) on the impact of pure mobile micro-financing on the poor was a case study of a single microfinance institution in Kenya and did not focus on customer over-indebtedness as a critical variable. The research by Totolo (2018) on the digital credit market demand in Kenya focused on the mobile borrowers and the use of borrowed funds, but did not focus on the informal economy, the data was collected from the public across the country using a representative phone survey while this study used structured interviews. The study by Litondo (2018) on the Mpesa usage and the prices of products in the informal sector did not investigate whether the sources of funds were loans from digital credit providers and it's context were not on digital credit . The research by Hwang and Tellez (2016) on the digital credit deployments in Malaysia included the elements of customer over-indebtedness, however, the other variables in the study were different and did not focus on informal economy.

Methodologically, no similar study had used more than one model on the same data like it has been used in this study. A study carried out in Brazil by Santos, Danilo and Braun (2018) on the poor household's access to informal loans, used only multinomial logit while this study used both binary logit model and linear probability model and had the ability to compare findings from the two models. The use of two models in this study provided a perfect reconfirmation of the findings and to find out if the results are consistent. The study focused on financial literacy as the main characteristic of the respondents while this research focused on customer characteristics (demographics). Another study by Dasho et al., (2016) analyzed the digital credit revolution across the world but missed to focus on the customer over-indebtedness as a key construct. On the study by Schicks (2011) on the indebtedness of micro-borrowers in Ghana, the researcher used regulatory controls as one of its variables and concluded that lack of regulation played a key role in the indebtedness of the respondents. This research used regulations as a control variable and was done in the Kenyan informal economy. Erumban and De Jong (2006) have done more than ten researches on the effect of culture in the adoption of technology in more than 40 countries across the world but none of their studies used culture as an instrumental variable.

Despite the great benefits of financial inclusion that the digital credit is bringing to the unbanked and underbanked within the informal economy, there still exist bigger threats, for example, over-indebtedness and price exploitations (Hwang & Tellez, 2016). Coincidentally, mobile lenders providing quick loans even in the mainstream banks are readily available with Safaricom's overdraft facility called 'Fuliza' recording over Kshs 27 billion in disbursements per month in 2019 (Safaricom, 2019). KCB bank increased their total loans disbursed through the phone five-fold from Kshs 54 billion in FY 2018/19 to Kshs 212 billion in FY 2019/20 (KCB Investor Report, 2019). The sharp rises in the volumes of loans were similar for the fintechs especially pre-COVID 19 pandemic.

This research aimed therefore to answer the following research question: Does digital credit revolution within the informal economy in Nairobi Kenya have an effect on customer over-indebtedness?

1.3 Research Objectives

The general objective of this research was to evaluate the relationship between digital credit revolution and customer over-indebtedness within the informal economy in Nairobi Kenya. The specific objectives were:

i. To determine the relationship between digital credit revolution and customer over-indebtness within the informal economy in Nairobi Kenya.
ii. To establish whether customer characteristics and regulatory controls have a control for effect on customer over-indebtedness within the informal economy in Nairobi Kenya.
iii. To determine the effect of culture on digital credit revolution within the informal economy in Nairobi Kenya.
iv. To establish whether customer characteristics and regulatory controls have a control for effect on digital credit revolution within the informal economy in Nairobi Kenya.

1.4 Value of the Study

The study provide recommendations that would be of additional knowledge to the digital credit regulators and the policy makers in Kenya. Due to the rapid growth of digital credit in Kenya, the patterns and its impacts especially on the informal economy have not been researched extensively. The findings are therefore important to policy makers in the country including Central Bank of Kenya and other policy makers. The study recommends key policy issues that will need to be taken into consideration in the policy formulation.

Any organization that wants to grow within an economy must have a good understanding of that economy and the potential challenges they could face. With respect to this, the concepts of digital credit revolution have brought about great opportunities and threats to the informal economy. Financial institutions need to know the negative implications of their trade so that they can curb it and ensure their sustainability. It is only after thorough understanding that they would be able to serve the informal economy and be of better use in their businesses.

Digital credit users within the informal sector also benefit from this research. It is an eye opener for most users who heavily consume the digital loans without thinking of consequences on their use of data, the amounts lost through punitive interest rates and high likelihood of being listed in CRBs due to loan defaults. The findings will also help them better understand the existing in terms of consumer protection, price transparency, customer data privacy and the right to recourse and redress whenever there is a complaint. The findings from this research would be key to any user who would want to avoid over-indebtedness.

1.5. Organization of the Thesis

This thesis has been organised into six chapters. The researcher has used easy and understandable language for all readers. The researcher has made it possible to follow the arguments in a simple manner.

Chapter one has introduced the topic and laid a background to the key concepts of the study. It has elaborately defined the key concepts, relating it to other researches done. It has also elaborated the research problem, the study objectives and the main significance of the study.

Chapter two reviews literature, looking at the key underpinnings from the theoretical and empirical review. The theories provide the explanation on why things are done the way they are done. It is out of the literature review that the researcher developed the conceptual framework and outlined the four key hypotheses of the study.

Chapter three lays out the research methodology and how data was collected. It looks at the population of the study and its sampling frame, the philosophy and the design. It also looked at how data were collected, analysed, and how the variables were operationalised.

Chapter four stipulates the results and the findings of the study. Findings are elaborately explained using descriptive statistics. Coding of the responses to a quantitative measurement were also explained at this chapter

Chapter five handles hypothesis testing and discussion of the findings. Each hypothesis was tested separately and the findings discussed in a manner that made it easy for the reader to follow the arguments

Chapter 6 laid out the conclusions and recommendations of the study. The researcher concluded this research based on the findings of the study. The hypotheses and objectives were linked to the findings. The researcher then made recommendations on how this research study can be utilized by industry stakeholders, highlighted the contributions to knowledge and practise, its limitations and recommended areas of further research.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

The chapter provides an analysis of the theories that guided this study. The chapter gives a literature review, investigates previous research carried out in relation to the constructs to be studied and gives a basis for the conceptual framework. It also gives a summary of theoretical and empirical findings from the previous studies and the gaps from those studies. Finally, this chapter provides the conceptual framework and conceptual hypothesis for the four hypotheses that were tested.

2.2 Theoretical Foundation

This section presents a theoretical framework that guided this research. The theories included: Diffusion of Innovation Theory (DIT), Theory of Reasoned Action (TRA), and the Unified Theory of Acceptance and Use of Technology (UTAUT). These three theories were used to provide a frame of reference for the study.

2.2.1 The Theory of Reasoned Action

The theory of reasoned action (TRA) is a theory of behavior that was largely developed to predict specific behaviors and was first introduced in 1967 by Martin Fishbein, and was extended by Fishbein and Icek Ajzen in 1980 (Ajzen & Fishbein, 1980). This theory makes it easy to understand individual’s normative beliefs and attitude since the model predicts the behavior. It explains why people take certain actions and not others. Financial decisions, just like any other decisions are crucial to the concerned individual. With theory of reasoned action, attitudes and beliefs are given great attention as it predicts how an individual will end up behaving.

Many researchers and financial institutions have used this theory to evaluate the attitude and the motivation of their customers towards their products and hence help them craft products and experiences that would meet their expectations. The model emphasizes on the decisions as guided by the individual’s beliefs, intentions, motivation and the actual behavior (Southey, 2011). The model is supported and anchored by earlier research done Ajzen and Fishbein (1980), in the fields of technology adoption. The theory also facilitated the development of technology acceptance model (TAM), which has been used by many scholars (Jeffrey, 2015).

The Theory of Reasoned Action is key in understanding users' technology adoption behaviors as it deals more with the prediction, adoption, implementation, and acceptance of technology. The researcher leveraged on the TRA's strength in technological innovation. This theory had a better foundation in studying adoption and spread of technology. It assisted the researcher to model key issues especially on culture as an instrumental variable and to predict acceptability and use of the digital credit technology.

2.2.2 The Diffusion of Innovation Theory

Diffusion of Innovation Theory (DIT) is a theory first introduced by an American communication theorist and sociologist, Everett Rogers, in 1962 and aims to explain how and why an innovation, service, or product spreads (Rogers E., 2003). The theory of diffusion of innovation provides ways and procedures involved in the adoption of new technology and how it is used to benefit an institution and its clients. The theory identifies the critical success factor in the adoption of new technology such as triability, complexity, relative advantage, compatibility, and observability. Monyoncho (2015) indicates the degree to which new technologies are seen to be giving a lot of benefits to the users than the system that is currently running in each organization, represents relative advantage. This system is assumed to increase efficiency, reduce cost and improves once status during operation. With this advantage in the mind of the client, then adoption of such a system becomes easier.

Compatibility is the extent to which the new system fits well to the available hardware devices and provides services that are consistent with the client's values, beliefs, habits, and experiences. Observability is the extent to which the new technology can be viewed by the social system and its benefit seen by the user, while triability is where the system can be tried and tested before its adopted for other services (Monyoncho, 2015). In this study, diffusion of innovation theory has been used to show how adoption of a new technological idea like the adoption of digital loans does not happen simultaneously across the population but rather is a process where a smaller portion of the population are early adopters as others follow progressively. It has been used specifically to understand the digital credit revolution as an independent variable and to give a background to understanding the early adoption and the diffusion of the innovation into the rest of the population.

2.2.3 Unified Theory of Acceptance and Use of Technology

This theory was first introduced in 2003 by Venkatesh, Morris, Davis and Davis; and focuses on the acceptance and the actual use of technology in certain areas of operation in a given business entity (Venkatesh, Morris, Davis & Davis, 2003). It synthesizes eight other models that focus on its acceptance and its use. This theory describes the performance expectance, social influence, effort expectance, and facilitating conditions that directly influence the uptake of technology in banking sectors (Mutlu & Der, 2017).

Performance expectancy (PE): It is the degree at which the adopted technology improves one's job performance or is believed to have a positive contribution to the performance. A positive attitude towards the newly adopted technology, drives improvement of performance (Mutlu & Der, 2017). In this study, the researcher concentrated on the derived usefulness of digital credit access, its intrinsic and extrinsic motivation to increased loan borrowing among the informal economy and its impact on the consumers (Attuquayefio & Addo, 2014).

Effort expectance: This is the easiness of using the technology. A user-friendly technology will be easy when it comes to using it and many users will be motivated to use it (Mutlu & Der, 2017). The research looked at the complexity in relation to the effort the user puts in the process of accessing the loan (Attuquayefio & Addo, 2014).

Social influence: It is the level at which the users perceive the benefits from the said system (Mutlu & Der, 2017). The researcher established the disruptions and opportunities of the digital revolution as perceived by the respondents within the informal economy (Attuquayefio & Addo, 2014).

Facilitating condition: The environment at which the technology is going to be used plays a key role in supporting innovations that are going to accelerate growth (Mutlu & Der, 2017). The perceived easiness, compatibility of the lenders' platforms and the mobile phones network accessibility, influenced the speed of adoption of digital credit (Attuquayefio & Addo, 2014).

This theory was relevant in this research as it showcased the role of user's involvement in the decision-making process and focused is focused on the reflection of the perceived risk of using digital credit. This model helped the researcher map out the most relevant factors within each construct that influence the use of digital credit as a new technology. The research by Attuquayefio and Addo (2014) showed in their findings the factors that influence the use of mobile services technology based on ease of use as modeled in UTAUT theory.

2.3 Empirical Review

All the constructs in the study have been researched on and key postulates brought out, which assisted the researchers in identifying key factors and indicators under each construct. Looking into the key construct, the digital credit revolution as a terminology was first used in 2008, during the global economic depression (Biscaye et al., 2017). Accoridng to Kaffenberger et al., (2018) digital credit revolution is a scenario where there is a rapid expansion of short-term digital lenders in a market mainly driven by a segment of youthful active users. The coming of mobile phones, the mobile money technology and the great developments within the financial technology space has seen many banks reach many people in the remote parts of the country where the normal bank coverage would not reach. The financial technology innovations have enabled the non-bank players and fintechs to equally offer credit to customers with ease. This has seen the percentage of digital and mobile loan users in Kenya rise above 60% (Kaffenberger et al., 2018). With ease of access to loans, the borrowers have continued to increase their usage and, in some cases, getting over-indebted.

Digital credit revolution has enabled the marginalized communities, the poor, those in remote areas, the unemployed and the under-banked and unbanked population to access both formal and informal loans (Biscaye et al., 2017). Through the use of the USSD technology, customers can now access credit services even with the feature phones. The financial technology has brought about financial inclusivity. This has exposed many non-bank financial institutions to new customers who would want to transact at their comfort of their homes due to technological revolution. According to Musau, Muathe and Mwangi (2018), financial inclusivity has enabled users to have access to bank accounts, enabling them access their credit cards, using their mobile phones to access loans, paybills and perform many other payment transactions.

With many financial service providers offering these services, the developing nations are witnessing the greatest innovations (Musau et al., 2018). Several innovations have emerged that has made it very easy for financial institutions to now targets the informal and the under-banked communities. AFI (2017) shows that this great proliferation of digital lenders, their speedy processing of the loans and the ready access by all and sundry has characterized the digital credit revolution studied in this research. It should also be noted that as financial institutions embrace technology, so are their clients.

The clients want simple user-friendly technology that can serve their interest comfortably (Njoroge, 2017). According to the report that was given by the Kenya's Central Bank (CBK) governor on 15th May 2018, Kenya still has a lot of challenges on financial inclusion although the access to financial services had improved from 26% in 2006 to 75.3% in 2016.

Several awards have been given to Kenyan banking sector for high achievements in financial inclusivity. This includes Tufts University in America that ranked Kenya fourth best country to embrace financial inclusion in its 2017 Report. This is tremendous for Kenyan banking sector. It shows a positive relationship between the digital credit revolution and financial inclusivity. This however does not go without challenge. Kenya is lagging on some other aspects of financial inclusion, participatory usage and quality and a lot of consumer complaints on the services provided (Njoroge, 2017)**.** Many lenders though promoting the financial inclusion agenda, their practices on predatory lending (charging exorbitant interest rates), data privacy breaches and unchecked customer over-indebtedness especially amongst the low-income earners in the informal sector needs to be checked and regulated.

2.3.1 The Digital Credit Revolution and Customer Over-Indebtedness

In his study (Schicks, 2011), over-indebtedness is caused by lack of financial debt literacy, taking loans from more than one lender, difficulty in assembling the cash for loan repayment and lack of proper planning on loan repayment. FDIC (2007) argues that a well-informed borrower cannot be a victim to predatory lending and are more likely to make informed choices during borrowing. Therefore, before money is released to the clients, then it is necessary for the lender to carry out a literacy program. According to a survey done by FSD in 2018, many Kenyans have taken loans that they cannot be able to repay and some are even borrowing for trivial reasons like for betting purposes.

Globally, customer over-indebtedness is characterized by economic dimension basing on the amount of debt that one is to pay, the medium to long term horizon, and the social dimension characterized by the psychological stress caused by the indebtedness (D'Alessio & Lezzi 2010). Today in developed countries, consumers are getting unsecured loans by relying on technology to register, score, approve and distribute funds to borrowers' digital gadgets (Biscaye et al., 2017).

Schicks (2011) in a study conducted in Ghana on indebtedness of micro borrowers found that many borrowers are making a lot of sacrifices when paying for the borrowed loans. The borrowers however are not protected from any form of embarrassment and mistreatment, and they must make the sacrifice of paying to avoid this. When payments are challenging, the customers tend to adopt other strategies like working extra hard, foregoing some important expenses, avoiding saving and these approaches are not sufficient for any form of loan commitment. The study by Persson (2010), concludes that proper legislation should also be put in place to protect the customers from greedy lenders and to protect the lender form defaulters and financial loss.

In the study by FSD (2018), late repayment of digital loans is widespread, with findings showing that up to 47% of digital borrowers in Kenya reported having repaid their loans late. This has been worsened by the increased availability of fintechs, and bank led digital lenders who are readily available and willing to lend without collateral or checking on the debt portfolio of the borrower (Musau et al., 2018). Since this study mainly focused on the low-income earners in the informal sector, the researcher was determined to find out if this percentage on defaulters was higher or lower and the reasons thereof. To add to the existing knowledge on the effect of digital credit revolution on customer over-indebtedness, the researcher hypothesized that:

Hypothesis: There is no significant relationship between digital credit revolution and customer over-indebtedness

2.3.2 Culture and the Digital Credit Revolution

It should be noted that culture in this study was used as an instrumental variable. Instrumental variable is the third variable in relationships and is used to account for the unexpected relationship between two variables. It does not affect the dependent variable directly, but it does it through the independent variable. This has been widely used in related studies including the study by Litondo (2010) where availability of electricity was used as an instrumental variable in analyzing the usage of mobile phones to improve firm performance. Another example of an instrumental variable would be in a case where you have access to employment directly affecting poverty reduction in a country; a variable like technical skills would be instrumental.

In their study (Kaffenberger et al., 2018), culture can be defined as the behavior, believes and attitudes learned from the society by those born into that society and in which one becomes embedded. Culture plays an important role in the successful digital transformation and the adoption of any technology across the world (Biscaye et al., 2017). In information systems (IS) research, Hofstede's model has been widely used and is popular among many researchers. Hofstede (2005) defines culture as the collective orientation of the societal norms and values that distinguishes one social group from another. Hofstede proposed four key dimensions to the national culture to include individualism or societal collectivism, gender orientation, power distance and uncertainty avoidance. Individualism is what has come to be known as Type I while collectivism is known as Type 2.

In this study, the researcher looked at five main indicators of culture as an instrumental variable (earlier defined in chapter 1). These are consumers trust on the service provider, self-financial discipline, guilt conscience on unpaid loans, risk taking tendencies and the attitude towards debt. The research by Hofstede and Hofstede (2005), on aspect of individualism indicated that there was a higher innovation factor with individuals who had high risk-taking attitudes. They were trailblazers in technology adoption but scored low on conforming to societal norm (general financial discipline). This means that Type II culture that is based on imitation has higher levels of trust built by witnessing others use the technology. The exploratory nature in Type 1 especially on digital credit has led many to not fear to get into debt and the associated troubles that it brings. In Kenya, the success of M-Pesa can be attributed to several factors but one of the main ones is the culture of Kenyans (Musau et al., 2018). This has a close relationship to the collectivism advanced by Hofstede and Hofstede (2005) in their study. In this study, culture is instrumental in understanding how and why the digital credit revolution has been a big success in Kenya. To add to the existing knowledge on role of culture on digital credit revolution, the researcher hypothesized that:

Hypothesis: There is no significant effect of culture on digital credit revolution

2.3.2 Customer Characteristics as a Control Variable

Customer characteristic is used as a control variable in this study. Control variables are often made to remain constant during research by randomizing individuals. When correctly randomized, each respondent has the same chance to be in each condition, making sure that no other factors are responsible for the results. For example, in this study, a customer characteristic like age had a significant effect on individual risk capacity which then led to massive accumulation of debt to a point of being over-indebted. If this had not been factored in the study, the outcome of interest in the main relationship would have been altered leading to wrong conclusions, hence the need to look at the variance in the outcome that could be explained by the phenomenon causing that difference.

Customer characteristic is defined as the customer's demographics and personal characteristics that guide or stimulate the motivation of a consumer to act in a specific manner (Totolo, 2018). Research done by Hwang and Tellez (2016), concluded that customer behavior towards the use and the adoption of technology depends on some selected demographic characteristics. Customer personal/ demographic characteristics such as gender, age, educational qualification, and ethnicity are explored and are regarded to be important when understanding technology adoption behavior as well as the behavior of technology users. AFI (2017) from their research concluded that customers continued intention to use internet banking in Egypt was strongly influenced by perceived ease-of-use. They further found out that the customer demographic characteristics did not have a significant effect on adoption of mobile and internet banking services. This differs from the conclusions by IN (2017) who found a significant positive relationship between customer demographics of level of education, gender, income, age, and occupation to the customer adoption of internet banking services.

Monyoncho (2015) showed in his literature review that there was a strong influence of customer demographics on technology adoption. He concluded that age is a strong factor with young people more likely to adopt technology than the old people. He also found out that education levels played a significant role in regards to the attitude toward technology use and adoption. Highly educated users such as university graduates are more likely to use technology than the non-graduates. These findings concur with Litondo (2010) where age and education level had a significant effect on adoption and usage of technology in the informal sector in Kenya.

A study carried out in Brazil by Santos et al., (2018) which differed with the researcher's findings in this study, concluded that low financial literacy increases the probability of individuals using informal loans. These individuals are usually unaware of alternatives and pushed by the urgency of getting the funds would then make them pick any lender leading to cases of financial indebtedness. Methodologically, the study by Santos et al., (2018) used multinomial logit while this study used binary logit model to investigate the effect of customer characteristics as a control variable among the informal economy players in Kenya.

In carrying out this research and to establish the control for effect of customer characteristics on this study, the researcher hypothesized that:

Hypothesis: Customer characteristics have no significant control for effect on digital credit revolution and customer over-indebtedness.

2.3.3 Regulatory Controls as a Control Variable

Regulatory controls have similarly been used as a control variable in this study. The covariates within this variable must be held constant during research so as to correctly establish the effect of the main independent variables on the dependent variable. Claessens and Suarez (2010) define regulation as the use of laws or instruments of the law to compel persons to behave in a prescribed manner failure to which they attract punishments. Schicks (2011) argues that a well-informed borrower cannot be a victim of predatory lending and are more likely to make informed choices during borrowing.

Absence of or lack of enforcement of regulatory controls therefore acts as a recipe for customer exploitation. Financial and non-financial institutions that give loans that violate the consumer protection act; violating data privacy of the clients and without clear terms and conditions needs to be punished (FDIC, 2007). Lack of sound laws violates the saving rule, harms individual's integrity, risks communities' wealth and complicates life and should be checked by having relevant laws in place. In Kenya, individuals and organizations are fighting for compliance to enhance credibility and protection but with the fast growth of the digital lenders, it has become hard for the Central Bank, which is the control body to manage it (D'Alessio & Lezzi 2010).

According to a report by FDIC in 2007, the only way to deal with predatory lending is through having a proper procedure and supervisory actions, encouraging banks or financial institutions to serve all members and areas within their reach equally and fairly. This will limit new market entrants. The financial literacy trainings and education to enlighten the consumers on their rights and their obligations too is important. The study by Persson (2010), concluded that proper legislation should also be put in place to protect the borrower from exploitation by the lenders and to protect the lender from defaulters and financial loss.

In this study, the researcher endeavored to find out whether regulatory controls have an effect on the relationships within the study. The researcher hypothesized that:

Hypothesis: Regulatory controls have no significant control for effect on digital credit revolution and customer over-indebtedness.

2.4 Summary of Knowledge Gaps

Table 2. 2: ***Summary of Knowledge Gaps***

Authors	**Focus**	**Methodology**	**Findings**	**Knowledge Gap**	**Gaps filled by this Research**
Totolo (2018)	The assessment of digital credit market demand, 5 years on.	This research was based on a phone survey with over 3150 Kenyans drawn from all regions of the country.	The findings emphasized the importance of monitoring the transparency and enhancing consumer protection in the digital credit marketplace. This is due to many unregulated players, who are not bound by any law or regulatory authority in their dealings. It recommended the use of tools to track over-indebtness and multiple borrowing. Many reports also showed borrowers dipping into their savings. Bureaus should also improve on data submission and listing.	The study focused more on the demand and not on customer over-indebtedness. It didn't even look at the aspects of culture and the customer demographics.	This research was conducted on the lower end of the economy (informal economy). Effect of customer characteristics and culture was measured and a relationship was established on how it had influenced the digital credit revolution. How to deal with the cases of customer over-indebtedness were also recommended.

Authors	Focus	Methodology	Findings	Knowledge Gap	Gaps filled by this Research
Musau, Muathe and Mwangi (2018)	Financial Inclusion, Bank Competitiveness and Credit Risk of Commercial Banks in Kenya	This research employed both quantitative and qualitative research designs with all the commercial banks in Kenya	The research concluded that most of the banks had adopted mobile banking in Kenya by integrating with Mpesa therefore boosting the financial inclusion agenda. Almost all commercial banks now allow their customers to make deposits directly to their accounts and access mobile loans from their phones.	The research didn't focus on digital credit as a tool for financial inclusion and neither focused on customer over-indebtedness	This research focused on the digital credit revolution and its impacts on over-indebtedness. Filled the gap on the effect of financial inclusion brought about by digital credit. Effect of customer over-indebtedness on digital credit users was also studied in detail. The study also found out that respondents who had bank accounts also had low chances of becoming over-indebted.

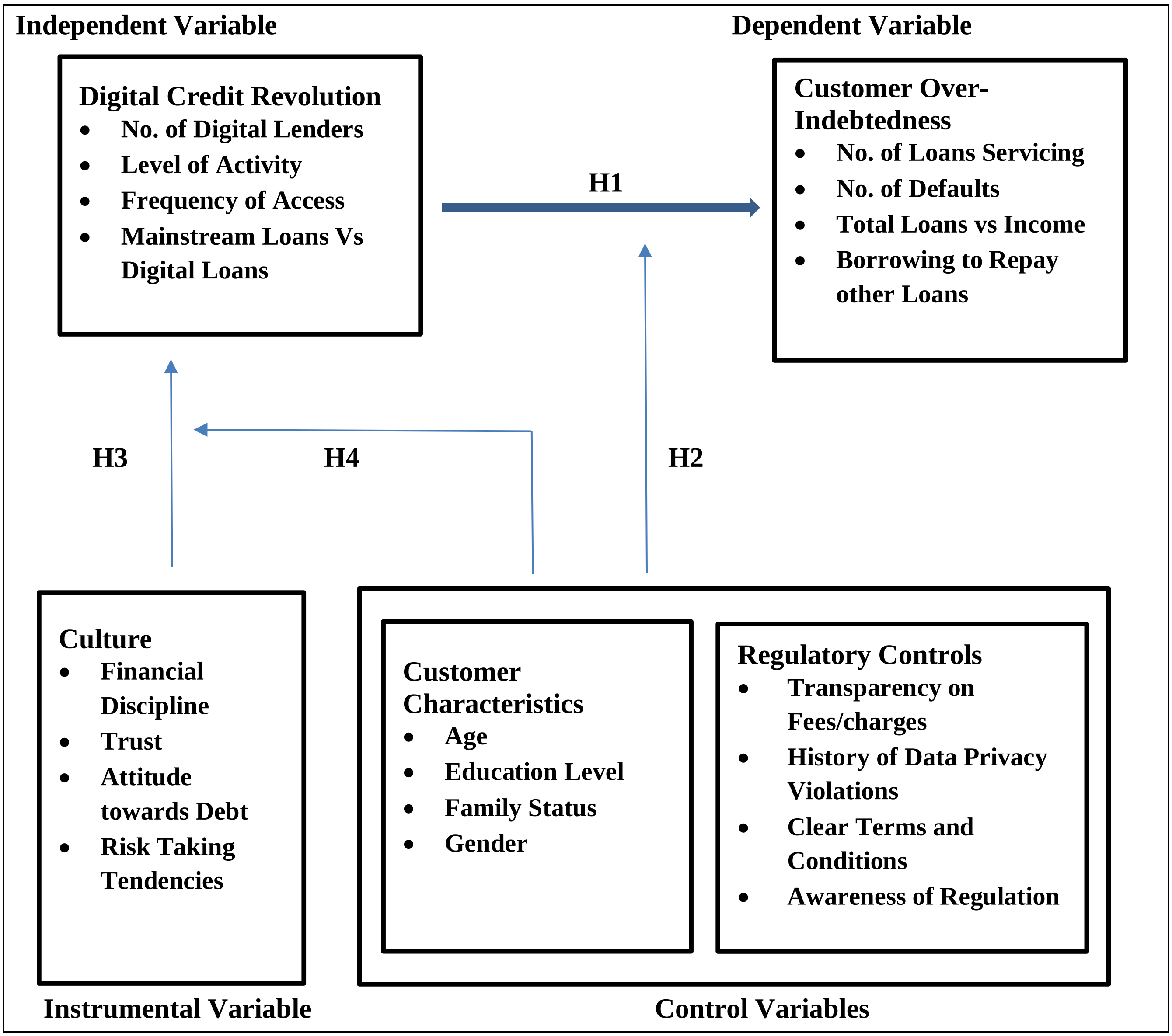
Authors	Focus	Methodology	Findings	Knowledge Gap	Gaps filled by this Research
Abbasi and Weigand (2017)	The Impact of Digital Financial Services on Firm's Performance	The research conducted an extensive literature review.	The study focused on reviewing the existing literature. They looked at the impact of digital financial services on firm's performance and came up with seven research gaps, which can be developed, into research areas. Its only 39 articles out of 100, which were investigated, which had relevant content on digital financial services. They concluded that despite digital services being very important on firm's performance, it was still not being given proper attention it deserves.	The study was purely on literature review; hence it's not based on actual data collection. There is need to conduct quantitative research on this. It's even worse that the data pertaining to the digital financial services is still limited and not well developed. Technology is very important in the performance of every company and due focus needs to be given.	This research was based on primary data collected from the target population. This research also focused on digital credit as a digital financial service and how it had impacted customer over-indebtedness within the informal economy. The research also focused on how firms by riding on digital credit technology improved their reach of services and subsequently their performance bu to the detriment of the customer.

Authors	Focus	Methodology	Findings	Knowledge Gap	Gaps filled by this Research
Kaffenberger et al., (2018)	The Digital Credit Insights from Borrowers in Kenya and Tanzania	The research used a phone survey method in collecting data and analyzed using multiple regressions. A sample size of 1,132 was picked in Kenya and 1,037 in Tanzania.	Mobile phone users in Kenya have access to digital loans that have proved to be cheap and faster as compared to other forms of loan. Digital revolution has also led to financial inclusion though with economic and social challenges. The study also suggested that digital credit providers, policy makers, investors and donors should be provided with important information before digital credit access for growth and sustainability.	The research focused on the digital revolution and the role of digital lenders. Nothing was done on the relationship between the digital lending and constructs like customer over-indebtedness.	This research used the quantitative and the qualitative data (interviews). The research analyzed in detail the relationship between digital credit and customer over-indebtedness which had not been analyzed earlier. The scope too was different with this research focusing on the informal economy.

Authors	**Focus**	**Methodology**	**Findings**	**Knowledge Gap**	**Gaps filled by this Research**
Omwansa and Waema (2014)	The Impact of Pure Mobile Micro-financing on the Poor: Kenya's Musoni Experience	The research obtained the quantitative and qualitative data from clients of Musoni Micro Finance in Nairobi. It focused on the impact of mobile micro finance on the poor.	The research found out that mobile money was convenient channel that encouraged customers to transact more safely and conveniently. They recommended that companies should bundle mobile money offerings with their traditional products, which will in turn increase the value and the transactions to the clients.	The research was a case study focused on the pure mobile micro financing on a general level. It did not focus on other individual constructs like culture and customer over-indebtedness. It also focused on the positive side of mobile money	The context of this research was based on the informal sector and not an individual firm (case study). This research also focused on both the positive and the negative side of mobile lending including customer over-indebtedness.

2.5 Conceptual Framework

Figure 2. 1: Conceptual Framework



Source: Author, (2019)

From the conceptual framework, the main relationship in this research, studies the effect of digital credit revolution (independent variable) on customer over-indebtedness (dependent variable). This is based on the literature reviewed and the assumption that the huge proliferation of digital credit providers in Kenya and the easy access to loans has led many people within the informal economy to borrow more loans than they can service hence getting over-indebted.

The conceptual framework also brings out the effect of both customer characteristics and regulatory controls in the study. It has been proven through previous research that customer characteristics and regulatory controls have an effect on technology adoption (Totolo, 2018). That is why the researcher kept these two constructs as control variables in the study. The researcher shows the need to keep them constant while studying the main relationship in the research since the control variables are not variables of interest.

The last assumption from the above conceptual framework is that culture is a determinant for digital credit revolution and is instrumental in determining customer over-indebtedness. From literature review, many scholars have found that culture has a role in technology adoption and how quickly it can spread (covered in chapter 2). In this study, researcher assumes that culture plays an important role in an individual's belief and attitude towards borrowing of a loan hence the need to study it as a construct of interest and establish its effect on the digital credit revolution currently being witnessed.

2.6 Conceptual Hypotheses

The choice of constructs used in the conceptual framework were mainly informed by the review of models and the literature as already covered in sections of chapter 2 above. From the literature, these constructs have been used widely by other researchers in the last 3 decades. The constructs were then converted to be variables defining the specific relationships in the study and researcher derived the factors to be tested in each variable. As guided by literature, the researcher made assumptions in prioritizing the specific factors in each construct. Several factors in each of the variables are technology-driven and new in the area of information systems research.

From the above proposed conceptual framework, the theoretical models and the arguments developed in the entire chapter, hypotheses were then formulated as follows:

H1: There is no significant effect of digital credit revolution on customer over-indebtedness

H2: Customer characteristics and regulatory controls have no significant control for effect on customer over-indebtedness

H3: There is no significant effect of culture on digital credit revolution

H4: Customer characteristics and regulatory controls have no significant control for effect on digital credit revolution.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1 Introduction

Research methodology is concerned with the collection and the analysis of research data. The elements discussed in this section include the research philosophy, research design, data collection, population sampling, sampling technique, reliability test, validity testing and data analysis.

3.2 Research Philosophy

Research philosophy is concerned with the way data is collected, analysed, and used. It guided the researcher in formulating the research beliefs and assumptions. The research philosophy takes different forms: pragmatism (often used for both qualitative and quantitative methods and gained through observation, measurement, and trust), positivism (typically quantitative and deductions strictly from data), realism (even facts have some social influence which can be unearthed by in-depth analysis) and interpretivist dimensions (argue that rich insights of this complex world can be generalised using data, often qualitative and inductive) (Dudovskiy, 2018).

This study adopted positivism philosophy since quantitative methods of data collection were used. Researcher used positivism philosophy because research adhered to factual knowledge gained from the data collected through observation and measurement. The collected data were analysed statistically and findings used to draw the conclusions of the study.

3.3 Research Design

The researcher used the survey research design to establish the effect of digital credit revolution on customer over-indebtedness. The survey research designs give procedures in main research which researchers follow to draft and administer a survey to a population of study. It goes ahead to describe the attitudes, opinions, behaviours, or characteristics of the population. In this procedure, survey researchers can collect quantitative data or qualitative data through interviews (e.g., one-on-one interviews) and statistically analyse the data to test research questions or hypotheses (Palinkas, Horwitz, Green, Wisdom, Duan & Hoagwood, 2016).

Survey research design was used because the researcher was collecting data through interviews following a structured interview questionnaire. Since it was a structured interview, the research was interactively linked to the findings within the context of the research (Creswell, Clark, Gutmann & Hanson, 2003).

3.4 Population of Study

This research looks at the digital credit revolution in Kenya and the population of study are the digital credit users in Nairobi City County. For all the five constructs under study, the unit of analysis is the individual digital credit user. According to a report by FSD in 2018, the digital credit users in the country were approximated to be more than 6.4 million people. It is not possible to collect data from all those users hence the researcher focused on a representative sample. The context of this research was in the informal economy in Nairobi, which is approximated to be 83% of all working class according to the research done by the Institute of Economic affairs in 2017 (IEA Report, 2017).

The researcher collected data from the sampled respondents in Nairobi primarily because it has highest number of the informal sector players, people from all backgrounds and ethnic backgrounds. Nairobi has a proper representation of all people from all parts of the country. It is a centralized point to obtain relevant data hence practicable for the researcher to collect lots of data within the shortest time and with a small budget. Respondents were sampled appropriately to ensure that the researcher got enough and relevant information for analysis.

3.5 Sample Size

Sample size is the miniature picture or the cross-section of the entire population of study. It can further be described as the selection of a small representation of the entire population that is selected for observation and analysis. The sample size was homogenised in nature, independent and a representative of the whole population. The researcher used stratified sampling techniques to identify the actual locations within Nairobi (Pandey & Pandey 2015).

Krejcei and Morgan (1970), developed a formula to calculate a representative sample for a population with more than 10,000 respondents as follows:

$$n_0 = \frac{z^2 pq}{e^2}$$

where, *no* is the sample size, z is the desired confidence level, p is the estimated proportion of an attribute that is present in the population, $q\ p = -1$ and e is the desired level of precision.

In this research, the population is more than 1 million and its size not exactly known. The researcher assumed maximum variability of equal to 50% ($p = 0.5$) and taking 95% confidence level with ±5% precision, the calculation for required sample size shall be:

$$p = 0.5 \text{ and hence } q = 1\text{-}0.5 = 0.5;\ e = 0.05;\ z = 1.96$$

$$\text{So,}\quad n_0 = \frac{(1.96)^2\,(0.5)\,(0.5)}{(0.05)^2} = 384.16 = 384$$

This is also supported by Pandey (2015) who argues that where there are more than 10,000 possible respondents, the ideal sample size would be 384 as per below formula.

$$\text{S ample size}(n) = \frac{(z_{1-\alpha/2})^{2*}\,(p)\,(q)}{(d)^2}$$

$$n = 384$$

Therefore, the sample size for this study was to be a minimum of 384 respondents.

3.6 Sampling Frame

Once the area under study was sampled through stratified sampling, the researcher adopted purposeful sampling to identify the respondents. Purposeful sampling technique is widely used in research because it helps in the identification and selection of information rich cases (Palinkas, et al. 2016). Nairobi has eight administrative divisions according to KNBS (2010), each with several locations. A map of these divisions is provided in the appendix 9.

Table 3. 1: ***Nairobi Administrative Areas***

No.	Division	Locations	Sub Locations	Target Respondents
1	Westlands	9	16	86
2	Kibera	9	12	54
3	Makadara	6	5	30
4	Kasarani	12	14	64
5	Embakasi	11	13	50
6	Pumwani	5	6	30
7	Dagoretti	4	7	36
8	Central	6	6	34
	Total		**79**	**384**

Source: KNBS (2010)

For each of the eight administrative areas, the researcher considered the 79 sub-locations as a stratum. The researcher chose every fifth informal sector player (enterprise owner or employee) within a sub-location. This was continued across the sub-location, until the required numbers of respondents had been obtained. Since not every informal sector player uses mobile loan products, the researcher used the filter question in the interview to ensure that only those who have used this service before get to continue with the interview. The researcher considered the possibility of hostility of unwilling participants, but since the researcher had ample time to complete the data collection exercise, and the widespread of informal economy players in the Nairobi County, it was not a such a great challenge to get the required number of respondents.

3.7 Data Collection Method

This study collected in-depth first-hand information from digital credit users in the informal sector through one-on-one interviews. It was mainly in regard to the access, the level of use, and the motivation in the use of digital credit services and to establish whether it led respondents into over-indebtedness. To carry out such a systematic interview into this specific subject and context, the researcher used structured interview questionnaire.

Structured interview questionnaire is an appropriate tool since the sample population is less than 500 respondents and it is a systematic compilation of questions administered to the strata with the intention of getting in-depth information from them. The researcher also wanted to be interactively linked to the data collection process hence allowing observatory benefits and further probe to the answers provided. The questions were organised systematically in way that it handled all significant topics of this research, answering the objectives and gathering data that the researcher was interested in.

3.8 Pilot Study

This is the first step in any research that is used to ascertain the clarity of questions captured in the interview guide. Piloting helped the researcher to ascertain whether the research can be done or not and to test the quality of questions. It also helped the researcher to test whether a full-scale implementation could be done. It also gave the researcher an opportunity to gauge the respondent's reactions, measure the success of the program and also effective time planning (IMPACT, 2011).

Piloting was undertaken to determine whether the research instrument was adequate to provide the data necessary and relevant to answer the research questions. The study questionnaire was first discussed with the supervisors, where some questions in the questionnaire were dropped while others were adjusted to provide clarity and specificity on the range of answers desired from the questions. The researcher also sampled 10 mobile loan users from the neighboring county of Kiambu (has similar characteristics like those of the Nairobi City County), who helped in checking the clarity of the questions, gauging the respondent's reactions and to establish feasibility of the study in large scale. The researcher thereafter reworded some of the questions to provide a better understanding of the study.

3.9 Instruments Validity

Instrument validity concerns itself with the quality of the data collection instrument. It determines if the research tool measures what is supposed to measure (Golafshani, 2009). Therefore, validity helped the researcher to determine whether the mode of measurement is accurate and measuring the required variable or the theoretical concepts. From content gathered from literature review, instrument validity usually takes different forms including; criterion validity which measure the concurrency and the predictive future of the variables and the construct validity which measure evidence of the relationship of the variables derived from the theories. Construct validity takes different forms including the convergent validity to measure same constructs in different ways, which must give similar results. It also takes the form of discriminant validity that gives different results for concepts that are closely related (Pandey & Pandey 2015).

Validity may also test the face value of the concepts by checking how the items match with one another. It further tests the content validity that regards the sample adequacy of the contents the instrument is measuring which is guided by researcher's judgement. Though face and content validity are judgmental, the criterion of measurement is different. Content validity measures the validity of the left-out items if it is necessary for them to be included in the concept (Pandey & Pandey 2015). Pilot testing was also used as a means of testing for content validity. Therefore, the researcher used both content validity and face validity to test for pre-data while for post data validity, the researcher used criterion and construct validity.

3.10 Reliability of the Research Instruments

Reliability measures the stability of the research instrument across two or more researches. According to Golafshani (2009), accurate representation of the target population and showing of the same result over time is referred to as reliability. This simply means that the researcher needs to ensure that the stability, equivalence and homogeneity remain the same every time the research is done with the same constructs. Cronbachs Alpha was used to measure the stability, equivalence and homogeneity of the items in the study.

The following formula was used:

$$\propto = \left(\frac{k}{k-1}\right)\left(1 - \frac{\sum_{i=1}^{k} \sigma_{yi}^2}{\sigma_x^2}\right)$$

Where:

k- number of items under study; σ_{yi}^2 – the variance amount associated with item i; and σ_x^2- concerns the variance of the total score of items. The α coefficient of research instrument reliability ranges from 0 to 1. If all research items are entirely independent, then α = 0; and, if all of the items have high covariance, then α will approach 1 as the number of research items increase (Goforth, 2015).

The reliability of the research instrument in this study was determined through Cronbach's Alpha. Cronbach's Alpha measured the stability, equivalence and homogeneity of the items under study (Goforth, 2015). Table 4.1 indicates the reliability statistics for digital credit revolution, customer indebtedness, customer characteristics, regulatory controls and culture. Customer over-indebtedness recorded the highest Cronbach's Alpha of 0.843 indicating a good internal consistency. Similarly, all the other four constructs indicated Cronbach's Alpha value of between 0.714 and 0.807 indicating good internal consistency of these measures, based on the questions used to describe the constructs.

Table 4. 1: ***Pilot Test and Reliability Analysis***

Scale	Number of Items	Cronbach's Alpha (α)
Digital Credit Revolution	7	.756
Customer Indebtedness	9	.843
Customer Characteristics	8	.714
Regulatory Controls	8	.807
Culture	7	.786

Source: Researcher, (2022)

3.11 Operationalization of the Key Study Variables

Operationalization is the process of developing operational definitions of terms that are inscribed in the concepts of the research. It is a clear way of defining the specifications of a variable so that it is not misunderstood. It helps the researcher to know exactly which questions to be asked in order to test each specific variable under the study. It also provides ways in which each variable will be measured. The operationalization of each variable is a shown in table 3.2 to table 3.6.

Table 3. 2: ***Operationalization of Digital Credit Revolution Variable (Independent Variable)***

Indicators	Operational definition	Implication	Measurement Scales	Section
Existing loan providers known to the customer	This is the number of digital loan providers the customer knows in Kenya.	The more the loan providers exposed to one customer, the deeper the digital credit revolution	Ratio scale	SECTION B
Last time the customer borrowed mobile loan	This shows how active the customer is, in using the digital credit services	The recent the last activity, the more active the customer, and the more entrenched in digital credit	Ratio scale	
Number of bank loans versus digital loans	This is a comparison on the number of mobile loans that a respondent is currently servicing versus the bank loans	The more the mobile loans compared to bank loans, the more the digital credit revolution	Ratio scale	
Access to financial services before the digital Loans	This is testing if the respondent previously had access to the bank loans	If more can now access digital loans but couldn't access the bank loans, then confirms the presence of digital credit revolution	Ratio scale	
Customers with bank accounts	This finds out the number of customers in the population that have access to bank accounts	The more the respondents without bank accounts but access mobile loans, the more the digital credit revolution and financial inclusion	Ratio scale	

Source: Researcher, 2019

Table 3. 3: ***Operationalization of Customer Over-Indebtedness variable (Dependent Variable)***

Indicators	Operational definition	Implication	Measurement Scales	Section
Number of loans currently servicing	This is the number of loans a respondent is currently servicing	The more the digital loans currently servicing, the more exposed a customer is to over-indebtedness	Ratio scales	SECTION C
Number of loans currently defaulted	This is the number of loans a respondent has defaulted	The more the number of defaulted loans, the more an over-indebted they get	Ratio scales	
Increased uptake of mobile loans after revolution	This is the number of customers whose loan uptake increased after the introduction of digital loans	The more the number, the stronger the link to the customer over-indebtedness	Nominal scales	
Late repayments	This is number of respondents who repaid loans after the loan due dates	The more the number of late repayments, the more the over-indebtedness	Nominal Scales	
Reasons for late repayments	This establishes the other reasons beyond over indebtedness that may cause a customer to default	Over-indebted customer would not have other main reasons for late repayment of loans except that they have borrowed more.	Theme Coding	
Borrowing to repay other loans	This finds out if the respondent borrows to repay other loans	A responsible borrower would not borrow to repay other loans nor for gambling or reasons that would be avoided	Theme Coding	

Source: Researcher, 2019

Table 3. 4: ***Operationalization of Customer Characteristics Variable (Control Variable)***

Indicator	Operational definition	Implication	Measurement scales	Section
Age	This is the age groups of the population	Establish the most over-indebted age group	Ratio Scales	SECTION D
Gender	This is the Male or Female categories	Find out the most over-indebted gender	Nominal Scales	
Education level	This is the education levels of the respondents	Find out if education levels have an impact on customer over-indebtedness	Ratio Scales	
Family status	Married or Single	Establish if family status has an effect on the levels of customer over-indebtedness	Nominal Scales	
Type of phone	Smart or Feature phone	Establish of the type of phone has effect on the access/ exposure to borrowing of more loans	Nominal Scales	
Mobile savviness	It’s the ability to use phone services efficiently	Find out if mobile savvy individuals are more exposed to over indebtedness	Nominal Scales	
Average income bracket	Income brackets in Kshs. (m)	Establish if income brackets affect the level of customer over-indebtedness	Ordinal Scales	

Source: Researcher, 2019

Table 3. 5: ***Operationalization of Absence of regulatory control variable (Control Variable)***

Indicators	Operational definition	Implication	Scales	Section
Customers awareness of the law	Checks customers awareness of the law and the role of the regulator	An informed customer is less likely to be exposed to the greedy lenders and would not be easily indebted	Nominal Scales	SECTION E
Full disclosure and transparency in fees charged	Establish if the customer is fully aware of his right to full disclosure in the fees charged	An aware customer is less likely to be swindled to using over-priced loan products	Nominal Scales	
Violation of Consumer Protection Act	Establish if the customer is aware of their rights to data protection and to know how their data shall be used	An informed customer is less likely to fall prey to misuse of their data	Nominal Scales	
What the customers want introduced in law	Establishes the key recommendations/ legal input from the borrowers	Key words from the respondents were used to enrich the recommendations section.	Theme Coding	
Handling of customer challenges	Checks whether the lenders are customer friendly and if they provide avenues for customers to raise their complains	Thematic areas were coded and analyzed. This was also used to enrich the recommendations to the policy makers	Theme Coding	
Customers reading terms and conditions	Establish if the customers read the terms and conditions and are aware of its effects	A customer who diligently reads terms and conditions would be more informed and less likely misused	Nominal Scales	

Source: Researcher, 2019

Table 3. 6: ***Operationalization of Culture Variable (Instrumental Variable)***

Indicator/ measures	Operational definition	Implication	Scales	SECTION
Consumer beliefs and attitude towards debt	This checks what are the customer beliefs about debt and the attitude towards having debt	Customers who don't fear getting into debt would most likely borrow more loans and be over-indebted.	Nominal scales	SECTION F
Customer financial discipline	Establishes if the customer has financial discipline, borrowing only as a last resort and for production	A customer without financial discipline would most likely borrow recklessly and be over-indebted.		
Guilt conscience on late repayments	Establishes whether a customer would be bothered with guilt conscience especially when they default a loan	A customer with guilt conscience on debt would most likely not be over-indebted		
Consumer trust on the service provider	This is the trust by the customer that the lender would not maliciously share their data and misuse the trust	A customer who easily trusts the lenders with their sensitive data would most likely be over-indebted		
Consumer risk taking tendencies	Establishes whether a customer has risk taking tendencies	A risk taker would most likely borrow more and be over-indebted		

Source: Researcher, 2019

3.12 Data Analysis

Binary Logit Analysis Model also known as Binary Logistic Model was used for the analysis of the answers in the structured interview. The logit model takes the form of:

Logit (Pi) = β0+β1Xi+e

Where, Pi = probability of the event occurring; Xi is the sample group; β0 is the log odds of occurring; β1 shows how the odds differ when (Xi=1) (Berger, 2017).

The estimations were done by use of Wald Test that uses maximum likelihood estimation (MLE). The label predicted in this study were binary, and the output of logistic regression function is supposed to be the probability that the label is extremely towards one or towards zero. Ordinary Least Squares (OLS) was used in the analysis of ratio scales.

The researcher also used Linear Regression Model for the answers that were not dichotomous. Through linear regression, the researcher was able to measure the accuracy of the model, the ANOVA test and to find out the effect of each independent variable on the dependent variable in the form of:

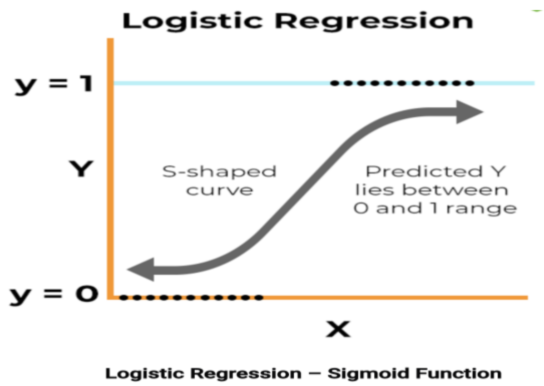
$$y_i = \beta_1 + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} + \varepsilon_i$$

y being the dependent variable while the value of βx is taken to be the z-value of a normal distribution. The higher values of βx mean that the event is more likely to happen. ε_i represents an error value

Binary Logit model and Linear Probability Model, both produced very similar estimates of the probability. The researcher specified the level of probability in both also known as level of significance (alpha p) where ($p < .05$). The acceptable level of significance is 0.05; the level of significance found to be greater than 0.05 implied the null hypothesis was rejected. On the contrary, a level of significance of less than 0.05 implied the researcher fails to reject the null hypothesis.

For the control variables of the study, that is customer characteristics and regulatory controls, the researcher used regression model with b-coefficient explaining the control for effect.

Figure 3. 1: Binary Logit models



Source: Berger, 2017.

Since the interview questionnaire also had open ended questions, the responses were transcribed and coded. The exercise of transcription, generation of thematic framework and data coding was done in preparation for analysis that took a quantitative approach.

Table 3. 7: ***Data Analysis Table***

Hypothesis	**Data Analysis Method**	**Model Estimation**	**Section**
H1: There is no significant relationship between digital credit revolution and customer Indebtness	Binary Logistic Regression model and Linear Probability Model also was used. Wald Test was used for Likelihood Estimations Pearson correlation coefficient (r) was used to determine the correlations	Binary Logit $(P_i)=\beta_0+\beta_1 X_i$ Where; P_i = probability of the event occurring; X_i is the sample group; β_0 is the log odds of occurring; β_1 shows how the odds differ when $(X_i=1)$. Linear probability Model: $P(Y) = \beta_0 + \beta_1 X_1 + \ldots\ldots + \beta_n X_n + \varepsilon$ Where X_1 to X_n are the factors of culture, customer characteristics and regulatory controls as described above while β_1 to β_{6n} are their coefficients respectively. β_0 and ε are regression constants. Pearson coefficient (r) = correlation The Wald Test Model is significant at $(p<0.05)$	SECTION B

Hypothesis	**Data Analysis Method**	**Model Estimation**	**Section**
H2: Customer characteristics and regulatory controls have no significant effect on the relationship between digital credit revolution and customer over-indebtedness	Binary Logistic Regression model and Linear Probability Model also was used. Wald Test was used for Likelihood Estimations Pearson correlation coefficient (r) was used to determine the correlations	Binary Log*it* $(P_i)=\beta_0+\beta_1 X_i$ Where; P_i = probability of the event occurring; X_i is the sample group; β_0 is the log odds of occurring; β_1 shows how the odds differ when $(X_i=1)$. Linear probability Model: $P(Y) = \beta_0 + \beta_1 X_1 + \ldots\ldots.. + \beta_n X_n + \varepsilon$ Where X_1 to X_n are the factors of culture, customer characteristics and regulatory controls as described above while β_1 to β_{6n} are their coefficients respectively. β_0 and ε are regression constants. Pearson coefficient (r) = correlation The Wald Test Model is significant at $(p<0.05)$	SECTION C
H3: There is no significant effect of culture on digital credit revolution	Linear Regression Model also was used. F test statistics was used to determine whether to reject or fail to reject the null hypothesis Pearson correlation coefficient (r) was used to determine the correlations	Linear Regression Model: $P(Y) = \beta_0 + \beta_1 X_1 + \ldots\ldots.. + \beta_n X_n + \varepsilon$ Where X_1 to X_n are the factors of culture, customer characteristics and regulatory controls as described above while β_1 to β_{6n} are their coefficients respectively. β_0 and ε are regression constants. Pearson coefficient (r) = correlation F test statistics – ANOVA Model's test of level of significance	SECTION D

Hypothesis	**Data Analysis Method**	**Model Estimation**	**Section**
H4: Customer characteristics and regulatory controls have no significant effect on the relationship between culture and digital credit revolution	Linear Regression Model was used. F test statistics used to determine whether to reject the null hypothesis Pearson correlation coefficient (r) was used to determine the correlations	Linear Regression Model: $P\ (Y) = \beta_0 + \beta_1 X_1 + \ldots\ldots.. + \beta_n X_n + \mathcal{E}$ Where X_1 to X_n are the factors of culture, customer characteristics and regulatory controls as described above while β_1 to β_{6n} are their coefficients respectively. β_0 and $\mathcal{E}$ are regression constants. Pearson coefficient (r) = correlation F test statistics – ANOVA Model's test of level of significance	SECTION E

CHAPTER FOUR: DATA ANALYSIS AND FINDINGS

4.1 Introduction

This chapter mainly covered how the data were cleaned up, described and analyzed. It showcased the overall response rates as well as how respondents answered to each question. The response rates were expressed in terms of descriptive statistics like the means and medians while the actual testing of hypotheses was done through the Binary logit analysis model, linear probability model and linear regression models. The association between variables in this study was determined by the use of Pearson correlation coefficient (r), which was used to determine the correlation between independent variable and the dependent variable.

Data collected were captured in a Google Form. The researcher then exported the data into Microsoft Excel, coded the qualitative findings and imported it into the IBM SPSS Statistics 25.0 software where the analysis was done.

4.2 Descriptive Statistics

Descriptive statistics were expressed using frequencies, mean, mode, standard deviation and percentages. Before the actual analysis, the researcher's first step was to clean-up the data collected which included the removal of duplicates and irrelevant responses. The researcher then established the correct response rates and carried out the descriptive statistics for all the four hypotheses under this study. The detailed descriptive statistics and findings from the study are as shown in the sections below:

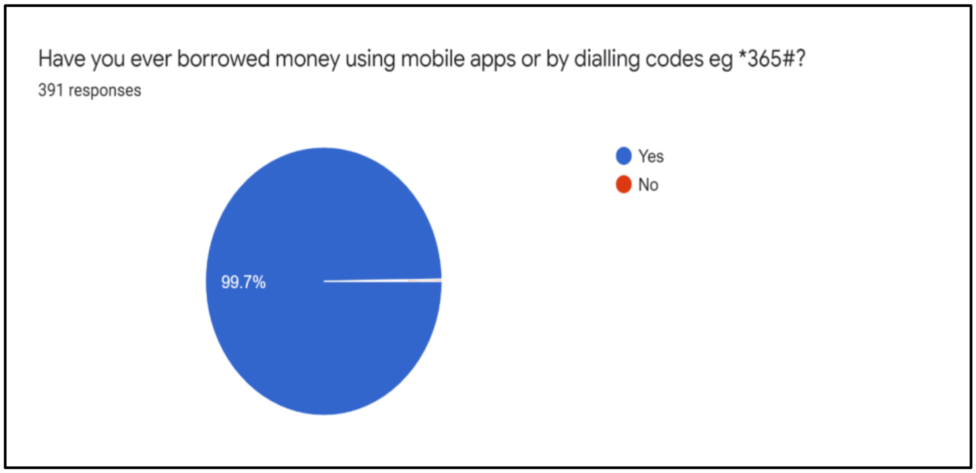
4.3 Response Rate

The study had a total of 391 respondents who were digital loan users in the informal sector. The researcher used Online Google Form questionnaires targeting respondents across the different regions in Nairobi County. The data was collected from 19th August 2021 to 30th October 2021. A total of 389 questionnaires were complete and suitable for analysis. The response rate was therefore 99.5% which was adequate for undertaking inferences about the population. The high response rate could be attributed to the fact that the informal sector is also enterprising and willing to engage other people freely. This was also experienced by Charmes (2012) while investigating trends and characteristics of the informal economy worldwide.

4.3.1 Previous Experience on Borrowing Digital Loans

In order to determine whether the respondents had prior experience of borrowing money through the phone, the respondents were asked whether they had ever borrowed money by dialing codes in their phones such as *365# or by using mobile apps. 99.7% of the respondents agreed that they had at least borrowed money using the mobile apps as indicated in figure 4.1.

Figure 4. 1: Percentage of Respondents who have Borrowed Money on phone

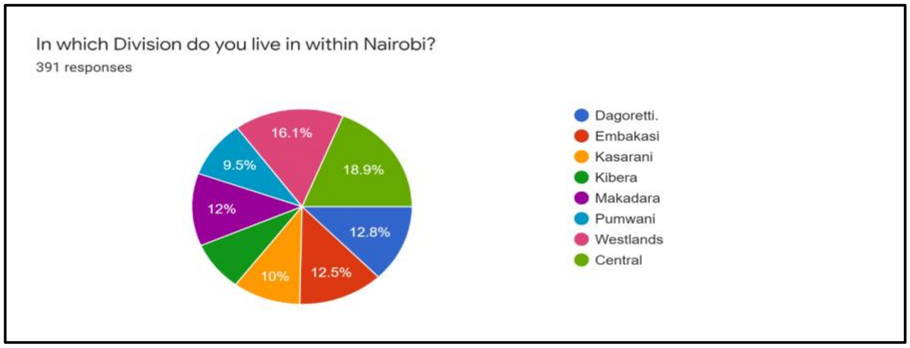


Source: Researcher, (2022)

4.3.2 Distribution of Study Respondents

The distribution of the respondents in regard to their area of residence indicate that all regions in Nairobi were well represented with the area with the highest percentage of respondents being Nairobi Central Division with a percentage of 18.9% while the least being Pumwani Division with a percentage of 9.5% of the respondents. The distribution is well indicated by figure 4.2. This indicates that study respondents were well distributed across the regions of Nairobi County as indicated in the sampling technique adopted by the study.

Figure 4. 2: Distribution of Study Respondents

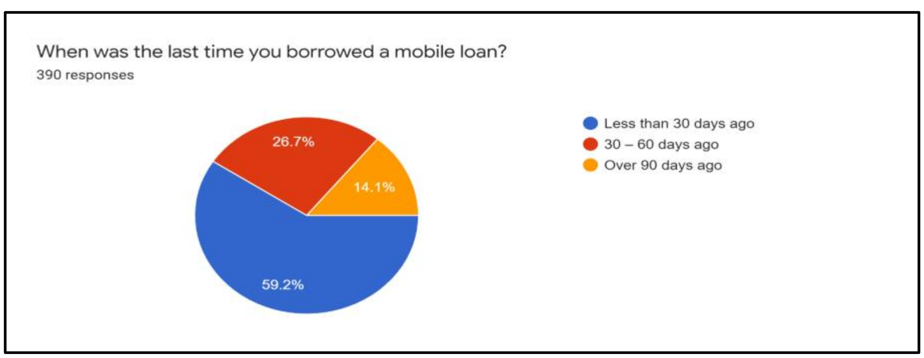


Source: Author, (2022)

4.4 Digital Credit Revolution

Digital credit revolution was an independent variable in the study, which assessed the rapid growth of the digital credit providers (mobile loan providers) in Kenya. The variable was assessed through a number of questions that included determining the frequency and the last time the respondent borrowed a mobile loan. The respondents that indicated that they had borrowed mobile loans within the last 30 days comprised the majority at 59.2% of all respondents. The percentage of respondents that indicated that they had borrowed a mobile loan in a period of 30-60 days ago were 26.7% and only 14.1% of the respondents indicated that they had borrowed a mobile loan over 90 days ago. This is indicated in the figure 4.3. The respondents who had borrowed a loan within the last 30 days were given a score of 3, those who had borrowed in a period of 30-60 days ago were given a score of 2 and those who indicated that they had borrowed a mobile loan over 90 days ago were given a scored of 1. Those who had not borrowed at all got a score of zero.

Figure 4. 3: Last Encounter with Mobile Loans



Source: Author, (2022)

Respondents were also asked to list the number of mobile/digital loan providers that they knew existed in Kenya. This was used to determine their level of awareness and knowledge of digital loan providers. The respondents who did not list any provider were given a score of 0, those who listed one provider scored 1, two providers 2 and respondents who listed three and above mobile/digital providers were given a score of 3. The frequency distribution table 4.2 indicates the extent to which respondents were aware of digital loan providers.

Table 4. 2: ***Digital Loan Providers Frequency Table***

How many mobile/digital loan providers do you know exist in Kenya? List them

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	34	8.7	8.7	8.7
	2	58	14.9	14.9	23.7
	3	297	76.3	76.3	100.0
	Total	389	100.0	100.0	

Source: Author, (2022)

The Table 4.2 indicates that there were only 34 respondents who only knew and listed one digital loan provider, that comprised of 8.7%. Respondents who knew and listed two digital loans providers were 58 that comprised 14.9%, while majority of the respondents (76.3%) knew and listed three or more, which is an indication that majority of the respondents know three or more digital loan providers. There are over 150 digital lenders in Kenya.

The respondents were also asked whether they had a bank account. A respondent who had a bank account is deemed to be less reliant on digital loan providers as they may be in position to access bank loans. The respondents were further asked whether they had any secured bank/ Microfinance Institution (MFI)/ Sacco loan and the responses for each of the questions are represented in frequency table 4.3. The respondents who agreed with each question has a score of 1 while those who disagreed were assigned a score of 0.

Table 4. 3: ***Statistics Table – Account holders and digital loan users***

		Have a bank account	Had secured bank/MFI/Sacco loan before digital/mobile loans	Currently have a secured bank/MFI/Sacco loan
Percent	Yes	75.1%	46.5%	21.3%
	No	24.9%	53.5%	78.7%
Median		.00	1.00	.00
Mode		0	1	0
Std. Deviation		.866	.499	.410

Source: Author, (2022).

Table 4.3 indicates that there were 75.1% respondents who had bank accounts while those who didn't, comprised of only 24.9%. This show that majority of respondents have a bank account. The standard deviation between those with bank accounts and those without is as high as 0.866. However, there are more respondents without secured bank/MFI/Sacco loan at 53.5% than those without. This therefore means that although more respondents had existing bank accounts, obtaining secured bank loans is not easy due to collateral requirements among other conditions. Similarly, there are fewer respondents with existing secured bank loans at 21.3% than those without (78.7%). It is an indication that although secured bank/MFI/Sacco loans have less interest charges, they are less accessible to respondents.

4.5 Customer Over-Indebtedness

According to Schicks (2011), customer over-indebtedness is where an individual or a corporate accumulates more debt to a level that their income cannot sustain the repayments of those debts. This variable is the dependent variable of the study and the number of loans a respondent is currently servicing determined it. The greater the number of loans, meant the greater the level of over-indebtedness. The study therefore assumed that the greater the number of loans undertaken by an individual, the greater the total amount of loans and vice versa. The number of loans currently at default was also a factor that enhanced customer over-indebtedness, the more the loans currently at default, the more the over-indebtedness of the respondent. The increased number of digital loans taken by a respondent also points towards, customer over-indebtedness.

Other factors that indicated increased over-indebtedness of customers were late repayments of loans, flimsy excuses for late repayments of loans, as well as borrowing to repay other loans. The respondents were asked whether they have any mobile/digital loans that they were currently servicing, or which were currently outstanding. 76.8% of the respondents agreed that they were currently servicing or had an existing digital loan, while only 23.2% of the respondents disagreed. The respondents listed the digital loans that they were servicing, where those without any loan were assigned a score of 0, those that listed only one digital loan, a score of 1, two digital loans, a score of 2 and 3 or more loans were assigned a score of 3.

Table 4. 4: ***Frequency Table for Existing Digital Loans***

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	91	23.4	23.4	23.4
	1	124	31.9	31.9	55.3
	2	95	24.4	24.4	79.7
	3	79	20.3	20.3	100.0
	Total	389	100.0	100.0	

Source: Author, (2022)

Table 4.4 indicates that there were only 91 (23.4%) respondents who were not servicing a digital mobile loan currently. 124 of the respondents comprising 31.9% of the respondents were servicing one digital loan, 24.4% of the respondents (79 respondents) were servicing 2 digital loans while 20.3% of the respondents (79 respondents) were servicing either three or more digital loans. Respondents were also asked whether they have ever defaulted on paying the mobile loans; where only 35.7% of the respondents (139) respondents indicated that they had never defaulted on repaying mobile loans, while majority of the respondents 64.3% (250 respondents) had at one time defaulted in repaying their mobile loans.

The respondents who had defaulted were asked to provide reasons for defaulting such mobile loans and the reasons were rated accordingly. 0 was assigned to respondents who had never defaulted on loans, 1 was assigned for an excuse that sounded to be genuine such as delayed salaries (payment) and family emergency, 2 was assigned for less serious reasons such as poor business environment, business emergencies among others, while 3 was assigned for flimsy excuses such as ignoring payment deadlines, increased bills and cost of living, and lack of cash. 60.9% of the respondents who had defaulted provided flimsy excuses on why they were in default, while only 5% of the respondents in default, could be said to have genuine reason for defaulting. Table 4.5 indicates the frequency for each response.

Table 4. 5: ***Frequency for Reasons for Defaulting***

If in default, what would you say was the reason for defaulting?					
		Frequency	Percent	Valid %	Cum %
Valid	1 (Genuine Reason)	13	5.0	5.0	5.0
	2 (Average Reason)	88	34.1	34.1	39.1
	3 (Flimsy Excuses)	157	60.9	60.9	100.0
	Total	258	100.0	100.0	

Source: Author, (2022)

Majority of the respondents (65.6%) indicated that the coming of digital/mobile loans increased their borrowing of loans. On the question whether the respondent always repaid their digital loans on time, majority of the respondents (65.6%) indicated that they did not repay their digital loans on time, while only 34.4% of the respondents agreed that they repaid their digital loans on time, despite the fact that 72.2% of the respondents knew the consequences of not repaying the loans on time. However, only 37% of the respondents agreed that they were aware that they had ever been listed in CRB while 63% of the respondent indicated that to the best of their knowledge, they have never been listed on CRB.

The respondents also cited reasons why they borrow mobile loans, 34.2% of the respondents provided one reason, where most of these respondents cited lack of funds due to loss of jobs or poor business environment, while 39.1% of the respondents cited two reasons why they borrowed mobile loans. These reasons were mainly lack of funds, loss of jobs, emergency, poor business environment. 26.5% of the respondents had three or more reasons why they borrowed mobile loans as shown in frequency table 4.6. This category of respondents apart from the reasons cited in the other categories also had reasons such as ease of getting loans, delayed income, pressure from peers, family needs, business troubles among other reasons.

Table 4. 6: ***Reasons for Borrowing Mobile Loans Frequency Table***

What would you say is the biggest reason why you borrow the mobile loans?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	1	.3	.3	.3
	1	133	34.2	34.2	34.4
	2	152	39.1	39.1	73.5
	3	103	26.5	26.5	100.0
	Total	389	100.0	100.0	

Source: Author, (2022)

Customer Over-Indebtedness was the dependent variable of the study. There are factors that were used to determine whether a respondent was over-indebted or not. This includes cases where the respondent must have at least one loan that is outstanding - the more the number of loans - the more the chance of being over-indebted. A respondent is also likely to be over-indebted if at any single time he/she has ever defaulted on a loan or failed to pay the loan in time, and more likely if there was no genuine reason why the outstanding amount was not paid.

A respondent who is over-indebted has a higher propensity of taking loans, and therefore the easiness in which it is possible to get mobile loans ought to increase his/her borrowing behavior. Similarly, an over-indebted individual is less likely to repay their loans on time, and they are ignorant of the consequences that come with not paying the loans on time. Over-indebted individuals are also likely to be negatively listed on CRB without caring so much about the repercussion for such listing.

All these factors were used to determine whether a certain respondent was over-indebted or not. The scores for each variable were added together. Respondents who had a score of 12 and above from a possible total score of 18 was indicated as over-indebted, while a respondent who had a total score of less than 12 was said not to be over-indebted. The table 4.7 indicates that 193 respondents were not over-indebted while 196 respondents were over-indebted. There were therefore more respondents who were over-indebted than those who were not over-indebted (50.4% and 49.6%).

Table 4. 7: ***Frequency Table of Customer Over-Indebtedness***

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Not Over-indebted	193	49.6%	49.6%	49.6%
	Over-indebted	196	50.4%	50.4%	100.0%
	Total	389	100.0%	100.0%	

Source: Author, (2022)

4.6 Culture

Culture orientation is a reflection of an individual's behavior, belief and attitude (Kaffenberger et al., 2018). In this study, culture was studied as an instrumental variable. The respondents were requested to answer questions that would indicate their culture. They were first requested to indicate whether they had ever borrowed a mobile loan just because it was available and not that they had an urgent need for the money. 47.6% of the respondents said that they had ever borrowed mobile loans just because it was available, and not that they had an urgent need for the money.

The other questions that depicted different culture of the respondent included whether the respondent feared borrowing and getting into debt where 57.6% of the respondent disagreed while 32.4% of the respondents agreed. When the respondents were asked whether they budget before spending any income/money they access only 45.5% agreed while the majority (54.5%) of the respondents disagreed.

Respondents were also asked whether late repayments of these mobile loans bothered their conscience where the majority of the respondents (64.5%) agreed that late repayment bothered their conscience while 35.5% of the respondents were not bothered at all. It is only 35.5% of the respondent who suggested that they borrow more loans than they can service, while only a meagre 4.9% of the respondents trust mobile loan providers with the information, they provide them.

Table 4.8: ***Culture Frequency Table***

	No Frequency	Yes Frequency
Have you ever borrowed a mobile loan just because it was available and not that you had an urgent need for the money?	204 (52.4%)	185 (47.6%)
Do you fear borrowing and getting into debt	224 (57.6%)	165 (42.4%)
Do you budget before spending any income/ money you access	212 (54.5%)	177 (45.5%)
Do late repayment of these mobile loans bother your conscience	138 (35.5%)	251 (64.5%)
Do you often borrow more loans than you can service	251 (64.5%)	138 (35.5%)
Do you trust mobile loan providers with the information you provide them (consumer trust)	370 (95.1%)	19 (4.9%)

Source: Author, (2022)

Table 4.8 indicate the responses that were obtained from the different questions that targeted to test culture. The table shows that a good number of respondents (47.6%) borrowed loan just because it was available and without necessary having any other need for the money. It shows that more people irresponsibly borrowed money, not that they intended to use the money on something urgent, but for the reason that the money was available for them. 57.6% of respondents did not fear getting into loans. It means that the culture of borrowing loans is entrenched in more people and as long as it is possible to secure a loan, then people do not fear getting into debt. There were more respondents who hardly budgeted for money they accessed. It indicated that it was more likely that if they obtained digital loans, they would spend these loans without having budgeted for them, and therefore the loans would less likely provide them the help they needed.

There were more respondents that indicated that these unpaid loans bothered their conscience, which is a good indicator that the borrowers were not comfortable with outstanding loans. The respondents also disagreed that they borrowed more loans than they could service. These are good indicators that would ensure that there is no over-indebtedness, and therefore harness positive loan repayments. 95% of the respondents indicated that they did not trust mobile loan providers with their personal data. This could be explained by the fact that mobile loan providers have in the past used such private data to harass borrowers who have not repaid their loans in time and the cases of private data being shared with third parties without direct authorization of the borrowers.

4.7 Customer Characteristics

Customer characteristics was a control variable in this study. The study sought to identify the characteristics of the respondents and check whether the presence of those characteristics would affect the main relationship between digital credit revolution and customer over-indebtedness and the relationship between culture and digital credit revolution.

57.4% of the respondents were male, while 42.6% of the respondents were female. The age group of the respondents was categorized into six groups and the frequencies are reflected in the table 4.7. The respondents were mainly young people below the age of 35 years as they comprised of 86.9% of the respondents, while only 13.1% of the respondents were above 35 years of age.

Table 4. 9: ***Age Group Frequency Table***

What is your age group?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (18-23 years)	39	10.0	10.0	10.0
	2 (24-30 years)	174	44.7	44.7	54.8
	3 (31-35 years)	125	32.1	32.1	86.9
	4 (36-40 years)	41	10.5	10.5	97.4
	5 (41-50 years)	9	2.3	2.3	99.7
	6 (51 and above)	1	.3	.3	100.0
	Total	389	100.0	100.0	

Source: Author, (2022)

Table 4.9 indicates that the largest group of the respondents were youth below 35 years. They comprised of a total of 86.9% of all the respondents. The largest age group were those between 24 to 30 years who made up 44.7% of the respondents. Nairobi City County being the capital city could explain why majority of the people living there were mainly young people looking for employment opportunities and other sources of income within the city. It is consistent across the world that majority of those who live in cities are young people looking for opportunities and those in the rural areas as older people who prefer quieter lives.

In terms of education levels, majority of the respondents at 57.4% had at least a KCSE certification as their highest education qualification. 13.4% of the respondents were graduates with bachelor's degree certification and 42.7% of the respondents had the highest educational qualification as being KCPE certification. From these findings, it is evident that these respondents were learned with ability to read and write and could easily maneuver through a loan application process. The city dwellers have high literacy levels.

In terms of family status, 65% of the respondents were single. This means that majority of the city dwellers are not married and do not have families. This could be explained by the fact that majority of the respondents were youth below the age of 35 years.

On the kind of jobs that the respondents were doing, they were classified based on the types; blue collar, white collar and manual jobs. Two respondents indicated that they had white-collar jobs, while a huge 99.5% were either on blue-collar jobs or manual jobs. Most respondents were boda boda operators, welders, hawkers, charcoal sellers, vegetable sellers, cloth sellers and stage touts. There were only two respondents who indicated that they were accountants and therefore classified under white-collar jobs as indicated by table 4.10.

Table 4. 10: ***Occupation Frequency Table***

What is your current occupation/Job?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Manual Job)	103	26.5	26.5	26.5
	2 (Blue-Collar e.g. Small business owners)	284	73.0	73.0	99.5
	3 (White Collar Job)	2	.5	.5	100.0
	Total	389	100.0	100.0	

Source: Author, (2022)

The frequency table 4.11 indicates the average monthly income received by each respondent where 1 represents a monthly income less than Kshs 10,000 while 2 represents a monthly income between Kshs 10,001 and Kshs 25,000, 3 represents Kshs 25,001-50,000 category while 50,001-75,000 is represented by 4 and 5 represents over Kshs 75,000.

Table 4.11: ***Monthly Income Frequency Table***

What is your average monthly income?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 Up to Kshs 10,000	90	23.1	23.1	23.1
	2 Kshs 10,001-25,000	199	51.2	51.2	74.3
	3 Kshs 25,001-50,000	97	24.9	24.9	99.2
	4 Kshs 50,001-75,000	1	0.3	0.3	99.5
	5 Over Kshs 75,000	2	0.5	0.5	100.0
	Total	389	100.0	100.0	

Source: Author, (2022)

The distribution income table above shows more than half of the respondents earn a total income of between Kshs 10,000 and Kshs 25,000. That is quite a low income compared to the cost of living in Nairobi City County. This means that the majority of the informal sector operators within this area of study do not earn decent income and therefore even struggle to make ends meet, leave alone getting the capital for their businesses. This could also explain the high rate of borrowing within this group and they try any any opportunity available to them to earn extra money. Unfortunately, these monies that they borrow come with huge cost in terms of interest rates.

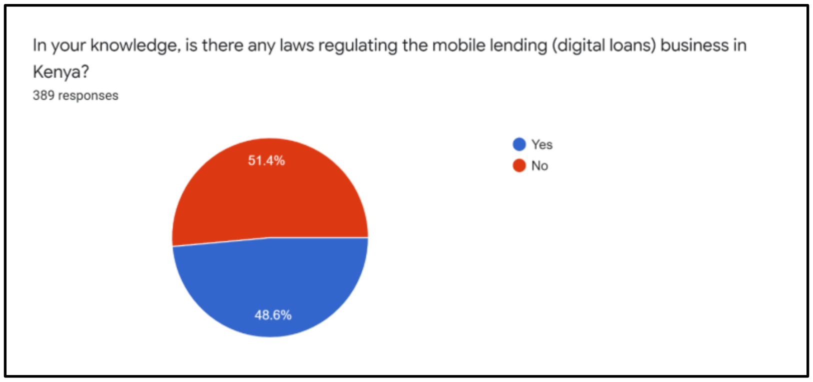
From the study findings, a huge majority of the respondents at 87.9%, have access and use smartphones and only 12.1% of the respondents were using feature phones. Also, 71.7% of the respondents indicated that they do not struggle at all when going through the process of borrowing loans using their phones.

4.8 Regulatory Controls

Regulatory controls were used as a control variable in this study. The respondents were asked several questions to determine the level and the presence of regulatory controls in the country of study and check whether its presence would affect the main relationship between digital credit revolution and customer over-indebtedness and the relationship between culture and digital credit revolution.

The respondents were asked whether there existed any laws that sought to regulate mobile (digital) loans and only 48.6% of the respondents answered in the affirmative. 51.4% of the respondents however believed that there were no existing laws regulating mobile lending in Kenya. This therefore shows that majority of the respondents were ignorant of regulatory laws in place for the digital credit providers. It gives the picture that borrowers are not well informed of their rights or legal implications of borrowing.

Figure 4. 4: Existence of Laws Regulating Mobile Lending Chart

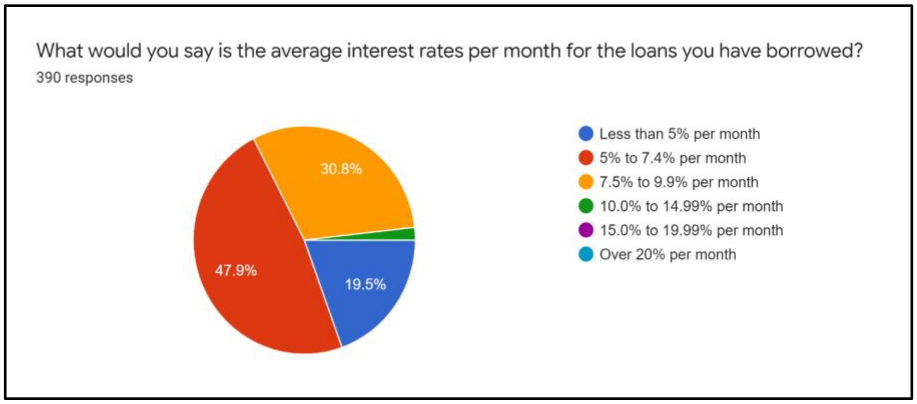


Source: Author, (2022)

Most respondents who suggested that there existed laws in relation to mobile lending in Kenya, suggested that the existing laws were CRB laws. When the respondents were asked whether they read terms and conditions before taking loans, the majority of the respondents (54.2%) said that they did not read terms and conditions of these loans while only 45.8% of the respondents agreed that they read the terms and conditions before taking mobile loans. When the respondents were asked on whether they had full transparency on the fees charged at the time of borrowing, 64.8% of the respondents disagreed and only 35.2% of the respondents agreed that they had full transparency. The data shows that there is high level of ignorance on the terms and conditions associated with the borrowing of digital loans. It also means that most respondents did not care on terms and conditions as long as they were able to secure a loan.

When the respondents were asked about the average interest rates that they were charged per month, majority of the respondents (47.9%) said between 5% to 7.4% per month which would translate to 60% - 88.8% annually. This is above the recommended interest rates by Central Bank of Kenya of 12%-15% annually. Figure 4.5 indicates the responses in regard to the monthly interest rates for digital loans borrowed.

Figure 4. 5: Monthly Interest Rates Chart



Source: Author, (2022)

A whooping 94.1% of the respondents said that the providers of digital loans did not explain on how they would use personal data they collected while issuing these digital (mobile) loans while only 5.9% of the respondents agreed that providers of these loans explained how they would use personal data collected. Similarly, majority of the respondents (53.7%) disagreed that the mobile loan providers had flexible repayment terms.

Only 46.3% of the respondents agreed that they were able to receive flexible repayment terms from these mobile loan providers. These findings indicate that there is no full compliance of the privacy and data protection laws by these digital loan providers. Stringent measures should therefore be developed to ensure that personal data collected by digital loan providers is protected and no improper use of such data, without direct authorization from the owner of the data.

It was also noted that majority of loan providers were not flexible to adjust repayment patterns as well as restructuring of debts to ensure that borrowers are listened to, and their situation considered in making loan adjustments. The respondents were requested to name issues they would want to be introduced/improved while regulating the mobile lending industry. The respondents gave several suggestions. The suggestions repeated by large number of respondents were; reducing interest rates, more time for loan repayment, stopping the shaming of defaulters and protection of personal private data.

The respondents were also asked whether they communicated with the lender whenever they wanted to raise an issue. 4.1% of the respondents said that they did not at any time communicate with the lender and 95.9% who communicated with the lender either called them, send them short messages or used the app to communicate to the lender. The responses therefore indicate that there were open communication channels between lenders and borrowers. The borrowers were able to reach the lenders either through the in-app messages , through calling or through use of short messages.

CHAPTER FIVE: HYPOTHESIS TESTING AND DISCUSSIONS

5.1 Introduction

The chapter tests the study hypotheses and provides answers to the research questions. The objectives were to determine the relationship between digital credit revolution and customer over-indebtedness, the effect of culture on digital credit revolution, the control for effect of customer characteristics and the regulatory controls on the relationship between digital credit revolution and customer over-indebtedness and the effect of customer characteristics and the regulatory controls on the relationship between culture and digital credit revolution . The chapter will first determine the correlation analysis of the study variables and later test the study hypotheses.

5.2 Correlation Analysis

The correlation analysis is a linear association between two variables in statistical research. It is not causal in nature. It therefore determines the level of change in the dependent variable after a certain change in the independent variable. Correlations between two variables can either be positive, negative or zero correlation. For example, in this study, respondents who were found to have an existing bank loan on top of digital loans were more likely to be over-indebted; but the reverse can also be true, meaning that over-indebtedness caused by digital loans is causing these customers to take bank loans.

Pearson correlation coefficient (r) was the statistical measure of choice in determining the correlation between variables. A value closer to +1 showed a stronger positive correlation between the variables while values closer to -1 showed the existence of strong negative correlation between variables. However, when a value is closer to zero, it indicates a weak correlation between the variables (Cooper & Schindler, 2003).

Correlational analysis was undertaken to check how the variables compared against one another. The variables that are closely related are said to have positive and strong correlation, while variables that are not related to one another are indicated as weak correlation. Correlational analysis is therefore a measure of relationships between the study variables that provides insight into the relationship that exist between the variables. Correlation analysis does not only indicate whether relationship exist between study variables, but it also indicates the nature and direction of the relationship.

5.2.1 Correlations between Digital Credit Revolution and Customer Over-indebtedness

In order to determine the correlation between digital credit revolution and customer over-indebtedness, each factor that comprises digital credit revolution was checked on its correlation with customer over-indebtedness. The factor of customer over-indebtedness had been determined by either yes or no (1 and 0) that indicated whether a respondent was over-indebted or not. Table 5.1 indicates the correlation of each factor of digital credit revolution on customer over-indebtedness.

Table 5. 1: ***Correlation between Digital Credit Revolution and Customer Over-indebtedness***

Correlations	Customer Over-Indebtedness	A	B	C	D	E
Customer Over-Indebtedness	1					
The last time borrowed a mobile loan (A)	.240**	1				
No. of mobile/digital loan providers in Kenya? List them (B)	.233**	0.013	1	-.223**		
Presence of bank account (C)	-.319**	0.048	-.223**	1		
Had a secured bank/MFI/Sacco loan before digital/mobile loans (D)	.291**	-.140**	.241**	-.594**	1	
Currently have a secured bank/MFI/Sacco loan (E)	-0.086	-.465**	0.049	-.228**	.398**	1

** Correlation is significant at the 0.01 level (2-tailed).

Source: Author, (2022)

The correlation between customer over-indebtedness and the last time a respondent borrowed a mobile loan was positive and significant at 0.01 level. The Pearson's Correlation (r) was 0.240 that indicated that respondents who had taken a longer period of time before they borrowed a digital loan were less likely to be over-indebted, while those who had taken a digital loan in the recent past, were more likely to be over-indebted. The correlation between customer over-indebtedness and whether a respondent had a bank account was also significant but negative with r = -0.319. This indicates that respondents who had bank accounts were less over-indebted, while respondents who did not have bank accounts indicated were more likely to be over-indebted.

Respondents had also been asked whether they had existing secured/bank loan before undertaking digital/mobile loans. Those who answered in the affirmative were more likely to be over-indebted as the correlation between the two variables was significant and positive at r = 0.291.

When the respondents were asked whether they had a current secured bank/MFI/Sacco (on-digital) loan, the correlation with customer over-indebtedness was insignificant and close to zero indicated that there was no correlation between the two variables.

5.2.2 Correlations between Customer Characteristics and Customer Over-indebtedness

Though the customer characteristics was a control variable in the study, the researcher decided to establish whether there was a significant correlation between customer characteristics and the main dependent variable of the study which is customer over-indebtedness. The correlation between customer characteristics and customer over-indebtedness was determined by the use of Pearson's Correlations. Table 5.2 indicates the result

Table 5. 2: ***Correlations on Customer Characteristics***

Correlations										
		Over-Indebtedness	A	B	C	D	E	F	G	H
Over-Indebtedness	r	1								
Gender (A)	r	-0.035	1							
Age Group (B)	r	0.083	.017	1						
Academic Qualification (C)	r	0.145^{**}	$-.122^{*}$	$.155^{**}$	1					
Family Status (D)	r	0.113^{*}	-.043	$-.482^{**}$	.006	1				
Job Occupation (E)	r	0.033	$-.105^{*}$	$.123^{*}$	.076	$-.140^{**}$	1			
Average Monthly Income (F)	r	0.108^{*}	-.026	$.521^{**}$	$.396^{**}$	$-.296^{**}$	$.210^{**}$	1		
Type of Phone (G)	r	0.058	-.081	$.329^{**}$	$.327^{**}$	$-.291^{**}$	$.154^{**}$	$.407^{**}$	1	
Complex to borrow loan (H)	r	-0.281^{**}	.058	$-.161^{**}$	-.027	.089	-.032	-.092	-.058	1
**. Correlation is significant at the 0.01 level (2-tailed).										
*. Correlation is significant at the 0.05 level (2-tailed).										

Source: Author, (2022)

The correlation between gender and customer over-indebtedness is insignificant at r = -0.035. This is closer to zero indicating that there is no correlation between gender and customer over indebtedness. This would mean that there is low probability/ tendency of a customer being over-indebted by the fact that they are either male or female. Similarly, the correlation between age group and customer over-indebtedness was insignificant and r = 0.083 that was also closer to zero. This indicated that the respondents age did not determine their level of indebtedness.

However, academic qualification was significant at r = 0.145 at 0.01 level. This indicates that although the correlation was weak, there was a positive correlation between academic qualification and customer over-indebtedness. This indicates that the more a respondent had increased their academic qualification, the more likely to be over-indebted. This could be explained by the fact that people who had increased academic qualification were more knowledgeable on the existing digital loans. They were also under higher pressure to increase their income and help solve their economic situations as well as the economic situations of their dependents.

The average income of the respondent and customer over-indebtedness had a positive and significant correlation of r = 0.108 the significance was only significant at the level 0.05 and the Pearson Correlation was weak as it was closer to zero. However, this indicated that an increase in the income level led to increase in customer over-indebtedness. This could be explained by the fact that the study respondents were drawn from largely the low economic class level whose monthly income was hardly Kshs. 50,000. This means that the higher the income they would receive, the more money they would seek to meet their needs and therefore led to increased over-indebtedness. The type of phone that the respondent used had zero correlation with their over-indebtedness as r was insignificant and very close to zero at r = 0.058. This would mean that both feature and smart phones were equally able to access mobile/digital loans. However, respondents that said that they found it complex to access or to maneuver in obtaining digital loans were less likely to be over-indebted as the correlation between the two variables was significant at 0.01 level and negative at r = -0.281.

5.2.3 Correlation between Regulatory Controls and Customer Over-Indebtedness

Regulatory controls variable was determined by a number of factors and the correlation between each of these factors to customer over-indebtedness is indicated in table 5.3.

Table 5. 3: ***Correlations on Regulatory Controls and Customer Over-Indebtedness***

Correlations												
			Over-Indebtedness	A	B	C	D	E	F	G	H
Customer Over-Indebtedness		r	1								
A	Laws regulating the mobile lending (digital loans)	r	.363**	1							
B	If yes above, explain?	r	.318**	.901**	1						
C	Is there a full transparency on the loan fees	r	-.065	.073	.083	1					
D	Normally read the terms and conditions given for the loans	r	.194**	.418**	.369**	.172**	1				
E	Do the providers of these loans explain to you how they will use your data?	r	-.078	-.112*	-.110*	.229**	.206**	1			
F	Do the providers give you flexible repayment terms	r	-.110*	-.134**	-.106*	.201**	.033	.226**	1		
G	What would you want to be introduced/ improved on the mobile lending industry	r	.558**	.538**	.495**	-.038	.344**	-.081	-.170*	1	
H	When you have and challenge or a complaint, how do you raise it to the lender?	r	.105*	.123*	.094	.097	.087	.052	.036	.204**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Source: Author, (2022)

The correlation between customer over-indebtedness and knowledge of laws regulating the mobile lending businesses in Kenya was significant at the level of 0.01 it was positive at r = 0.363. This indicates that the more the respondents were aware of the existing regulatory laws, the more they were over-indebted. It shows that the respondents were less concerned of the legal consequences of over-indebtedness. It's also evident that you cannot use laws to curb over-indebtedness. Similarly, the correlation between customer over-indebtedness and the number of laws stated by the respondent was significant at the level 0.01, positive and relatively strong at r = 0.318. This observation would generally attract a similar conclusion that the more the respondents knew of the available regulation in regard to digital loans, the more they defaulted and the more they were over-indebted.

In regard to whether the respondents were clearly notified of the existing loan fees, interest rates and hidden terms and its correlation with customer-over indebtedness, it was found that there was weak insignificant correlation of $r = -0.065$. The Pearson's Correlation was therefore close to zero that indicated that there was no correlation between the two variables. This could be explained by the fact that the respondents within the informal economy did not care about loan terms and loan fees. A point of more concern was the ability to access credit rather than the cost or terms of the credit itself.

The correlation between customer over-indebtedness and whether the respondent usually reads terms and conditions before taking up a mobile loan was positive and significant at level 0.01 ($r = .194$, $P<0.01$). This shows that the more respondents read terms and conditions given for digital loans, the more they were over-indebted. It would be indicative of the fact that the presence of terms and conditions would not prevent the informal economy operators from borrowing from digital lenders. The correlation between whether digital loan providers explained how they use personal data and customer over-indebtedness was not significant and very close to zero ($r = -.078$, $P < 0.05$). It indicates that there was no correlation between the two variables and therefore borrowers were not keen on how their personal data was used. This emphasized the conclusion that the focus of the borrower at the time of borrowing was to fulfil their need and did not care about the terms nor the cost of the loan.

The correlation between flexible loan repayment terms and customer over-indebtedness was significant and negative at 1% ($r = -.110$). This indicates that the more digital lenders provided flexible loan repayment terms, the less customer over-indebtedness. On the other hand, the more the borrowers found areas where digital/mobile lenders were not performing well, and therefore needed improvement, the more the customer over-indebtedness. It indicates that customer over-indebtedness is associated with poor policies such as interest rates, poor debt recovery habits, and non-flexible loan terms. The correlation between the two variables was significant and strong ($r = .558$, $p < 0.01$).

The correlation between the ability of the borrower to raise concerns to the lender and over-indebtedness was also positive at ($r = .105$, $p <0.05$). More informed customers were showing tendencies of being over-indebted.

5.2.4 Correlation between Culture and Digital Credit Revolution

Culture is noted to be an important component in adoption and implementation of new technology across the world. In this study, the researcher sought to seek how five key constructs of culture influenced digital credit revolution in Kenya. The correlation of culture and digital credit revolution was undertaken, and results presented in table 5.4.

Table 5. 4: ***Correlation between Culture and Digital Credit Revolution***

Correlations								
		Digital Credit Revolution	Borrowed due to accessibility	Borrows more than can afford	I budget before spending	Late repayments is a bother	Borrow more loans than can pay	Consumer Trust with private data
Digital Credit Revolution	r	1						
Borrowed due to accessibility	r	.128*	1					
Borrows more loans than can afford	r	-.169**	-.182**	1				
I budget before spending any money	r	-.175**	-.415**	.375**	1			
Late repayment of these mobile loans bothers my conscience	r	.092	.179**	-.103*	-.250**	1		
Fears borrowing and being in debt	r	.130*	.660**	-.310**	-.526**	.123*	1	
Consumer Trust- personal Information	r	-.119*	-.049	.168**	.128*	.043	.056	1
*. Correlation is significant at the 0.05 level (2-tailed).								
**. Correlation is significant at the 0.01 level (2-tailed).								

Source: Author, (2022)

The correlation between digital credit revolution and whether a respondent had ever borrowed a loan just because it was accessible was positive and significant at level of 0.05 ($r = .128$, $P < 0.05$). This means that the more borrowers borrowed money for the fact that it was accessible, the higher the digital credit revolution. The correlation between credit digital revolution and whether the borrower feared getting into debt was significant and negative at the level of 0.01 ($r = -.169$, $P < 0.01$). This indicates that the more borrowers fear getting into debt, the lower the digital credit revolution. Similarly, the correlation between digital credit revolution and budgeting before spending any cash received was also negative and significant at 0.01 level ($r = .175$, $P < 0.01$). This means that the more respondents write budgets before spending any cash received, the lower the digital credit revolution. Since this is an instrumental variable, the lowering of digital credit revolution chances therefore leads to lower chances of getting over-indebted.

The aspect of whether late repayment bothers the borrowers' conscience and digital credit correlation had an insignificant correlation that was close to zero ($r = .092$, $P < 0.05$). This indicates that the bother of late repayment of loans did not have an influence on digital credit revolution. On the other hand, borrowing more loans than the borrowers could service had positive significant correlation ($r = .130$, $P < 0.05$) while trusting mobile service providers with personal data had significant and negative correlation with digital credit revolution ($r = -.119$, $P < 0.05$). These means that the culture of borrowing more loans than one could service leads to increase in digital credit revolution while the increasing level of customer trust with personal data had a negative effect on digital credit revolution.

5.3 Hypotheses Testing

The null hypothesis of this study was that, there is no significant effect of digital credit revolution on customer over-indebtedness in the informal economic sector in Nairobi Kenya.

H_1: There is no significant effect of digital credit revolution on customer over-indebtedness

The researcher first used the Binary Logistic Regression model to test this hypothesis. There are not many key assumptions in binary logistic regression using the ordinary least squares algorithms. Assumptions regarding homoscedasticity, normality, linearityas and measurement level do not apply while undertaking binary logistic regression. However, the assumptions that are applicable include; the dependent variable must be binary, there should be very little to no multicollinearity in the independent variables. The observations from the findings should not be coming from matched data or from repeated measurements. It also assumes that there is linearity of independent variables and log odds, and that the independent variables are linearly related to the log odds. Binary logistic regression also requires a large sample size. All these assumptions were met in the study.

Thereafter, the researcher also used the Linear Probability Model to test the model and confirm whether the results would change. All results have been tabulated and explained below.

5.3.1 Diagnostic Tests

The researcher undertook various diagnostic tests as shown below to ensure that the data complies with the assumptions for undertaking binary logistic regression.

5.3.1.1 Binary Dependent Variable

The dependent variable of the study is customer over-indebtedness. The study identified different factors that when combined together would classify a person as either over-indebted or not over-indebted. The dependent variable was converted into dummies (zeros and ones), so that they are categorical. The dependent variable was therefore binary in nature where 49.6% of the respondents were not over-indebted and 50.4% of the respondents were over-indebted. The multicollinearity tests were also carried out as follows.

5.3.1.2 Multicollinearity Test

The researcher used the test for multicollinearity to ensure that the independent variables are indeed independent and therefore they are not related to one another. The study used variation inflation factors (VIF) to test whether there exists collinearity between independent variables. Variables with VIF factors of 10 and above are said to have a problem of multi-collinearity while VIF values below 10 do not indicate significant multi-collinearity issues that will be problematic.

Table 5. 5: ***Multicollinearity Test Table***

Model	Collinearity Statistics	
	Tolerance	VIF
(Constants)		
Digital Credit Revolution	0.988	1.013
Customer Characteristics	0.884	1.132
Regulatory Controls	0.822	1.217
Culture	0.916	1.092

Source: Author, (2022)

Table 5.5 indicates that all variables have VIF factors of below 10, which indicates that there is no multi-collinearity between these variables. Similarly, the Tolerance level is below 1, which further indicates that there is no multi-collinearity between the independent variables.

5.3.1.3 Linearity of Independent Variables and Log-Odds Test

The linearity test that is undertaken in binary logistic regression considers linearity of independent variables and log-odds. The assumption taken is that each continuous independent variable and the logit (log-odds) of the outcome is linear. The logit is the logarithm of the odds ratio, where p is the probability of a positive outcome.

$$\text{logit}(p) = \log\left(\frac{p}{1-p}\right)$$

The Box-Tidwell Test is used in checking for linearity between the predictors and the logit, and it is done when log-transformed interactions terms are added between the continuous independent variables and their corresponding natural log into the model.

Table 5. 6: ***Linearity of Variables***

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	LogDigCreRev	.110	.038	8.281	1	.004	1.116
	LogCustChar	-.011	.017	.397	1	.528	.989
	LogRegCon	.168	.021	61.649	1	.000	1.183
	LogCult	.322	.062	27.164	1	.000	1.380
	Constant	-3.455	.770	20.151	1	.000	.032

a. Variable(s) entered on step 1: LogDigCreRev, LogCustChar, LogRegCon, LogCult.

Source: Author, (2022)

Table 5.6 indicates that all the variables are significant ($P<0.05$) apart from customer characteristics that is insignificant. This indicates that digital credit revolution, regulatory controls and culture do not have linear relationship between them and the log of these variables. These variables that failed the test would therefore be transformed by calculating the square of each variable.

5.3.2 Digital Credit Revolution and Customer Over-Indebtedness

In order to test the hypothesis that there was no significant effect of digital credit revolution on customer over-indebtedness. Binary regression was first used to test the hypothesis and thereafter a linear probability model was also carried out.

5.3.2.1 Digital Credit Revolution and Customer Over-indebtedness - Testing by Use of Binary Logit Model

The Logit model was of the form Logit (Pi) = $\beta_0 + \beta_i X_i$. (As indicated in Chapter 3 Table 3.2). The factors that were used to determine digital credit revolution included: the last time respondent borrowed a mobile loan, knowledge of mobile loan providers, presence of bank account and presence of other secured loan(s) before using digital loans.

The explained difference in the dependent variable was explained by Nagelkerke R^2 method which is a modification of Cox & Snell R Square, and which indicated a value of 0.287. This indicates that the model could explain changes in customer over-indebtedness to the extent of 28.7%.

Table 5. 7: ***Model Summary - Digital Credit Revolution and Customer Over-indebtedness - Binary Logit Model***

Step	-2 Log likelihood	Cox & Snell R^2	Nagelkerke R^2
1	444.997[a]	0.215	0.287

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001

Source: Author, (2022)

The classification table 5.8 pins the observed cases from the predicted cases by the model. It therefore provides the accuracy of the model which indicates that it has an overall accuracy of 72.2%. The main diagonal of the table indicates the cases that were correctly classified by the model while the other diagonal indicates the cases that were wrongly classified by the model.

There were an observed 193 cases of respondents who were not over-indebted, of which 133 of them were correctly classified as not over-indebted while only 60 cases were predicted as being over-indebted. The accuracy rate was therefore 68.9%. On the other hand, there were a total of 196 respondents who were over-indebted, out of which 148 were correctly classified as over-indebted and indicating an accuracy rate of 75.5% as indicated in table 5.8.

Table 5. 8: ***Sensitivity Analysis Table - Digital Credit Revolution and Customer Over-indebtedness - Binary Logit Model***

Sensitivity Analysis				
Observed		Predicted		
		Customer Over-Indebtedness		Percentage Correct
		No	Yes	
Customer Over-Indebtedness	No	133	60	68.9
	Yes	48	148	75.5
Overall Percentage				72.2
a. The cut value is .500				

Source: Author, (2022)

In order to determine the significance of each factor, Wald test was undertaken, and the results were indicated in the table 5.9. The significance of each factor was less than 0.05 and therefore the null hypothesis is rejected. This indicates that there is significant effect of digital credit revolution on customer over-indebtedness.

Table 5.9: ***Test Results - Digital Credit Revolution and Customer Over-indebtedness - Binary Logit Model***

Digital Credit Revolution								
	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
The last time borrowed a mobile loan	0.75	0.186	16.2	1	0.000	2.117	1.469	3.05
No. of mobile/digital loan providers	0.543	0.197	7.58	1	0.006	1.721	1.169	2.534
Presence of bank account	-1.09	0.334	10.667	1	0.001	0.336	0.175	0.647
Had a secured bank/ Sacco loan before digital/mobile loans	1.021	0.299	11.634	1	0.001	2.777	1.544	4.994
Currently have a secured bank/MFI/Sacco loan	-0.652	0.335	3.796	1	0.048	0.521	0.27	1.004
Constant	-3.432	0.755	20.643	1	0	0.032		
a Variable(s) entered on step 1: Factors of Digital Credit Revolution								

Source: Author, (2022)

The findings as indicated in table 5.10 shows that all factors of the independent variable are significant in the model. The B value for the first factor (The last time borrowed a mobile loan) is positive and significant indicating that as the value increases (less time before the last loan) then there were higher chances of over-indebtedness. FSD (2018) found that Kenyans in the informal sector took loans for more trivial reasons, and this could be the reason why in less than 30 days majority of the respondents had already taken loans.

The second factor showed the number of digital lenders that were known by the respondents. The more the digital lenders known to the respondent, the more the probability of over-indebtedness. The presence of bank account could signify that the lender does not rely on mobile and digital loans as they are likely to get loans from the bank. The negative relationship was significant indicating that the less the people had bank accounts, the more the chances of getting over-indebted.

The presence of other unsecured loans was represented by the fourth factor, and the positive relationship indicated that the more one had other unsecured loans, the more they were likely to be over-indebted. Musau et al. (2018) indicated that late loan repayments in Kenya had been made worse by increased presence of digital lenders and therefore conforms to the findings of this study. On the other hand, the study by Schicks (2011) indicated contrary findings where they said that embarrassment to the borrower and other mistreatment increased efforts for the borrower to pay their dues to avoid such.

5.3.2.2 Digital Credit Revolution and Customer Over-indebtedness: Testing by Use of Linear Probability Model and its Interpretation

Linear probability is used to estimate a relationship among two or more variables. In this study, the researcher tested the hypothesis using the Linear Probability Model to confirm whether results would be similar to the results obtained from the binary logit model. Because of the binary nature of the binary logit regression, the totals of covariates were converted into dummies (0 and 1). Similarity of the two would explain a strong probability of the variables in predicting the change of the dependent variable.

Table 5.10: ***Model Summary - Digital Credit Revolution and Customer Over-indebtedness – Linear Probability Model***

Model Summary				
Model	R	R Square	Adjusted R^2	Std. Error of the Estimate
1	.472a	0.223	0.212	0.444
Predictors: (Constant), The last time borrowed a mobile loan, No. of mobile/digital loan providers in Kenya, Presence of bank account, had a secured bank/ Sacco loan before digital/mobile loans, currently have a secured bank/MFI/Sacco loan				

Source: Author, (2022)

The model above indicates that the model could explain changes in customer over-indebtedness to the extent of 21.2%. This is as per the adjusted R^2 value of the model.

In order to determine the significance of each factor, the results were indicated in the table 5.12. The significance of each factor was less than 0.05 and therefore the null hypothesis is rejected. This indicates that there was significant effect of digital credit revolution on customer over-indebtedness. Please note that the level of significance across all the five factors were significant, similar to the findings that researcher had earlier indicated under binary logistics model.

Table 5. 11: ***Test Results - Digital Credit Revolution and Customer Over-indebtedness – Linear Probability Model***

Coefficients a							
Model	Unstandardized Coefficients	Standardized Coefficients				95.0% Confidence Interval for B	
Co- variates	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
The last time borrowed a mobile loan	0.153	0.035	0.222	4.343	0.000	0.084	0.222
No. of mobile/digital loan providers in Kenya	0.111	0.037	0.14	2.987	0.003	0.038	0.184
Presence of bank account	-0.226	0.065	-0.196	-3.476	0.001	-0.354	-0.098
Had a secured bank/ Sacco loan before digital/mobile loans	0.22	0.06	0.22	3.657	0.000	0.102	0.339
Currently have a secured bank/MFI/Sacco loan	-0.148	0.067	-0.121	-2.203	0.028	-0.28	-0.016
(Constant)	-0.199	0.141		-1.41	0.159	-0.476	0.078
a Dependent Variable: Customer Over-Indebtedness							

Source: Author, (2022)

The results on the significance of each variable as modelled through Linear Probability Model were exactly the same as the level of significance for each variable as obtained through binary logit model. All the variables within digital credit revolution had significant effect on customer over indebtedness.

The B values (coefficients of probability) for each variable as obtained through Linear Probability Model and the binary logit model were also similar. In both models, the first factor (the last time of borrowing a mobile loan), how many mobile/digital loan providers does the respondent know exist in Kenya and whether the respondent had any secured bank/MFI/Sacco loan before starting to use the digital/mobile loans; were all significant and had positive coefficients; meaning that as the value of the covariate increases then there was higher probability of over-indebtedness witnessed.

The factors: do you have a bank account and do you currently have a secured bank/MFI/Saccoloan, had negative coefficients though significant meaning that as the value of the covariate increases then there was lower probability of over-indebtedness witnessed. The similarity in the results of the two models clearly indicate the strength of the model. In conclusion, both models have shown that the null hypothesis is rejected

Table 5. 12: ***Summary of Results of Study: Digital Credit Revolution and Customer Over-indebtedness***

H	Null Hypothesis	Results	Interpretation
H_1	There is no significant effect of digital credit revolution on customer over-indebtedness	The Wald Test Model is significant ($p<0.05$)	The null hypothesis is rejected
H_a	There is no significant effect of the last time one borrowed a loan and over-indebtedness.	Positive correlation and Wald Test is significant ($p<0.05$).	Null hypothesis rejected and therefore the longer the period from the last time a borrower borrowed loan, the lower the chance of being over-indebted.
H_b	There is no significant effect of knowing mobile loan providers on customer over-indebtedness.	Positive correlation and Wald Test is significant ($p<0.05$).	Null hypothesis is rejected which implies there is significant and positive effect of knowing mobile loan providers on customer over-indebtedness.

H	Null Hypothesis	Results	Interpretation
H_c	There is no significant effect of having a bank account on customer over-indebtedness.	Negative correlation and Wald test is significant ($p<0.05$).	The null hypothesis is rejected which implies that there is a significant negative effect of having a bank account on customer over-indebtedness.
H_d	There is no significant effect of Prior use of Secured loans on customer over-indebtedness	Positive correlation and Wald test is significant ($p<0.05$).	The null hypothesis is rejected which implies that there is a significant positive effect of having prior used the secured loans on customer over-indebtedness.
H_e	There is no significant effect of having existing secured bank/Sacco/MFI loan on customer over-indebtedness	Negative correlation and Wald test is significant ($p<0.05$)	The null hypothesis is rejected which implies that having other existing secured loans led to customer over-indebtedness.

Source: Author, (2022)

5.3.3 The Customer Characteristics and Regulatory Controls as Control Variables on Customer Over-Indebtedness

Customer characteristics and regulatory controls were used as control variables in the study. Control variables are factors that must be held constant on a relationship so as to establish the exact effect of independent variables on the dependent variable. The customer characteristics focused on the factors that are demographic in nature. These demographics were those that are likely to trigger specific behavior. Demographics assessed were; age, family status, level of income, gender, academic qualifications, occupation and technological savviness of the customer.

Concerning regulatory controls, the factors used in the study included: Knowledge of Regulatory laws on digital lending, the number of laws cited, the transparency on loan fees, the tendency to read terms and conditions before undertaking digital loans, the use of private data by digital loan providers, the flexibility in loan repayments, number of items to be introduced, and the ability to raise complains to lender.

H_2: Customer characteristics and regulatory controls have no significant control for effect on customer over-indebtedness

In this specific hypothesis test, the factors of customer characteristics and regulatory controls were jointly included in the model and the impact of those factors on the results monitored. The results of the model without the control variables as shown in Hypothesis 1 above were then compared with the results of the model where the customer characteristics factors and regulatory controls factors have been included on the factors of the main independent variable.

Both binary logistic model and linear probability model were both used in this study. Binary logistic regression was used since the dependent variable in the main relationship (customer over-indebtedness) is dichotomous (had been converted into dummies), and the linear probability model was also based on the binary variables. The dependent variable was Customer over-indebtedness and the independent variable factors included digital credit revolution as well as factors of the control variables.

The logit model was represented by Log*it (Pi)=β0+βiXi*. The specific model took the form:

$$\text{Logit (Pi)} = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6 + \ldots\ldots + \beta_nX_n + \mathcal{E}$$

Where X_1 to X_n represent factors of digital credit revolution, customer characteristics and regulatory controls. $B_1$to B_n represents their corresponding coefficients.

5.3.3.1: The Model Summary

The model summary – Nagelkerke R-Square (Pseudo R^2) was represented by the coefficient of variation. Pseudo R^2 shows the level at which the model determines changes in the dependent variable. In this case, the model without the control variables were compared to the model with the control variables. Any differences were noted and explained below.

Table 5. 13: *Model Summary – Digital Credit Revolution and Customer Over-indebtedness*

Step	-2 Log likelihood	Cox & Snell R^2	Nagelkerke R^2
1	444.997[a]	0.215	0.287

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Source: Author, (2022)

The model below in Table 5.14, shows the results with control variables incorporated:

Table 5. 14: ***Model Summary - Digital Credit Revolution and Customer Over-indebtedness - with Control Variables***

Model Summary			
Step	-2 Log likelihood	Cox & Snell R^2	Nagelkerke R^2
1	350.435a	0.385	0.513

a Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Source: Author, (2022)

From the results, it is evident that the model becomes more predictive when the control variables are added. This indicates that the model could explain changes in customer over-indebtedness to the extent of 51.3% up from 28.7%.

5.3.3.2: Sensitivity Analysis

The sensitivity analysis of both models with and without the control variables, were also tested and the results compared below.

Table 5. 15: ***Sensitivity Analysis – Digital Credit Revolution and Customer Over-indebtedness - Without the Control Variables***

Sensitivity Analysis					
Observed			Predicted		
			Customer Over-Indebtedness		Percentage Correct
			No	Yes	
Step 1	Customer Over-Indebtedness	No	133	60	68.9
		Yes	48	148	75.5
	Overall Percentage				72.2

a. The cut value is .500

Source: Author, (2022)

The results of Table 5.15 above show an average accuracy level of 72.2%. This means that the model is fairly accurate even without the control variables.

Table 5. 16: ***Sensitivity Analysis – Digital Credit Revolution and Customer Over-indebtedness - With the Control Variables***

Classification Tablea				
Observed		Predicted		
		Customer Over-Indebtedness		Percentage Correct
		0	1	
Customer Over-Indebtedness	No	155	38	80.3
	Yes	36	160	81.6
Overall Percentage				81
a The cut value is .500				

Source: Author, (2022)

After the introduction of control variables, the classification table 5.16 indicates an increase in the overall percentage of model accuracy from 72.2% to 81%.

The model therefore becomes more accurate in predicting cases when the factors of control variables are introduced. The accuracy levels of both models are above of 62.2% which is acceptable. (Field, 2005).

5.3.3.3 Results of the Model and its Interpretation

The variables in the model equation explains whether each variable is positively or negatively correlated. When $Exp(B)<1$ then its negatively correlated and $Exp (B) >= 1$ shows positive correlation to the dependent variable.

The significance of the model on the other hand indicates whether the variable contributes significantly to the model or does not contribute significantly to the model ($p<0.05$ - contributes significantly; $p > 0.05$ - does not contribute significantly).

Below are the findings of the tests – with and without the control variables

Table 5.17: ***Empirical Results: Digital Credit Revolution and Customer Over-indebtedness - Without the Control Variables***

Variables in the Equation								
	B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
							Lower	Upper
The last time borrowed a mobile loan	0.75	0.186	16.2	1	0.000	2.117	1.469	3.05
No. of mobile/digital loan providers in Kenya	0.543	0.197	7.58	1	0.006	1.721	1.169	2.534
Presence of bank account	-1.09	0.334	10.667	1	0.001	0.336	0.175	0.647
Had a secured bank/ Sacco loan before digital/mobile loans	1.021	0.299	11.634	1	0.001	2.777	1.544	4.994
Currently have a secured bank/MFI/Sacco loan	-0.652	0.335	3.796	1	0.048	0.521	0.27	1.004
Constant	-3.432	0.755	20.643	1	0	0.032		

a Variable(s) entered on step 1: When was the last time you borrowed a mobile loan?, How many mobile/digital loan providers do you know exist in Kenya? Do you have a bank account?, Did you have any secured bank/MFI/Sacco loan before you started using the digital/mobile loans?, Do you currently have a secured bank/MFI/Sacco (on top of digital) loan?.

Source: Author, (2022)

Each of the factors of digital credit revolution (the independent variable) in Table 5.17 above is significant in the model. The factors: the last time of borrowing a mobile loan, how many mobile/digital loan providers the respondent know exist in Kenya and if they had any secured bank/MFI/Sacco loan before starting to use the digital/mobile loans; were positively correlated to customer over-indebtedness.

While the factors of: Having a bank account and whether they currently have a secured bank/MFI/Sacco loan; were negatively correlated.

The researcher then went ahead to test the results with the control variables added into the model. The results obtained were as follows:

Table 5.18: ***Empirical Results: Digital Credit Revolution and Customer Over-indebtedness – With Control Variables – Using Binary Logit Model***

Factors:	**B**	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**95% C.I.for EXP(B)**	
The last time borrowed a mobile loan	0.729	0.211	11.981	1	0.001	2.074	1.372	3.134
No. of mobile/digital loan providers in Kenya	0.414	0.245	2.863	1	0.091	1.514	0.936	2.446
Presence of bank account	-0.561	0.454	1.529	1	0.216	0.571	0.234	1.389
Had a secured bank/ Sacco loan before digital/mobile loans	0.037	0.386	0.009	1	0.924	1.038	0.487	2.209
Currently have a secured bank/MFI/Sacco loan	-0.532	0.388	1.883	1	0.17	0.587	0.275	1.256
Customer Characteristics (Control Variable)								
Gender	-0.254	0.288	0.778	1	0.378	0.775	0.441	1.365
Age	0.371	0.192	3.733	1	0.053	1.449	0.995	2.112
Academic Qualification	0.328	0.207	2.509	1	0.113	1.388	0.925	2.083
Family Status	-0.517	0.341	2.296	1	0.13	0.596	0.305	1.164
Occupation	0.158	0.309	0.261	1	0.609	1.171	0.64	2.144
Average income	-0.343	0.248	1.916	1	0.166	0.709	0.436	1.154
Type of Phone	0.474	0.5	0.902	1	0.342	1.607	0.604	4.279
Technological savviness of the customer	1.203	0.321	14.038	1	0.00	3.329	1.775	6.246
Regulatory Controls (Control Variable)								
Knowledge of Regulatory laws	0.853	0.649	1.727	1	0.189	2.346	0.658	8.373
The number of laws cited	-0.514	0.528	0.95	1	0.33	0.598	0.212	1.682
The transparency on loan fees	0.108	0.301	0.127	1	0.721	1.114	0.617	2.011
The tendency to read terms and conditions before undertaking digital loans	0.094	0.33	0.081	1	0.777	1.098	0.575	2.096
The use of private data by digital loan providers	-0.121	0.621	0.038	1	0.846	0.886	0.262	2.996
The flexibility in loan repayments	-0.053	0.299	0.032	1	0.859	0.948	0.527	1.705
Number of items to be introduced	1.298	0.207	39.194	1	0.00	3.663	2.44	5.5
Ability to raise complains to lender	0.666	0.806	0.683	1	0.408	1.947	0.401	9.441
Constant	-7.187	1.625	19.569	1	0.00	0.001		

Source: Author, (2022)

In the model without the control variables, all the factors of the independent variable (digital credit revolution) are all significant at ($p > 0.05$). But once the control variables are included, four out of five factors of the independent variable become insignificant in the model and only one factor remain as significant (the last time the respondent borrowed a loan). The B value for the first factor (the last time borrowed a mobile loan) remains positive (B=0.729) and significant indicating that as the value increases (less time from the last loan or more recently the respondent borrowed) then there was higher probability and 2.074 time more likely to be over-indebted.

Among the control variables, technological savviness of the customer, knowledge on what needs to be improved in the digital lending process and the ability to raise complains; were all significant in the model. This means that even as control variables, they contribute significantly to the model ($p > 0.05$) and are positively correlated (Exp(B)>1).

From the findings above, control variables were found to significantly alter and affect the model. The null hypothesis was rejected meaning that customer characteristics and regulatory controls as control variables had significant effect on the relationship between digital credit revolution and customer over-indebtedness.

The researcher repeated to test the same hypothesis using Linear Probability Model with the control variables added to the model. The results are as shown in Table 5.19 below:

Table 5.19: ***Empirical Results: Digital Credit Revolution and Customer Over-indebtedness – With Control variables – Using Linear Probability Model***

Coefficients a					
Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
Determinants:	**B**	**Std. Error**	**Beta**		
Constant	-4.44	2.778		-1.598	0.111
The last time borrowed a mobile loan	2.655	0.382	0.287	6.959	0.00
No. of mobile/digital loan providers in Kenya	0.746	0.412	0.07	1.808	0.071
Presence of bank account	-1.08	0.785	-0.07	-1.376	0.17
Had a secured bank/ Sacco loan before digital/mobile loans	0.594	0.722	0.044	0.823	0.411
Currently have a secured bank/MFI/Sacco loan	-1.627	0.732	-0.1	-2.224	0.27

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Determinants:	**B**	**Std. Error**	**Beta**		
Customer characteristics (Control Variable)					
Gender	0.379	0.506	0.028	0.75	0.454
Age	0.599	0.351	0.081	1.704	0.089
Academic Qualification	0.658	0.354	0.077	1.86	0.064
Family Status	0.081	0.603	0.006	0.135	0.893
Occupation	-0.541	0.548	-0.036	-0.986	0.325
Average income	-0.591	0.446	-0.065	-1.325	0.186
Type of Phone	-0.265	0.881	-0.013	-0.301	0.764
Technological savviness of the customer	-2.062	0.561	-0.139	-3.675	0.00
Regulatory Controls (Control Variable)					
Knowledge of Regulatory laws	1.796	1.18	0.134	1.523	0.129
The number of laws cited	-0.833	0.947	-0.075	-0.88	0.38
The transparency on loan fees	-0.12	0.532	-0.009	-0.225	0.82
The tendency to read terms and conditions before undertaking digital loans	0.13	0.287	0.019	0.454	0.65
The use of private data by digital loan providers	-0.264	1.131	-0.009	-0.233	0.82
The flexibility in loan repayments	0.917	0.517	0.068	1.774	0.07
Number of items to be introduced	3.351	0.36	0.461	9.307	0.00
Ability to raise complains to lender	0.223	1.235	0.007	0.181	0.857
a Dependent Variable: Customer Over-Indebtedness					

Source: Author, (2022)

Using Linear Probability Model, researcher obtained results with similar significance of variables as earlier tested using Binary Logistic Model. With Linear Probability Model, four out of five factors of the independent variable also become insignificant in the model once the control variables were added to the model. This indicates that the factor: time from the last loan (the only variable that remained significant once the control variables were introduced); was indeed a strong prediction variable as showcased by both models.

Similarly, while testing using the linear probability model, there are three factors of control variables that are significant in the model as earlier witnessed using binary logistic model. The similar results in the two models, were a confirmation of the strength of these variables in the model.

5.3.4 Culture and Digital Credit Revolution

Culture refers as the behavior, beliefs, as well as attitudes learnt from the society by people who are born in that society (Kaffenberger et al., 2018). In adoption of technology, the cultural connotation is a significant factor as it influences the behavior of the people in regard to the adoption of the new technology. In this study, Culture was an instrumental variable meaning that it would not directly influence the dependent variable but it would do so through an influence of the digital credit revolution which is an independent variable in this study. This specific hypothesis was therefore established to determine the extent of the effect of culture on digital credit revolution.

H3: There is no significant effect of culture and digital credit revolution

Digital credit revolution is the independent variable of the study, and it is comprised of factors such as the last time respondent borrowed a mobile loan, knowledge of mobile loan providers, ownership of bank account, and ownership of other secured loan(s) before using digital loans. Some of these factors were categorical variables, they were represented by values of 1 and 0 and as such they were added together to form a scale variable of digital credit revolution. The higher the scale variable the higher the respondent was assumed to have embraced digital credit revolution.

Culture on the other hand was comprised of six factors that were categorical variables. They included that the respondent: financial indiscipline, fears borrowing and being in debt, budgeting before spending borrowed cash, is bothered by late loan repayment, borrows more loans than can afford, easily trusts loan providers with private data.

Since digital credit revolution was not dichotomous (were not converted into dummies but was rather continuous variables), only linear regression model was adopted to test the significance of the effect of culture on digital credit revolution. The model took the form:

$$P(Y) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6 + \mathcal{E}$$

X_1 to X_6 are as described as factors of culture variable while β_1 to β_6 are their coefficients respectively. β_0 and $\mathcal{E}$ are regression constants.

5.3.4.1 Model Summary

The model summary indicates the coefficient of determination (R square) which determines the extent to which changes in the dependent variable could be brought about by changes in the model. The model has a co-efficient of determination R-Squared of 0.164 and therefore the model would influence changes in digital credit revolution by 16.4%. The other changes in digital credit revolution are associated by other factors outside the model.

Table 5.20: ***Model Summary - Culture and Digital Credit Revolution***

Model Summary[b]				
Model	R	R Square	Adjusted R^2	Std. Error of the Estimate
1	.405[a]	.164	.151	0.953
a. Predictors: (Constant)				
b. Dependent Variable: Digital Credit Revolution				

Source: Author, (2022)

5.3.4.2 Test Statistic

F-test statistics was used to determine whether to reject or fail to reject the null hypothesis. The p value of the F test was p=0.000 which was less than the p-value ($p < 0.05$). This indicates that there is a statistically significant effect of culture on digital credit revolution.

Table 5.21: ***Anova Table - Culture and Digital Credit Revolution***

Anova[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	68.296	6	11.383	12.521	.000b
	Residual	347.277	382	0.909		
	Total	415.573	388			
a. Dependent Variable: Digital Credit Revolution						
b. Predictors: (Constant), Financial Indiscipline, Fears borrowing and being in debt, Budgets before spending any cash, Is bothered by late loan repayment, Borrows more loans than can afford and Easily trusts loan providers with private data.						

Source: Author, (2022)

5.3.4.3 Results of the Model and its Interpretation

The coefficients table indicates the t-test undertaken to determine the significance of each factor on the model. The results were as follows:

Table 5:22: ***Results of the Model - Culture and Digital Credit Revolution***

Coefficients[a]							
Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	6.334	0.134		47.44	0	6.071	6.596
Financial Indiscipline	0.087	0.132	0.042	0.659	0.51	-0.172	0.346
Fears borrowing and being in debt	-0.539	0.108	-0.258	-4.975	0.000	-0.752	-0.326
Budgets before spending any cash	-0.248	0.123	-0.12	-2.02	0.044	-0.49	-0.007
Is bothered by late loan repayment	0.11	0.106	0.051	1.042	0.298	-0.098	0.318
Borrows more loans than can afford	0.126	0.15	0.058	0.838	0.402	-0.169	0.421
Easily trusts loan providers with private data	-0.425	0.234	-0.089	-1.815	0.07	-0.884	0.035

a. Dependent Variable: Digital Credit Revolution

b. Predictors: (Constant), Financial Indiscipline, Fears borrowing and being in debt, Budgets before spending any cash, Is bothered by late loan repayment, Borrows more loans than can afford and Easily trusts loan providers with private data.

Source: Author, (2022)

The results above indicate that three factors of culture; ‘fears borrowing and being in debt’, ‘budgets before spending any cash’ and ‘easily trusts loan providers with private data', had a significant contribution to the model at $p < 0.05$. These three factors also had negative coefficients meaning that as the value of the factor increases then there was lower probability of digital credit revolution being witnessed.

It also means that when a respondent fear getting into debt, when they start to develop the budgets before spending their money, and when they do not easily trust the loan providers, then they were adopting a risk averse culture which is instrumental in making them not over-indebted. The other three factors in the model did not have significant contribution to the model.

In conclusion, the findings supported rejection of null hypothesis and hence there was a significant effect of culture on digital credit revolution.

5.3.5 Effect of Control Variables (Customer Characteristics and Regulatory Controls) on Digital Credit Revolution

Culture was used as an instrumental variable in this research. An instrumental variable is the third variable in relationships and is used to account for the unexpected relationship between the two main variables. In this research, digital credit revolution was the main independent variable and customer over indebtedness was the dependent variable. Since instrumental variable does not affect the dependent variable in the main relationship directly, but it does it through the independent variable, then the researcher found a need to analyze resulting relationship of culture and digital credit revolution.

Customer characteristics and regulatory controls were used as control variables in the resulting relationship of culture and digital credit revolution. The customer characteristics factors included in the study included: age, family status, level of income, gender, academic qualifications, occupation and technological savviness of the customer. Regulatory control factors used in the study were: the knowledge of regulatory laws on digital lending, the number of laws cited, the transparency on loan fees, the tendency to read terms and conditions before undertaking digital loans, the use of private data by digital loan providers, the flexibility in loan repayments, number of items to be introduced, and the ability to raise complains to lender. All the factors of customer characteristics and regulatory controls were applied jointly into the model.

H_4: Customer characteristics and regulatory controls have no significant effect on the relationship between Culture and Digital credit revolution

Like in hypothesis three, digital credit revolution which was the dependent variable in this specific relationship, was not dichotomous (were not converted into dummies but was rather continuous variables), linear regression model could be used. However, in this hypothesis, the independent variables were more than one, hence Multiple Regression Model was adopted in the test. The factors of customer characteristics and regulatory controls were jointly included in the model and the impact on the results compared. The results of the model without the control variables as shown in Hypothesis 3 above were then compared with the results of the model where the control variable factors have been included.

Linear Regression Model was used to test this hypothesis. The model took the form:

$$P(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots.. + \beta_n X_n + \mathcal{E}$$

Where X_1 to X_n are the factors of culture, customer characteristics and regulatory controls as described above while β_1 to β_{6n} are their coefficients respectively. β_0 and $\mathcal{E}$ are regression constants.

5.3.5.1 Model Summary

The model efficiency for this hypothesis was calculated using coefficient of determination (R square) which determines the extent to which changes in the dependent variable could be brought about by changes in the model. Both the model without the control variables and the one with the control variables were compared as shown below. This was meant to bring out the changes caused by the presences of the control variables.

Table 5.23: ***Model Summary – Culture and Digital Credit Revolution - Without the Control Variables***

Model Summary[b]				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.405[a]	.164	.151	0.953
a. Predictors: (Constant), Financial Indiscipline, Fears borrowing and being in debt, Budgets before spending any cash, Is bothered by late loan repayment, Borrows more loans than can afford and Easily trusts loan providers with private data.				
b. Dependent Variable: Digital Credit Revolution				

Source: Author, (2022)

In table 5.23 above, the model has a co-efficient of determination R-Square of 0.164 and therefore the model would influence changes in digital credit revolution by 16.4%.

The model which included the factors from both culture and the control variables (customer characteristics and regulatory controls) were then calculated and the results shown as follows:

Table 5.24: ***Model Summary – Culture and Digital Credit Revolution - With the Control Variables***

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.459a	0.211	0.163	0.947
a Predictors: (Constant), all fctors of culture, all factors of customer characteristics, and all factors of regulatory controls				

Source: Author, (2022)

From the results in Table 5.24, it was evident that presence of control variables increased the extent to which changes in the dependent variable could be brought about by changes in the model from 16.4% to 21.1% as indicated in the R^2.

5.3.5.2 Test Statistic

F-test statistics is used to determine whether to reject or fail to reject the null hypothesis. In order to show whether control variables had any impact on the model, an F-test statistics was calculated as shown below and results compared.

Table 5.25: ***Anova Table – Culture and Digital Credit Revolution - Without the Control Variables***

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	68.296	6	11.383	12.521	.000b
	Residual	347.277	382	0.909		
	Total	415.573	388			
a. Dependent Variable: Digital Credit Revolution						
b. Predictors: (Constant), Financial Indiscipline, Fears borrowing and being in debt, Budgets before spending any cash, Is bothered by late loan repayment, Borrows more loans than can afford and Easily trusts loan providers with private data.						

Source: Author, (2022)

In Table 5.25 above, the p value of the F test was p = 0.000 which was less than the p-value ($p < 0.05$). This indicates that there is a statistically significant effect of culture on digital credit revolution. An analysis with the control variables included was also carried out and results indicated as follows.

Table 5.26: ***Anova Table – Culture and Digital Credit Revolution - With the Control Variables***

ANOVAa						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	87.547	22	3.979	4.44	.000b
	Residual	328.026	366	0.896		
	Total	415.573	388			
a Dependent Variable: Digital Credit Revolution						
a Predictors: (Constant), all fctors of culture, customer characteristics, and regulatory controls						

Source: Author, (2022)

In both models, (with and without control variables), the p value of the F test was p = 0.000 which was less than the p-value ($p < 0.05$) which means that both models are statistically significant. F-test value usually gives the ratio of the mean squared error of any two groups. This means that when the F-value in an ANOVA test is high, the variation between sample means relative to the variation within the samples is also higher. The higher the F-value, the lower the corresponding p-value.

In the above two cases, the F-test Value for the model without the control variables is 12.521 and the F-test Value for the model with the control variables reduced significantly to 4.44. This means that the model with the control variables included is a better model. Presence of control variables improved the model.

5.3.3.3 Results of the Model and its Interpretation

Using Linear Regression Model, the researcher then compared the findings of the regression tables coefficients.

The coefficients table indicates the t-test undertaken to determine the significance of each factor on the model - both with and without the control variables and results compared below:

Table 5:27: ***Test Results – Culture and Digital Credit Revolution - Without the Control Variables***

Coefficients[a]							
Model	Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	6.334	0.134		47.44	0	6.071	6.596
Financial Indiscipline	0.087	0.132	0.042	0.659	0.51	-0.172	0.346
Fears borrowing and being in debt	-0.539	0.108	-0.258	-4.975	0.000	-0.752	-0.326
Budgets before spending any cash	-0.248	0.123	-0.12	-2.02	0.044	-0.49	-0.007
Is bothered by late loan repayment	0.11	0.106	0.051	1.042	0.298	-0.098	0.318
Borrows more loans than can afford	0.126	0.15	0.058	0.838	0.402	-0.169	0.421
Easily trusts loan providers with private data	-0.425	0.234	-0.089	-1.815	0.07	-0.884	0.035

a. Dependent Variable: Digital Credit Revolution

b. Predictors: (Constant), Financial Indiscipline, Fears borrowing and being in debt, Budgets before spending any cash, Is bothered by late loan repayment, Borrows more loans than can afford and easily trusts loan providers with private data.

Source: Author, (2022)

In Table 5.27 above, the results of the Linear Regression Model indicate that three factors (Fears borrowing and being in debt, Budgets before spending any cash and easily trusts loan providers with private data) had significant contribution to the model at $p < 0.05$. These three factors also had negative coefficients meaning that as the value of the factor increases then there was lower probability of digital credit revolution being witnessed.

It also means that when a respondent fear getting into debt, when they start to develop the budgets before spending their money, and when they do not easily trust the loan providers, then they were adopting a risk averse culture which is instrumental in making them not over-indebted. The other three factors in the model did not have significant contribution to the model.

Table 5:28: ***Results – Culture and Digital Credit Revolution - With the Control Variables***

Coefficients[a]							
Unstandardized Coefficients	Unstandardized Coefficients		Unstandardized Coefficients			Unstandardized Coefficients	
	B	Std. Error	Beta	T	Sig.	Lower Bound	Upper Bound
Financial Indiscipline	0.078	0.136	0.038	0.577	0.564	-0.188	0.345
Fears borrowing and being in debt	-0.428	0.13	-0.205	-3.281	0.001	-0.685	-0.172
Budgets before spending any cash	-0.219	0.134	-0.106	-1.635	0.103	-0.483	0.044
Is bothered by late loan repayment	0.117	0.108	0.054	1.083	0.279	-0.095	0.329
Borrows more loans than can afford	-0.002	0.156	-0.001	-0.014	0.989	-0.309	0.304
Easily trusts loan providers with private data	-0.302	0.241	-0.063	-1.253	0.211	-0.776	0.172
Customer Characteristics (Control Variable)							
Gender	-0.026	0.102	-0.013	-0.26	0.795	-0.226	0.173
Age	-0.068	0.071	-0.06	-0.954	0.341	-0.208	0.072
Academic Qualification	0.004	0.072	0.003	0.056	0.956	-0.137	0.145
Family Status	-0.132	0.123	-0.061	-1.074	0.284	-0.375	0.11
Occupation	-0.066	0.111	-0.029	-0.591	0.555	-0.284	0.153
Average income	0.126	0.091	0.09	1.396	0.164	-0.052	0.304
Type of Phone	0.141	0.174	0.044	0.809	0.419	-0.202	0.484
Technological savviness	-0.037	0.114	-0.016	-0.327	0.744	-0.261	0.186
Regulatory Controls (Control Variable)							
Knowledge of Regulatory laws	-0.139	0.24	-0.067	-0.58	0.562	-0.612	0.333
The number of laws cited	0.14	0.193	0.081	0.724	0.47	-0.24	0.52
The transparency on loan fees	0.036	0.11	0.017	0.327	0.744	-0.181	0.253
The tendency to read terms and conditions before undertaking digital loans	-0.007	0.058	-0.007	-0.122	0.903	-0.122	0.108
The use of private data by digital loan providers	-0.607	0.228	-0.138	-2.657	0.008	-1.055	-0.158
The flexibility in loan repayments	0.167	0.105	0.081	1.595	0.112	-0.039	0.373
Number of items to be introduced	0.155	0.081	0.138	1.916	0.056	-0.004	0.313
Ability to raise complains to lender	-0.305	0.252	-0.059	-1.212	0.226	-0.8	0.19
a Dependent Variable: Digital Credit Revolution							

Source: Author, (2022)

The significance level of this model indicates whether the variable contributes significantly to the model or does not contribute significantly to the model at ($p<0.05$). While the correlations of the variables in the model equation explains whether each variable is positively or negatively correlated.

With introduction of control variables into the model as shown in Table 5.27 above, only factor; 'Fears borrowing and being in debt' remains as significant. The other two factors (budgets before spending any cash and easily trusts loan providers with private data) have now become insignificant in the model.

The B value for factor: 'Fears borrowing and being in debt' is negative ($B=-0.428$) and significant indicating that as the value increases (the more respondent fear getting into debt) then there was reduced probability of witnessing more digital credit revolution. The control variable that is significant in the model is 'the use of private data by digital loan providers' and is negatively correlated is the factor that touches on customer data. This means that customers are very sensitive and are concerned on how their data is accessed and used by the digital credit providers.

From the findings above, the control variables were found to significantly alter and affect the model. The null hypothesis was therefore rejected meaning that customer characteristics and regulatory controls as control variables had significant effect on the relationship between culture and digital credit revolution.

5.4 Discussion of The Research Findings

The general objective of this research was to evaluate the effect of digital credit revolution on customer over-indebtedness within the informal economy in Nairobi Kenya. Based on the findings, the research confirmed that the study objectives were met. To establish the correlation between the variables in the study, the researcher undertook correlation analysis. Pearson's Correlation was used to determine the correlation between the study variables, where variables with significant correlation were particularly noted. The researcher used both the Binary Logistic Regression model and the Multi-Linear Probability Model to test the hypotheses of the study.

The correlation between digital credit revolution and customer over-indebtedness was the first to be determined in the study. Digital credit revolution factors comprised of: number of digital lenders, level of borrowing activity, frequency of access, and mainstream loans versus digital/mobile loans.

The correlation between customer over-indebtedness and the last time a respondent borrowed a mobile loan was positive and significant at 0.01 level. The Pearson's Correlation (r) was 0.240 that indicated that respondents who had taken a longer period of time before they borrowed a digital loan were less likely to be over-indebted, while those who had taken a digital loan in the recent past, were more likely to be over-indebted. The findings were consistent with the findings of FSD (2018), that found that Kenyans in the informal sector took mobile loans more frequently and majority were borrowing for trivial reasons and not because they had an emergency.

The correlation between customer over-indebtedness and whether a respondent had a bank account was also significant but negative with $r = -0.319$. This indicates that respondents who had bank accounts were less over-indebted, while respondents who did not have bank accounts were more likely to be over-indebted. Respondents had also been asked whether they had existing secured/bank loan before undertaking digital/mobile loans. Those who answered in the affirmative were more likely to be over-indebted as the correlation between the two variables was significant and positive at $r = 0.291$. This showed that these respondents had more loan providers within their reach increasing the chances of taking loans. Musau et al. (2018) indicated that late loan repayments in Kenya had been made worse by increased presence of digital lenders and therefore conforms to the findings of this study. When the respondents were asked whether they had a current secured bank/MFI/Sacco (on-digital) loan, the correlation with customer over-indebtedness was insignificant and close to zero indicated that there was no correlation between the two variables.

The correlation between culture and digital credit revolution was also undertaken using Pearson's Correlation. The correlation between digital credit revolution and whether a respondent had ever borrowed a loan just because it was accessible was positive and significant at level $p< 0.05$ ($r = .128$). This means that the respondents who borrowed money just because it was accessible, showed higher probability of digital credit revolution being witnessed. The correlation between credit digital revolution and whether the borrower feared getting into debt was significant and negative at the level of 0.01 ($r = -.169$, $P < 0.01$). This indicates that the more borrowers fear getting into debt, the lower the probability digital credit revolution. Similarly, the correlation between digital credit revolution and budgeting before spending any cash received was also negative and significant at 0.01 level ($r = .175$, $P < 0.01$). This means that the more respondents write budgets before spending any cash received, the lower the digital credit revolution.

The aspect of whether late repayment of loans bothers the borrowers' conscience and its correlation to digital credit correlation was insignificant and close to zero ($r = .092$, $P < 0.05$). This indicates that the bother of late repayment of loans did not have an influence on digital credit revolution. On the other hand, borrowing more loans than the borrowers could service had positive significant correlation ($r = .130$, $P < 0.05$) while trusting mobile service providers with personal data had significant and negative correlation with digital credit revolution ($r = -.119$, $P < 0.05$). Since culture was an instrumental variable, each correlation that lowered the chances of digital credit revolution therefore led to lower chances of getting over-indebted.

The correlation between customer characteristics and customer over-indebtedness was also tested. Factors such as gender, age group, occupation and type of phone had almost zero correlation to customer over-indebtedness. However family status, academic qualification and the income component had significant positive correlation to customer over-indebtedness. This means that the more these characteristics were manifested in the borrowers the more they were likely to be over-indebted. The findings were in agreement with the findings by AFI (2017) on customer demographics not being of significant influence on technological adoption. The study by Hwang and Tellez (2010) were consistent with the findings of this research since both indicated that customer behavior towards use and adoption of new technology depended not on all demographics but only on selected demographics. The findings by findings by Litondo (2010) were also consistent with the findings of this research which found that the level of education was significant on influencing the adoption of technology since more educated respondents had positive correlation to over-indebtedness (access to loans). The findings were also inconsistent to the findings by Santos et al., (2018), who found that financial literacy decreased the probability of using informal loans.

The relationship between regulatory controls and customer over-indebtedness were also determined to establish whether changes in regulatory controls would have significant effect on customer over-indebtedness. Regulatory control factors that had significant and positive correlation on customer over-indebtedness were knowledge of laws regulating lending at $r = 0.363$, number of laws known to respondent at $r = 0.318$, read terms and conditions before taking loans at $r = 0.194$ and factors that ought to be improved at $r = 0.558$. These factors increased the chances for a customer to be over-indebted. The factor that had significant negative correlation was availability of flexible repayment terms at $r = -0.11$. This indicates that the more a customer had flexible repayment terms, the more likely was the chance for the customer not to be over-indebted. FDIC (2007) advocated for penalties for institutions that did not bring out clear terms and conditions for loans advanced, though from the findings of this study, the terms and conditions did not deter the borrowers from borrowing more. The findings of the study were however inconsistent to findings by FDIC (2007) who found that laws would help on cautioning borrowers against predator lending.

The first hypothesis (no significant effect of digital credit revolution on customer over-indebtedness) was rejected by the use of logit model. The model was found to be significant at p = 0.000. The explained variation in the dependent variable was shown by Nagelkerke R^2 method which is a modification of Cox & Snell R Square, and which indicated a value of 0.287. This indicates that the model could explain changes in customer over-indebtedness to the extent of 28.7%. The model had an overall accuracy of 72.2%. The findings showed that all factors of the independent variable are significant in the model. FSD (2018) found that Kenyans in the informal sector took loans for more trivial reasons, and this could be the reason why in less than 30 days, majority of the respondents had already taken loans. The more the digital lenders known to the respondent, the more the level of over-indebtedness.

The presence of bank account could signify that the lender does not rely on mobile and digital loans as they are likely to get loans from the bank. The presence of other unsecured loans had positive correlation to customer over-indebtedness, which indicated that the more one had other unsecured loans, the more they were likely to be over-indebted. The study by Schicks (2011) which found that embarrassment to the borrower and other mistreatment increased efforts for the borrower to pay their dues to avoid such, was not supported by this study. In fact, this research (within the informal sector) showed that the respondents were more likely to pay back their loans if the repayment terms were flexible and more likely to default if the terms of the loans given to them were punitive.

The other hypothesis was established to determine the extent of the effect of culture on digital credit revolution. The factors of culture were: financial indiscipline, fears borrowing and being in debt, budgeting before spending borrowed cash, is bothered by late loan repayment, borrows more loans than can afford and easily trusts loan providers with their private data. A multiple linear probability was adopted to test the level of significance. The model had a co-efficient of determination R-Square of 0.164 and therefore the model would influence changes in digital credit revolution by 16.4%. The p value of the F test was significant at p = 0.000.

The results showed that three factors (respondent fear getting into debt, when they start to develop the budgets before spending their money, and when they do not easily trust the loan providers) had significant contribution to the model at $p < 0.05$. These three factors had negative coefficients meaning that as the value of the factor increases then there was lower probability of digital credit revolution being witnessed.

It also means that when a respondent exhibits these three factors, then they were adopting a risk averse culture which is instrumental in making them not over-indebted. The findings supported rejection of null hypothesis and hence there was a significant effect of culture on digital credit revolution.

The hypothesis (customer characteristics and regulatory controls as control variables on the relationship between digital credit revolution and customer over-indebtedness) was also tested and the null hypothesis rejected. The control variables were found to significantly alter and affect the model The customer characteristics focused on the factors that are demographic in nature and were likely to stimulate and push a customer to behave in a certain manner while regulatory controls focused on: knowledge of regulatory laws on digital lending, the number of laws cited, the transparency on loan fees, the tendency to read terms and conditions before undertaking digital loans, the use of private data by digital loan providers, the flexibility in loan repayments, number of items to be introduced, and the ability to raise complains to lender.

The factors of control variables were jointly included in the model and the impact on the results monitored. With addition of control variables, the coefficient of variation Nagelkerke R Square (Pseudo R^2) became more predictive and could explain changes in customer over-indebtedness to the extent of 51.3% up from 28.7%. The average accuracy level also increases in the overall percentage from 72.2% to 81%. The model therefore becomes more accurate in predicting cases when the factors of control variables are introduced. Though both models (with and without the control variables) were significant, the model with the control variables made four out of five factors of the independent variable that were initially significant to become insignificant and only one factor remained as significant (the last time the respondent borrowed a loan) with B value remaining positive ($B = 0.729$). This indicates that control variables had significantly altered the model hence the need to hold it constant.

The fourth hypothesis focused on the effect of control variables (customer characteristics and regulatory controls) on the relationship between culture and digital credit revolution. Culture was used as an instrumental variable in this research which then turns digital credit revolution to be dependent variable for its effect to be studied. Linear Regression Model was used to test this hypothesis and compare the results of the model when control variables had been added and when it had not been added.

The model's coefficient of determination (R square) without the control variables was 16.4% which changed to 21.1% when control variables were added as indicated in the R^2. Meaning that control variables improved the predictability of the model. F-test statistics in both models were significant but the F-test value for the model reduced drastically from 12.521 to 4.44 once the control variables were added. This means that the model with the control variables included is a better model.

Using Linear Regression Model, the researcher then compared the findings of the regression tables coefficients. With introduction of control variables into the model, only one factor (fears borrowing and being in debt) remains as significant. The control variables were found to significantly alter and affect the model. The null hypothesis in Hypothesis 4 was therefore rejected. This indicates that customer characteristics and regulatory controls had significant effect on the relationship between culture and digital credit revolution.

CHAPTER SIX: SUMMARY, CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

The purpose of this study was to establish the relationship between digital credit revolution and customer over-indebtedness in the informal economy in Nairobi - Kenya. The rapid expansion of short-term lenders and the increased uptake of these loans, showed that the borrowers were not bothered by the pricing of these loans as well as other malpractices in the industry that included misuse of borrowers' private data, among others (Kaffenberger et al., 2018). This chapter therefore summarizes the findings of the study in regard to all the four hypotheses tested, the conclusions arrived at, the contributions of the study findings to the body of knowledge and provides suggestions on managerial practices and policies that needs to be implemented. The chapter also brings out the various limitations of the study and areas for future research.

6.2 Summary of Findings

This research was motivated by a recent mass increase in digital/mobile loan providers in the country as well as more youths in the informal sector being negatively listed by the credit reference bureaus. The study identified the problem and formulated the strategies to be followed in order to address the problem. The study then developed the study objectives which were summarized into the four study hypotheses.

The correlation between the various variables in the study was undertaken by use Pearson's Correlation. Some of the conclusions from the correlation findings were as follows: The respondents who had taken digital loans in the recent past (within 30 days) from the date of collecting these data, were more likely to be over-indebted. The respondents who had bank accounts were less likely to be over-indebted, while respondents who did not have bank accounts were more likely to be over-indebted. Respondents who had initially accessed the secured Sacco or bank loans before they started using digital/mobile loans were found to be more likely to be over-indebted. The respondents who confirmed to have taken mobile / digital loans just because of their availability and not because they had an emergency, had positive and significant correlation to over-indebtedness. Those who feared getting into debt and are risk averse, had significant and negative correlation to customer over indebtedness.

The correlation between digital credit revolution and budgeting before spending any cash received was also negative and significant. Respondents who were bothered by late repayment of loans or non-repayment affected their conscience, had negative and significant correlation to customer over-indebtedness. Academic qualification, family status and average monthly income all had positive significant correlation to customer over-indebtedness. This implied that the more these characteristics were manifested in the borrowers, the more they were likely to be over-indebted. Due to low literacy levels, the un-educated respondents could have lacked the technical know-how of maneuvering the digital loan apps.

From hypothesis testing, the findings of the study indicated that the null hypotheses of all the four hypotheses were rejected. The findings have been summarized in table 6.1 below:

Table 6.1: ***Summary of Results of the Study Hypotheses***

H	Null Hypothesis	Results	Interpretation
H1	There is no significant effect of digital credit revolution on customer over-indebtedness	The null hypothesis was rejected by the use of binary logit model. The model was found to be significant (p<0.05)	Digital credit revolution has a significant effect on customer over-indebtedness
H2	Customer characteristics and regulatory controls have no significant effect on the relationship between Digital credit revolution and Customer over-indebtedness	The null hypothesis was rejected by the use of binary logit model. The model was found to be significant (p<0.05)	Control variables (Customer characteristics and regulatory controls) jointly have a significant effect on the relationship between Digital credit revolution and Customer over-indebtedness
H3	There is no significant effect of Culture on Digital Credit Revolution	The null hypothesis was rejected. F-test statistics was significant at (p<0.05)	Culture has a significant effect on digital credit revolution
H4	Customer characteristics and regulatory controls have no significant effect on the relationship between Culture and Digital credit revolution	The null hypothesis was rejected. F-test statistics was significant at (p<0.05)	Control variables (Customer characteristics and regulatory controls) jointly have a significant effect on the relationship between Culture and Digital credit revolution

Source: Author, (2022)

6.3 Conclusions of the Study

The focus of the study was to determine the relationship between digital credit revolution and customer over indebtedness in the informal sector in Nairobi - Kenya. The researcher divided this section into two conclusion areas, which are, conclusions on the theoretical foundations of the study and the conclusions from the study findings.

6.3.1 The Theoretical Foundation of the Study

The study was anchored on three theories. These were: Diffusion of Innovation Theory (DIT), Theory of Reasoned Action (TRA), and the Unified Theory of Acceptance and Use of Technology (UTAUT). The Theory of Reasoned Action was key in understanding users' technology adoption behaviors as it deals more with the prediction, adoption, implementation, and acceptance of technology. The researcher leveraged on the TRA's strength in technological innovation. It assisted the researcher to model key issues especially on culture as an instrumental variable and to predict acceptability and use of the digital credit technology.

The diffusion of innovation theory was used to show how adoption of a new technological idea like the adoption of digital loans does not happen simultaneously across the population but rather as a process where a smaller portion of the population start as early adopters as others follow progressively. It was used by the researcher to specifically understand the digital credit revolution as an independent variable and the key factors that leads to early adoption. UTAUT theory was relevant in this research as it showcased the degree of user involvement in the decision-making process and focused on the reflection of the perceived risk of using digital credit. This model helped the researcher identify the most relevant factors in the behavior of adoption and use of digital credit as a new technology.

The study confirmed the proposition of the DIT theory when it tested the hypothesis and found out that there was indeed significant effect of digital credit revolution on customer over indebtedness. It indicated that availability of digital loans increased digital credit revolution and also increased over indebtedness. It was evident from this study that the respondents did not bother about the costs or repercussions of excessive borrowing but ease of access and the convenience were the main drivers on their usage. This was consistent with the postulates of the UTAUT theory that focused on performance expectancy and effort expectancy as factors that drive usage of technology. The effort and performance expectancy therefore were key to them, knowing that these loans are easily accessible, with least effort and at the comfort of their homes by just dialing of a phone.

Another key theory in this study was the theory of reasoned action (TRA). It predicts the intention of an individual to perform a behavior based on self normative beliefs and attitude. This study solidified the proposition of the theory through its findings that there is significant effect of culture on digital credit revolution. The study concludes that people's behavior forms their culture, which is composed of attitude, beliefs and intentions. Despite the fact that the model developed to predict digital credit revolution from culture factors was weak with a coefficient of determination of 16.4%, the effect of culture was statistically significant at 95% confidence level.

6.3.2 Conclusion of the Study from the Findings

The research findings confirmed that there was significant effect of digital credit revolution on customer over-indebtedness among the population of the study. Most respondents that were over-indebted confirmed to have been motivated to borrow more by a recent mass increase in digital/mobile loan providers in the country. The study was formulated and executed through the four study hypotheses as covered in chapter 5 above. In all the four hypotheses, the null hypotheses were rejected.

The findings of the study showed that the more the respondent understood the digital loans landscape and could name more lenders, the more likely they were to get over-indebted. This showed that these respondents had more loan providers within their reach increasing the chances of taking loans. Musau et al. (2018) indicated that late loan repayments in Kenya had been made worse by increased presence of digital lenders and therefore conforms to the findings of this study. This also clearly showed that the mass proliferation of digital lenders into this population had significantly increased the chances of loan users getting over-indebted.

The respondents who had good knowledge of laws regulating lending and knew the terms and conditions before taking loans had significant and positive correlation to over-indebtedness. This confirmed that most over-indebted respondents knew the consequences and most borrowed loans because it was available and not necessarily because they were in dire need for it. Most were not bothered by the predatory interest rates nor even cared about the consequences of loan defaulting. These issues raise concerns on the role of punitive rates, mistreatment or use of regulation to curb customer over-indebtedness. This finding however disagreed with the finding by Schicks (2011), who concluded that embarrassment of the borrower and other mistreatment tactics increased efforts by the borrower to pay back their loans.

The factor that had significant negative correlation to over indebtedness was the availability of flexible repayment terms. This is a key point that must be considered by majority of digital credit providers struggling with huge default rates. The lenders could easily turn around their fortunes by giving their customers some flexibility in repayment terms.

Customer characteristics and regulatory controls as control variables in the study were found to have significant effect on the relationship between digital credit revolution and customer over-indebtedness and the relationship between culture and digital credit revolution. The control variables significantly improved the predictive nature of the models. This means that the control variables could cover part of the unexplained effects on the model. It therefore postulates that for meaningful analysis of the effects of the independent variables on the dependent variables, the factors of control variables need to held constant. The study also identified the key factors of control variables that were significant in model which includes; the respondents who fear borrowing and getting into debt and factor on customer data privacy.

The respondents who feared into debt, could budget before taking loans and were also bothered by late loan repayments, were found to show high aspects of financial discipline and were less likely to be over-indebted. This means that policy makers need to come up with financial training programs and initiatives that promote aspects like budgeting and understanding importance of borrowing loans within someone’s ability to repay.

It is important to note that the control variable that was most significant in hypothesis four is negatively correlated to the factor that touches on customer data. This means that customers are very sensitive and are concerned on how their data are accessed and used by the digital credit providers. This finding was consistent with finding by Pearson (2010) who found that proper legislation was required to be put in place to protect consumers data from exploitation as it was one of the biggest concerns for majority . It was however evident from the study that regulatory controls will not negatively affect over-indebtedness. Hence to curb excessive borrowing within this population, further policy issues need to be considered beyond regulations.

6.4 Contributions of the Study to the Body of Knowledge

The study makes several contributions to the body of knowledge. The researcher has grouped these contributions into two: contributions to theory and contributions to the knowledge of the topic under study.

In the two models used in the study, that is, Binary Logit Model and the multiple Linear Probability Model, the significance of the factors within the variables and the research findings re-affirmed the strength of the constructs as postulated in the Diffusion of Innovation Theory (DIT), Theory of Reasoned Action (TRA), and the Unified Theory of Acceptance and Use of Technology (UTAUT). In a similar fashion that the constructs would influence the adoption of technology in those theories, most of the constructs in this study indeed influenced the spread of the digital credit within the population. The study contributes to the body of knowledge by validating their constructs in the context of this research.

From the findings of the study, the body of knowledge within digital credit space and understanding on over-indebtedness was broadened by this research. The finding that majority of respondents in the informal sector borrowed digital loans not necessarily because they were in need of loans but because these loans were readily available to them, is a wakeup call for the leaders in charge of MSMEs and SMEs development in the country. It shows that there is need to be intentional on financial prudentency trainings and capacity building programs

Smart phones have become increasingly popular among the informal economy in Kenya and digital lenders have taken advantage of this platform to ensure that it is able to reach many people through social media. The resulting digital revolution has therefore led to significant increase in customer over-indebtedness.

From regulatory perspective, the findings confirmed that regulatory controls and availability of laws did not necessary deter customer over-indebtedness. The study showed that most respondents were getting over-indebted even though they great understanding of the digital loans landscape. These respondents could name more lenders and had good knowledge of laws regulating lending. These respondents still went ahead to borrow even in cases where the pricing, terms and conditions were punitive and predatory. This confirmed that most over-indebted respondents knew the consequences and most borrowed loans because it was available and not necessarily because they were in dire need for it. The researcher raised doubts on the role of regulation in curbing customer over indebtedness.

Despite the fact that the model developed to predict digital credit revolution from culture factors was statistically significant at 95% confidence level, culture as a construct was weak with a coefficient of determination of only 16.4%. This is an important point for future researchers in the area of culture especially in regards to technology adoption. From the researcher's perspective, convenience, ease of use, and the availability of digital loans, were the main drivers for the current revolution witnessed within digital loan provision.

Generally, the data collected from this research will form a foundation for future researchers who want to understand more concerning the credit landscape in the informal economy. The findings as captured from the study models, are systematically presented to make it easy for future review by other researchers. The findings have practical solutions that can be used by policy makers. With the launch of Hustler Fund in Kenya, the findings contribute significantly to the policy formulation now that the Hustler Fund is mainly targeting the same population as that covered under this study. It is important for people in charge of this new product to think about the constructs and the findings of this study.

6.5 Recommendations for Policy and Practice

Though there have been enhanced efforts to improve borrowers' data privacy by the recently formed office of the Data Commissioner in Kenya and the new Digital Credit Providers regulations (Central Bank of Kenya (Amendment) Act, 2021), the study showed that the borrowers in the informal sector cared less about the terms and conditions and the predatory interest rates that were punitive. This then calls for review in policy to help these borrowers at the bottom of the pyramid who might not be able to stand on their own despite the new regulations favoring them. The findings also indicated that regulatory controls and availability of laws did not necessary deter customer over-indebtedness. The study showed that most respondents were getting over-indebted even though they great understanding of the digital loans landscape. The study recommends a keener re-look into regulations and its enforceability. This is because a significant number of people in the informal sector would borrow loans, not necessarily because they need to attend to an emergency or to undertake a certain investment that would guarantee them returns than the cost of the loan, but only take up loans because of its availability.

The government especially those in charge of trade, commerce and industry also needs to start focusing on training the members of the informal economy on prudent finance practices. A lot of trainings need to be done on capacity building and how they can manage their finances. They need to learn on the effects of reckless borrowing and not to borrow for consumption but for production. They also need to be taught on the importance of keeping their credit worthiness on check so that they do not end up being at risk of being not able to borrow due to bad credit scores.

With the launch of Hustler Fund in 2022, the fund managers and the policy makers need to move with speed to address the capacity building and the training aspect. If this is not addressed at this stage, the researcher is worried that borrowers within the informal economy will end up borrowing just because of its availability as its been seen in this study. The borrowers need to be driven by financial prudency guidelines to borrow mainly for production and not consumption.

The study also recommends that government should have policies that are designed to help the informal sector, particularly, apprentice programs that are designed to target people in the informal sector. These kind of apprentice programs would offer basic trainings on business management, entrepreneurship, financial skills that include loans and savings. Majority of the country's population being in the informal sector, would mean that such a policy would not be far-fetched, and would therefore address the needs of people in the informal sector.

The study also recommends a further review in the data privacy and protection Act. Though the laws are now operational, more will need to be done. Consent from these borrowers to access their data is not sufficient. This mean that private data obtained by lenders even though with consent should be treated confidentially and would only be used to assess the eligibility of the borrower for the loans and not for other purposes. The study recommends full enforceability of the Data Protection regulations that would ensure that privacy of mobile loan borrowers is not only upheld but also guaranteed with serious consequences for non-compliance. Digital lenders should be in a position to demonstrate their willingness and ability to protect private data from misuse.

This study findings are also of key importance to the individuals and to the companies that offer digital loans. The researcher recommends that these concerned parties take time to review the findings of this research and pick the aspects that would enrich their offering and overall sustainability of the product. The researcher made effort to ensure the language used is simple and presentation of facts is in a systematic manner, ensuring that it is easier to follow and to be understood by everyone.

6.6 Assumptions of the Study

The researcher made a number of assumptions. This included the honesty of the respondents. The researcher assumed that the respondents would give truthful information as they answered the questions. The researcher mitigated this by assuring the respondents of their privacy and re-framing the questions in a way that would be comfortable to the respondent. The other assumption was the rationality of the respondent. The researcher assumed that the respondents were rationale beings, able to make choices and decide freely without coercion or influence.

Influence by the environmental factors or emotional state of the respondent would not be ruled out. The researcher assumed that all respondents were in good emotional state to answer the questions and were not influenced by what was going on in their lives or environment. The researcher also assumed that the respondents could bold enough to voice their disagreements to be enjoined in the study and to share any reservations they might have. This would ensure that only the willing respondents participated in the study and gave the accurate information.

6.7 Limitations of the Study

There were limitations in undertaking this study, however, the researcher made every effort to ensure that these limitations would not significantly affect the findings of the study. The study adopted a cross sectional study design where people in the informal sector were targeted in Nairobi. The cross-sectional design enables the researcher to collect relevant data that exists during the period of data collection and therefore it is time saving and would need less resources. However, the data collected may not provide historical data unless a longitudinal study would be conducted where data is collected over a certain period of time. The data collected is therefore limited to the prevailing situation at the time data was collected and may perhaps not be related to data in previous periods.

The study targeted people in the informal sector in Nairobi; the study estimated the number of digital loan users in the country to be around 6.4 million people with the majority of these users being in

Nairobi. The study would require a lot of resources to undertake a countrywide sample of digital loan users, which would be beyond the scope of this study. However, the study was able to use random stratified sampling technique as suggested by Krejcei and Morgan (1970), to target a minimum of 384 study respondents for populations above 10,000 people. The study was therefore able to meet this target respondents as it was able to collect data from 389 respondents. Statistical tools were therefore carefully used to assess the qualities of the respondents in order to infer the characteristics of the sample to be the characteristics of the population. With this, other bodies with bigger capacity can carry out research across the country and also in the regions to establish whether the findings would be consistent across the several counties and regions.

The research relied heavily on the responses from the respondent although the researcher took effort to explain some questions in the questionnaire to ensure that the respondent understood the questions clearly. The researcher was also keen to ensure that confirmation and clarification was received when there was any kind of inconsistence in the responses provided by the respondent. As such the study enhanced the quality and accuracy of responses. Future research can use several sources of data both primary and secondary data and can also include other data collection methods like observation over a long period of time.

Not many researches have been done in this area of digital credit since it’s still a relatively new concept. Reference materials are not many compared to other areas of research. However, the research used the available materials as well as well-known theories to validate the findings of this study

6.8 Suggestions for Further Research

From the time of data collection, a number of things have occurred within the population of this study that would be significant to research on. The new government in Kenya is now in place and they have rolled out a new loan product sponsored by government dubbed ‘Hustler Fund’. The hustler fund is mainly a loan product targeting the population of this study. Researcher recommends further research on what would be the impact of Hustler Fund on the other digital loan providers and its effect on customer over-indebtedness.

In the main constructs of this study, the researcher recommends that culture as a construct needs to be studied more deeply. Culture as a construct was weak with a coefficient of determination of only

16.4%. Future researchers can re-look into this especially in regards to technology adoption. Further research will need to be undertaken to establish other factors that would increase the accuracy of predicting digital credit revolution.

The use of a cross sectional study design was a limiting factor to the study. The study therefore suggests that future research should be undertaken, where use of longitudinal design would be possible to track changes on respondents’ preferences over certain period of time.

A similar study may also need to be adopted where different customer specific attributes would be assessed differently. The oldest respondent in the study was not more than 55 years. Perhaps a future study would be undertaken where the age of the respondent should be well inclusive, where borrowing among the old people would be assessed and compared to borrowing among the youth. The study would be informative to bring into light digital borrowing practices of the old people as compared to the young people.

Since this research was only limited to Nairobi, research may be carried out across the country and also in the other countries to establish whether the findings would be consistent across the several counties and countries.

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Appendix 1: Structured Questionnaire

The primary aim of this questionnaire was to collect data for analyzing the digital credit revolution and its effect on Customer Over-Indebtedness within the informal economy. The questionnaire was used in a form of structured interview. The respondents were randomly selected digital credit users within the informal sector across the 9 divisions of Nairobi. Protecting the privacy of the respondent was paramount; all personal information was kept confidential and used only for the intended study.

A. BACKGROUND INFORMATION

1. Are you a Digital (mobile) loan user?

☐ Yes ☐ No

If Yes, proceed to the other sections of the interview below.

2. Name (Optional): ____

3. Division: ____

4. Sub-Location: ____

5. Mpesa Shop: ____

B. DIGITAL CREDIT REVOLUTION (Independent Variable)

1. When was the last time you borrowed a mobile loan?

☐ Less than 30 days ago ☐ 30 – 60 days ago ☐ Over 90 days ago

2. How many mobile/digital loan providers do you know exist in Kenya?

…………………………………………………………………………………………………

List them here ……………………………………………………………………………

3. Do you have a bank account?

☐ Yes ☐ No

4. Did you have any secured bank/MFI/Sacco loan before you started using the digital/mobile loans?

☐ Yes ☐ No

If Yes, how many? ………………………………………………………………………….

5. Do you currently have a secured bank/MFI/Sacco (non-digital) loan?

☐ Yes ☐ No

If Yes, how many? ………………………………………………

C. CUSTOMER INDEBTEDNES (Dependent Variable)

1. Do you have any mobile/digital loans that you are currently servicing or outstanding?

□ Yes □ No

If yes, list them here ……………………………………………………………………

2. Do you have any mobile/digital loans that you are currently in default mode?

□ Yes □ No

If yes, what would you say has been the main reason for defaulting? …………………………………………………………………………………………………… ……………………………………………………………………………………………………

3. Would you say the coming of the digital/mobile loans has increased your borrowing of loans

□ Yes □ No

4. Do you always repay all the digital loans on time?

□ Yes □ No

If no, Use percentage to approximate the number of times you have repaid late …………………

5. Do you always know the consequences of NOT repaying the loans on time?

□ Yes □ No

If yes, what are these consequences? …………………………………………………………

6. What would you say is the biggest reason why you borrow the mobile loans? (Up to three reasons) **…………………………………………………….**

……………………………………………………

D. CUSTOMER CHARACTERISTICS (Control Variable)

1. Gender: □ Female □ Male

2. Your age group: □ 18 – 20 □ 21-25 □ 26-30 □ 31-35 □ 36-40

□ 41- 50 □ 50 – 65 □ Over 65 years

3. Highest Academic Qualification: □ KCPE □ KCSE □ Certificate/ Diploma □ Degree & Above

4. Family status: □ Married □ Single

5. Occupation?..

6. Average monthly income in Kshs (Optional)?

□ Below kshs 10,0000 □ Kshs 10,001 – 25,0000 □ Kshs 25,001 – 50,000 □ Kshs 50,001 – 75,000 □ Kshs 75,001 – 100,000 □ Kshs 100,001 – Ksh 200,000 □ Over Kshs 200,000

7. Type of phone used: □ Smart Phone □ Feature phone

8. The process of borrowing the loan; Do you find it challenging (mobile savviness)?

□ Yes □ No

If yes, what exactly would you want changed? ....

E. REGULATORY CONTROLS (Control Variable)

1. In your knowledge, is there any laws regulating the mobile lending (digital loans) business in Kenya?

□ Yes □ No

If yes above, explain? ....

2. Do you have full transparency (clearly notified) on the loan fees at the time of borrowing?

□ Yes □ No

If yes, what is the average interest rates per month for these loans?

……………………………………………………………………………………….

3. On the terms and conditions given for the loans, do you normally read them before taking the loan?

□ Yes □ No □ Sometimes

4. Do the providers of these loans explain to you how they will use your data?

□ Yes □ No

Explain ………………………………………………………

5. Do the providers give you flexible repayment terms?

□ Yes □ No

Explain? …………………………………………………………

6. In your own words, what would you want to be introduced/ improved on the aspect of regulating the mobile lending industry?

……………………………………………………………………………………………………….

7. When you have and challenge or a complaint, how do you raise it to the lender?

……………………………………………………………………………………………………

……………………………………………………………………………………………………

F. CULTURE (Instrumental Variable)

1. Have you ever borrowed a mobile loan just because it was available and not that you had an urgent need for the money?

□ Yes □ No

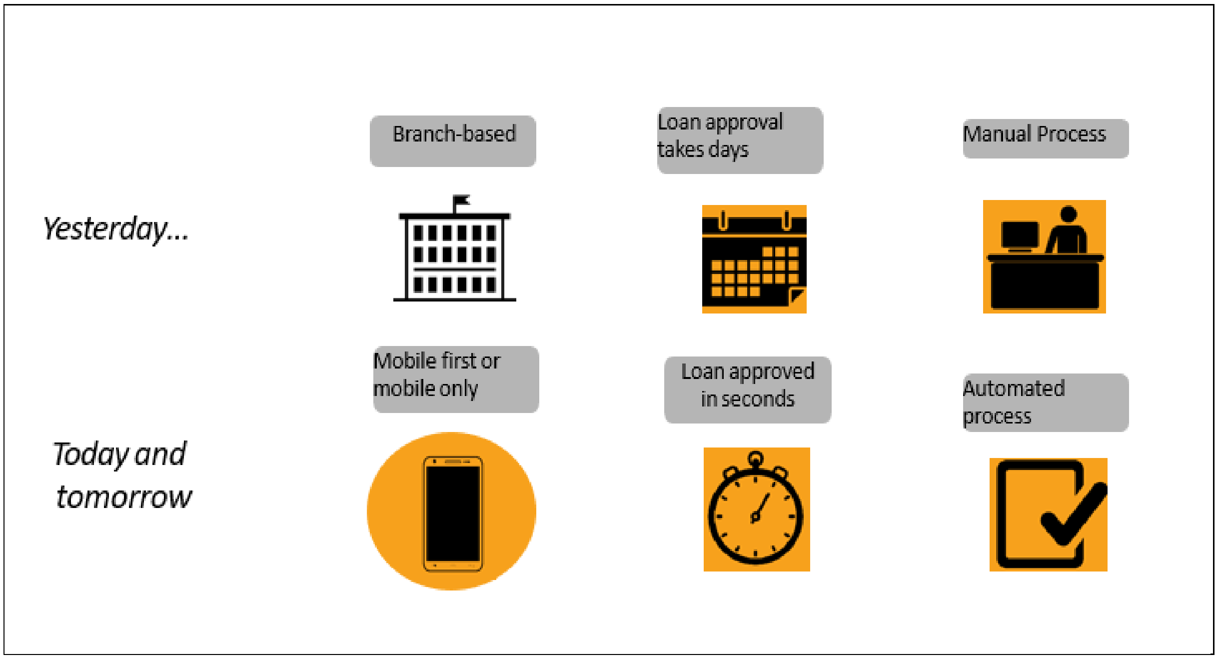
If yes, explain? …………………………………………………………

2. Tick appropriately on the selection below

ents		
rrowing and getting into debt		
t before spending any income/ money you access		
ayment of these mobile loans bother my conscience		
orrow more loans than I can service		
mobile loan providers with my information I them (consumer trust)		

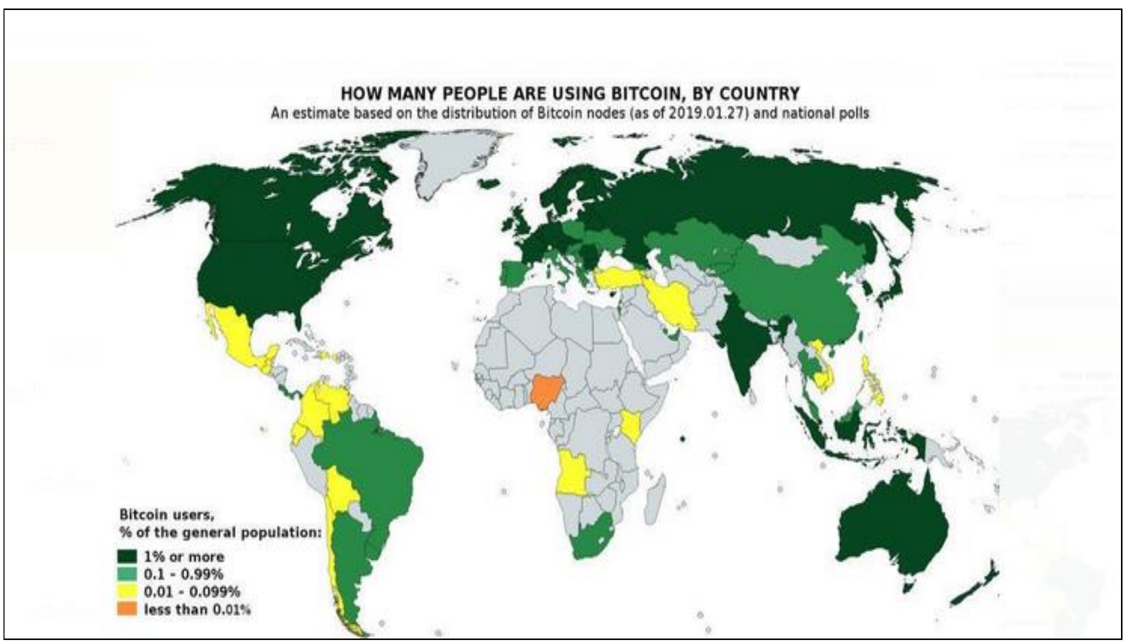
The End!

Appendix 2: Changing Customer Expectations



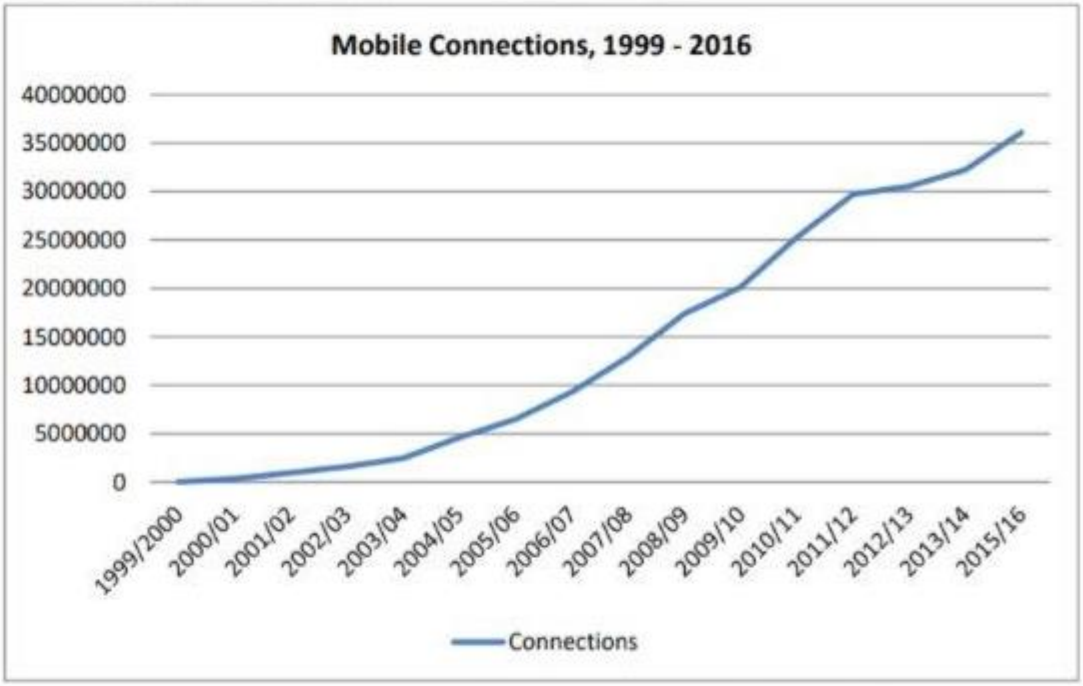
Source: Finance Plan Micro-Finance Presentation, 2018

Appendix 3: Spread of Bitcoin by Country



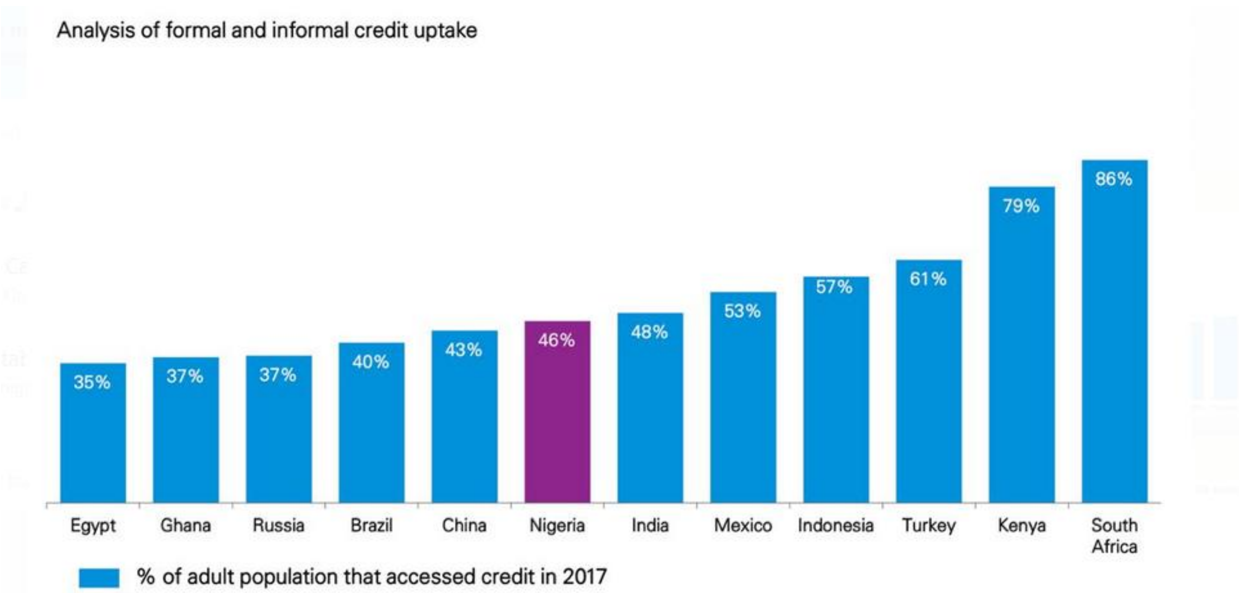
Source: 2nd CryptoAsset Benchmark Study, UK 2018

Appendix 4: Mobile connections in Kenya 1999 - 2016



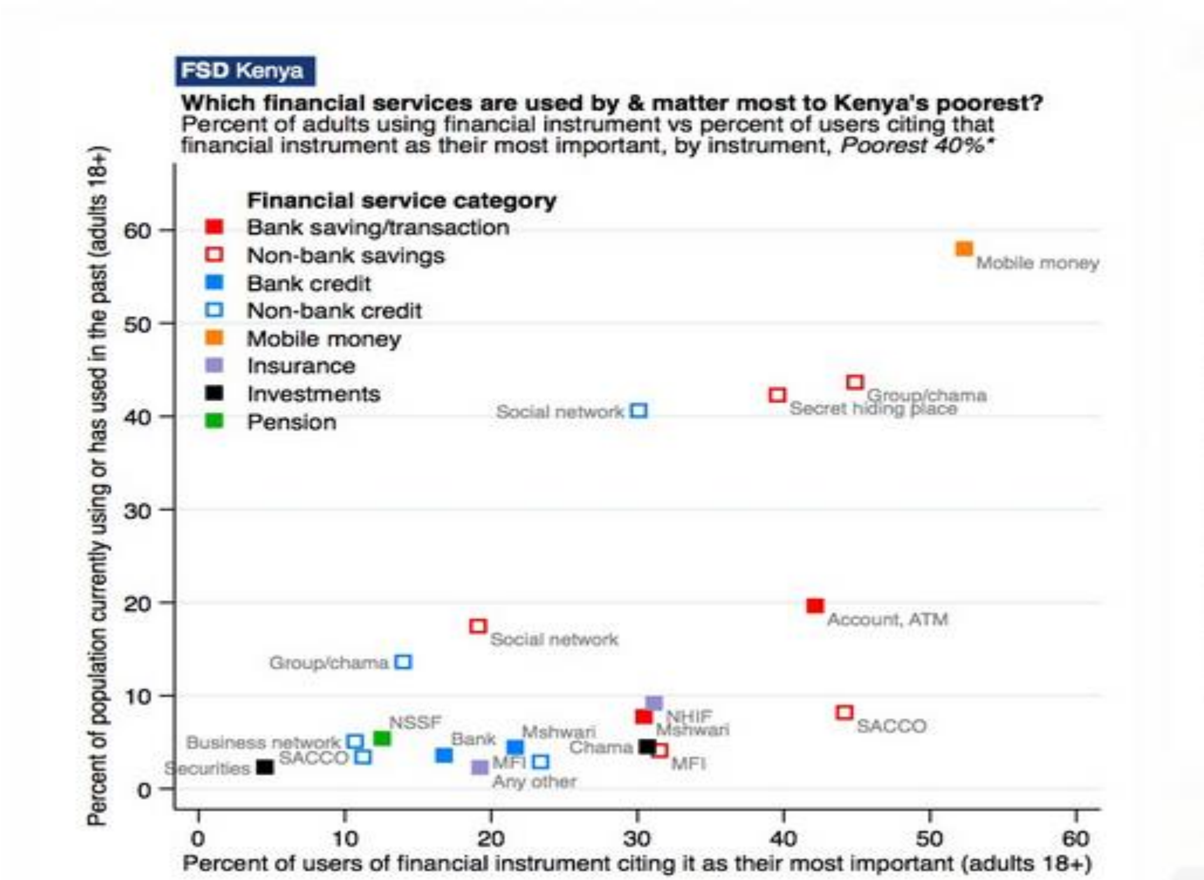
Source: CCK Annual Report, 1999 - 2016

Appendix 5: Formal and Informal Credit Uptake



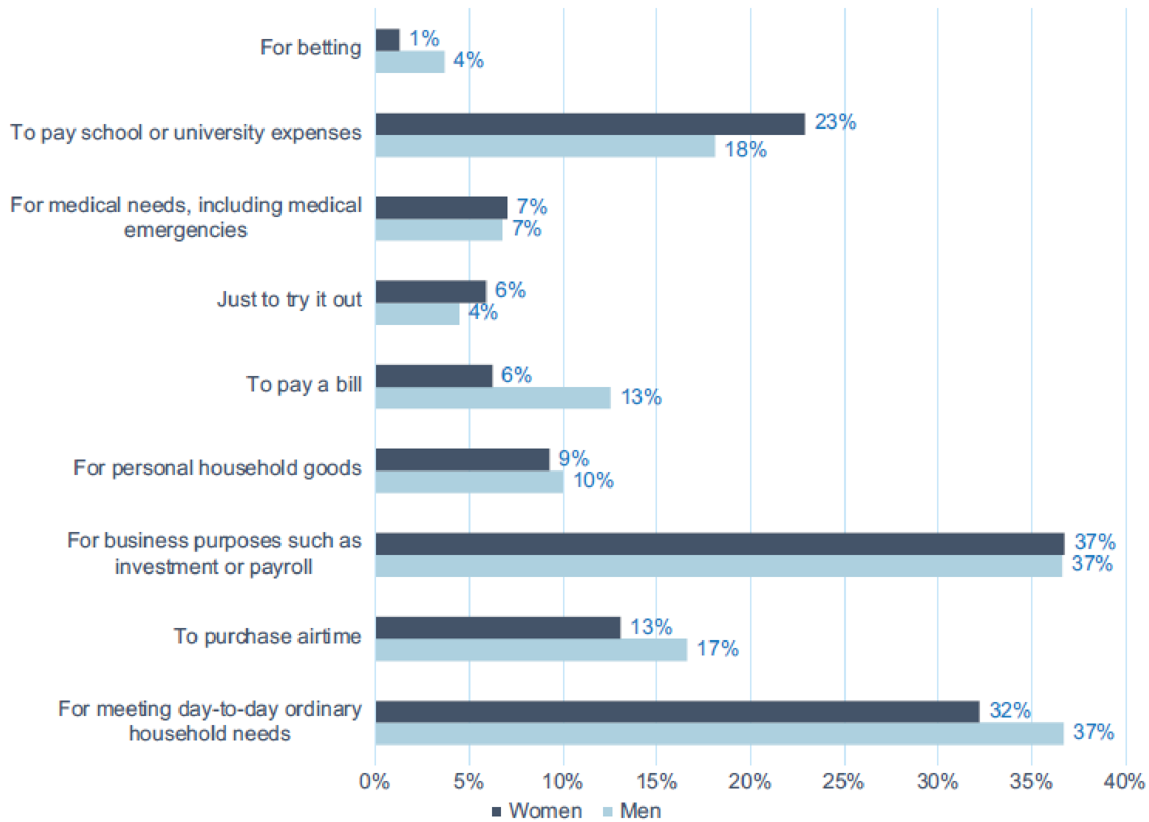
Source: World Bank Report, 2017

Appendix 6: Financial Services Analysis Kenya



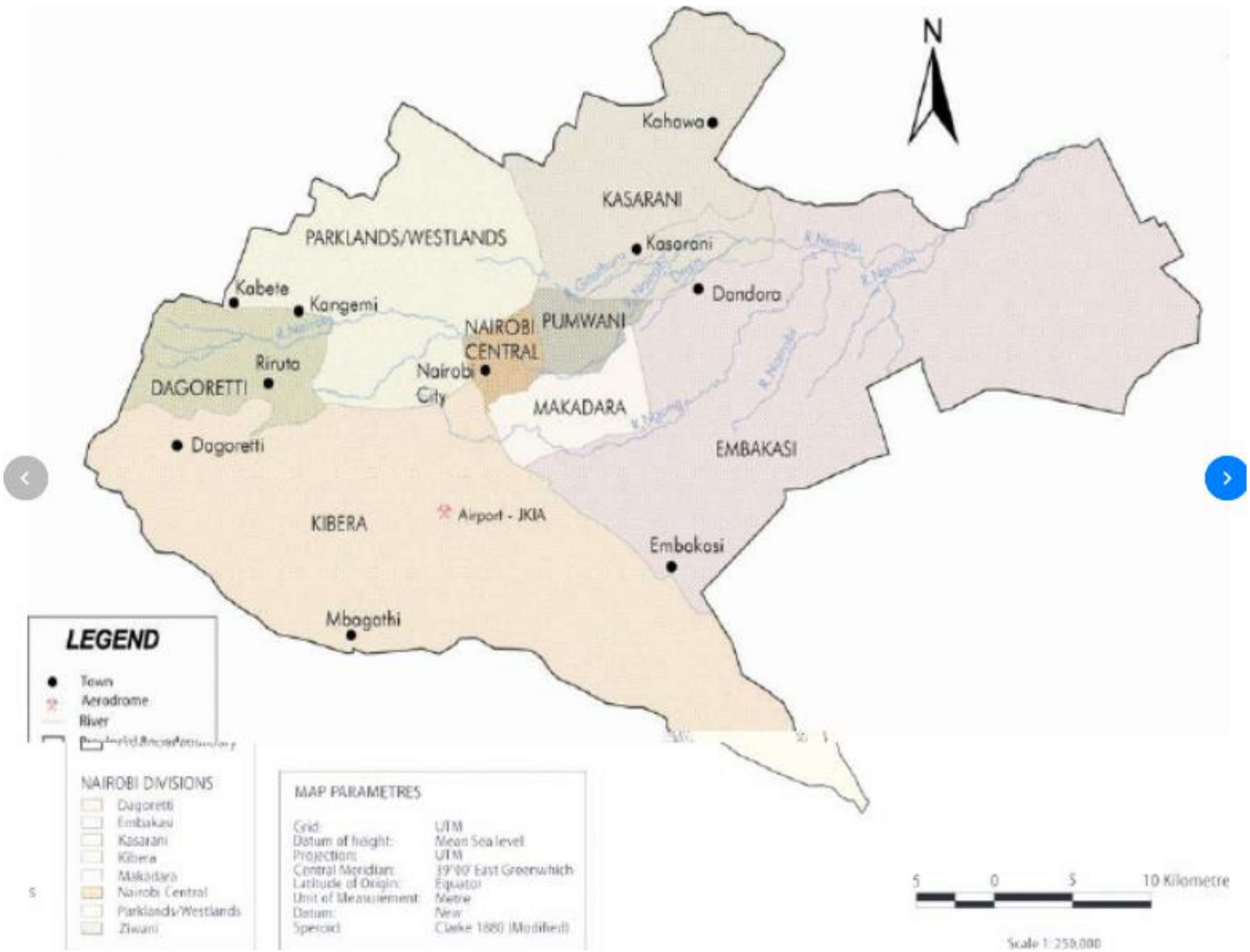
Source: 2016, FinAccess Household survey report by FSD Kenya

Appendix 7: Reasons for Borrowing Digital Loans

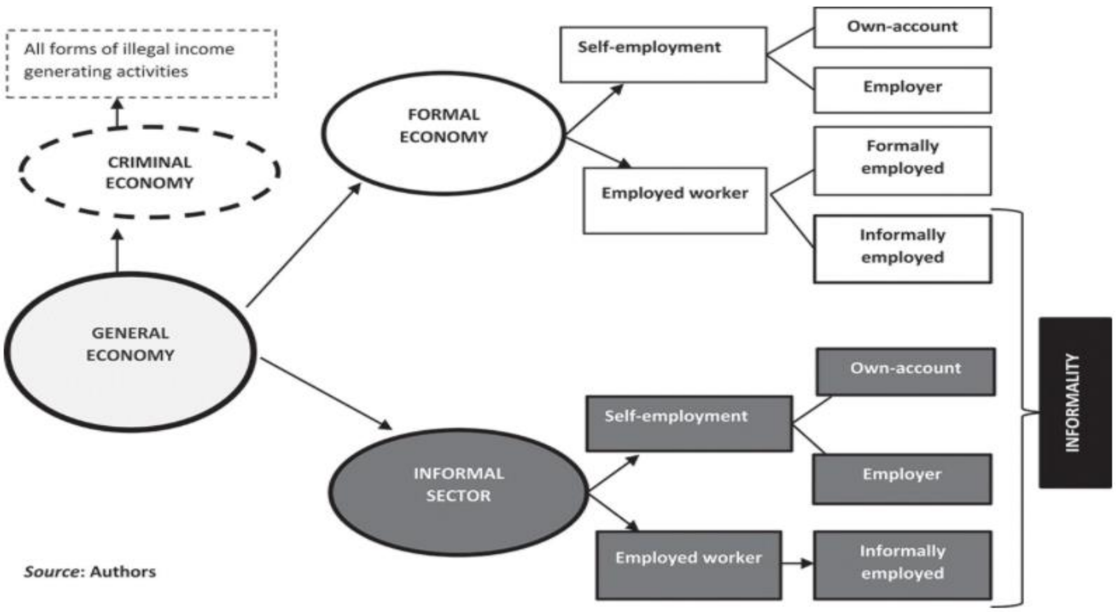


Source: National phone survey conducted by FSD in Kenya of whom 1,132 respondents who have used digital credit gave their input. Both surveys were conducted June-August 2017.

Appendix 8: Map of Nairobi Administrative Areas 2010

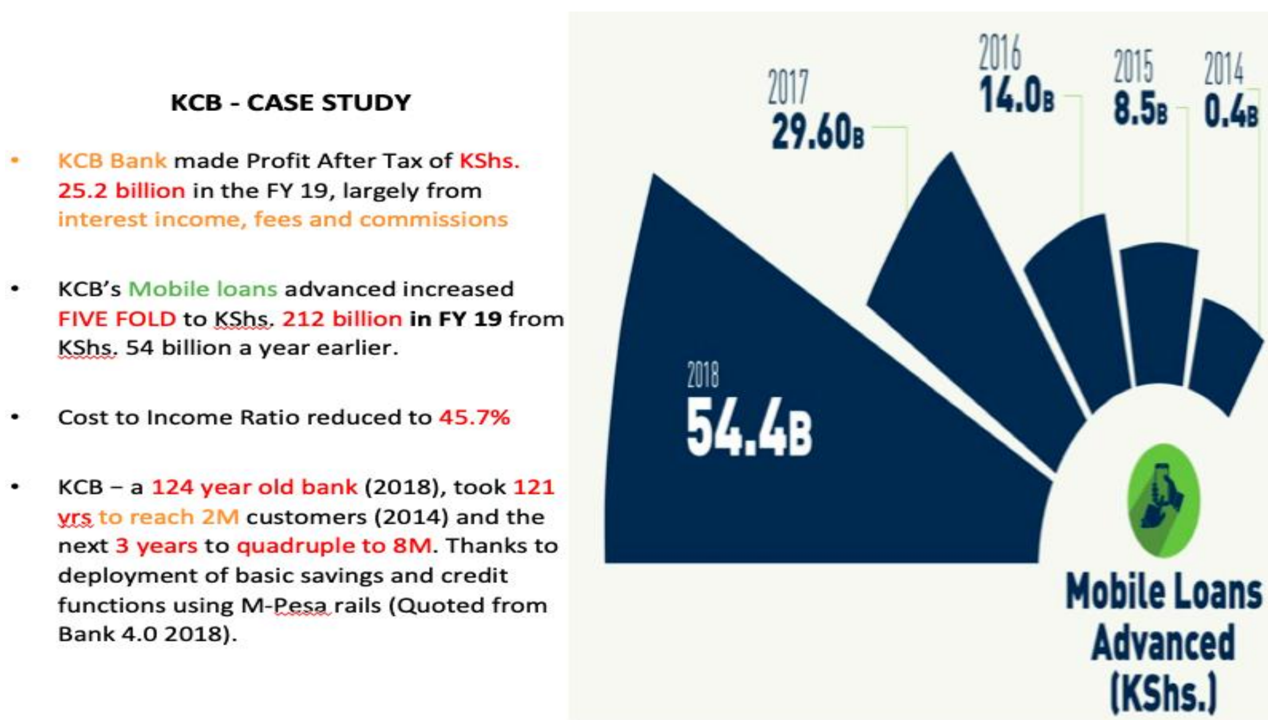


Appendix 9: A Graphical Distinction of the Informal Sector Economy from Other Sectors of the Economy



Source: World Health Organization, Universal health coverage report of 2012

Appendix 10: KCB Bank Case Study



Source: KCB Bank report 2019