2021

# Portfolio manager's perception of the determinants of digital credit repayment in Kenya.

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# PORTFOLIO MANAGER'S PERCEPTION OF THE DETERMINANTS OF DIGITAL CREDIT REPAYMENT IN KENYA

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**(102921)**

**A Dissertation Submitted in Partial Fulfillment of the Requirements for Award of Degree of Master of Science in Development Finance, Strathmore Business School at Strathmore University**

**Strathmore University**

**Nairobi, Kenya**

**March, 2021**

## DECLARATION AND APPROVAL PAGE

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



**Eva Wangari Ndung'u**

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**Supervisor's Approval**

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Signature: ……………………  Date: ……………………….

## ABSTRACT

The critical problem most digital credit-lending agencies face is poor loan repayment. Statistics show that loan default has been a tragedy and loan repayment problem is an unsolved issue faced by the majority of digital lending institutions. The study sought to establish the perception of the determinants of digital credit repayment in Kenya. The study specifically looked into the effect of individual/borrowers factors, loan factors and lender factors on digital credit repayment in Kenya. The research was based on prospect theory and the theory of delegated borrowers monitoring. To determine and be able to characterize the features of variables of interest, a descriptive research design was used. The study targeted all the main credit digital lenders in Kenya but the unit of observation was the credit managers, credit analysts and account relationship managers. The study adopted stratified sampling and employed the Yamane (1967) formula below to calculate the sample size of 204 respondents. The study relied on primary data gathered through questionnaires. The questionnaires were self-administered using a drop-and-pick method. Both descriptive and inferential statistical approaches were used to analyze the data. For simplicity of analysis, the data was sorted, categorized, and coded before being tabulated. The information was grouped and summarized based on common topics. The data was analyzed using descriptive statistics. The Statistical Package for Social Sciences (SPSS) was used to conduct the analysis (SPSS Version 25.0). The qualitative data from the open-ended questions was evaluated and presented in prose using content analysis. Further, inferential statistics was done using multiple regression and correlation analysis. Tables and other graphical presentations as appropriate were used to present the data collected for ease of understanding and analysis. The study established that the number of dependants; marital status; level of education; and gender affect digital credit repayment to a great extent. The study also found that repayment period and type of loan/security provided affect digital credit repayment to a great extent. The study found that number of loan installments affect digital credit repayment to a moderate extent. The study concludes that individual/borrowers factors positively and significantly affect digital credit repayment in Kenya ($\beta=0.792$, $p=.000<0.05$). The study further deduced that there is a negative but significant relationship between the loan factors and digital credit repayment ($\beta=-0.229$, $p=.006>0.05$). The study also concluded that there was a negative but significant relationship between lender factors and digital credit repayment in Kenya ($\beta=0.457$, $p=.000<0.05$). The study therefore concluded that individual/borrowers had the greatest effect on the digital credit repayment in Kenya, followed by lender factors while loan factors had the least effect on the Digital credit repayment in Kenya. When building loan products for the Kenyan market, digital credit lenders should take into account borrowers' demographic factors such as age, gender, marital status, occupation, education, and income, according to the study. This is because demographic elements are important and measurable population data that aid in the identification of target markets, are easier to quantify, and are appropriate for psychographic and sociocultural research. Furthermore, Kenyan digital credit lenders should take more steps to perform broad market surveys so that they can better understand the regions where they can tap into and produce lending products that are relevant to market needs. Lenders should do a better job of reporting and clarifying key loan elements so that borrowers have a clear understanding of the loan's cost, payment due dates, and the repercussions of late repayment and default.


**Key words:** digital credit repayment, individual/borrowers factors, loan factors and lender factors

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| | |
|---|---|
| **CBA** | Commercial Bank of Africa |
| **CBK** | Central Bank of Kenya |
| **CRB** | Credit Reference Bureau |
| **FSD** | Financial Sector Deepening |
| **GPS** | Global Positioning System |
| **KCB** | Kenya Commercial Bank |
| **MBA** | Master of Business Administration |
| **MNO** | Mobile Network Operators |
| **MVNO** | Mobile Virtual Network Operators |
| **NPL** | Non-Performing Loan |
| **P2P** | Peer to Peer |
| **SMEs** | Small and medium-sized enterprises |
| **SPSS** | Statistical Package for Social Sciences |
| **USD** | United States Dollar |
| **USIU** | United States International University |

## ACKNOWLEDGMENTS

A special thanks to Dr. Mathuva, my supervisor for his countless hours of reflecting, reading and most of all patience throughout the entire process. I would like to acknowledge and thank my clients for allowing me to conduct my research and providing any assistance requested. Finally I would like to thank my lecturers and administrators in the Strathmore Business School community who assisted me with this dissertation. Their excitement and willingness to provide feedback made the completion of this research an enjoyable experience.

## DEDICATION

I dedicate my dissertation to my wonderful daughter Gia for always inspiring me to do better and be better. May my works inspire you to do more for our society.

# CHAPTER ONE
# INTRODUCTION TO THE STUDY

This chapter contains the background to the study, digital lending in Kenya, borrower behavioral patterns, problem definition, research objectives, research questions, scope of the study and significance of the study.

## 1.1 Background to the Study

Globally, technological innovation in the financial sector has been seen, particularly in the business of lending via digital credit. The majority of individuals used informal lenders (shylocks) and family members and friends for loans before digital lending was developed. Banking services were only accessed by rich persons or those with collateral, and the fees charged for access to bank branches could be paid. Consequently, financial institutions had little reason to assist the poor, because not only were the products expensive, they were also unavailable. On the other hand, the emergence of digital credit has everything changed (Katakam et al., 2016).

The foundational pieces of digital credit—mobile phones, identity-linked digital footprints, automated credit scoring, agent networks, and credit information sharing—have enabled suppliers to deliver loans swiftly and at scale. The possibility of borrowing through mobile phones has opened the door for millions of individuals to private and formal loans. The pricing, marketing and possible misuse and extensive negative reporting of borrower borrowers who defaulted on these small loans, however, have generated increasing concerns about their design and the adverse effects they have on borrowers and on the broader financial system (Ravikumar, Murugan & Suhashini, 2019).

Since its launch in 2012, digital credit has touched millions of Kenyan borrowers. For many borrowers, its primary features—immediate loan access, automated credit decisions, and remote distribution and repayment—make it a quick, discreet, and handy alternative. However, these features may pose a concern. Understanding the significance of digital credit in borrowers' financial portfolios and how it affects financial inclusion requires identifying who is using it, how it is utilized, and the risks borrowers face. A better understanding is also necessary for determining what steps providers, policymakers, investors, and development actors may take to maximize the benefits of digital credit while limiting the hazards (Microsave, 2019).

While the first digital credit was provided to commercial banks and mobile network carriers, a number of new start-ups have emerged to supply loans via applications. In Tala and Branch, for example, credit risk and credit customization offers are assessed with alternative data such as call records, GPS, social network data and user permission contact lists (such as reductions in interest rates as users build a credit history). Tala and Branch both have more than one million Kenya Google Play downloads (Costa, Deb & Kubzansky, 2015). Data on the size and performance of app-based loan accounts shall not be made public, since financial services firms that issue credit but do not collect deposits are unapproved and not controlled by CBK. This also imposes a limit on the loan interest rate to the 4percentage points higher than the central bank rate of the app-based lender, which came into force in September 2016 with the adoption of the Banking Amendments Act. Since its March 2014 inception (then known as M- Kopo Rahisi), Tala has disbursed over 5.6 million loans worth Ksh 28 billion to over 1 million customers, according to press sources, while Branch has disbursed 1.5 million loans for Ksh 3.63 billion to 350,000 customers since its April 2015 launch (Microsave, 2019).

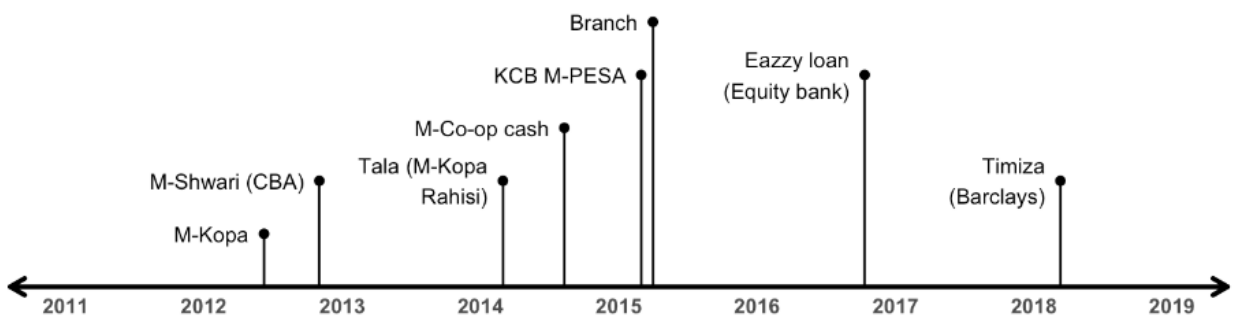


**Figure 1. 1: Digital Loan Products by Launch Date**

Source (xxx)

One of Kenya's three listed credit reference bureaus (CRBs), one of the growing digital lending issues is that 2.7 million of TransUnion's 10,6-million lenders were negative, which meant that their names had been submitted to CRB by lenders due to a failed loan (NPL). When it comes to CRB reporting, lenders have varying policies. If an M-Shwari loan is not paid off by the 30th day, the balance is automatically rolled over for another 30 days, plus a 'roll-over fee.' CBA uses a variety of measures to induce repayment, including sending SMS warnings that the borrower will be reported to the Credit Reference Bureau (CRB). However, the borrower will not be listed until 120 days after the loan was taken out (FSD Kenya, 2019).

In Kenya, submitting a report based on an NPL is referred to as blacklisting, which has a sinister ring to it. TransUnion's 2.7 million negative reports on digital loans include 400,000 for amounts of less than USD 2. Borrowers confront a difficulty in that a single negative report, regardless of their total borrowing history, might impair their chances of securing a loan from any lender (Shema, 2019b).

One of the concerns with how lenders have handled CRB data in the past is, rather than using the borrower's whole credit performance as a binary red flag check (say, based on a credit score). Most banks demand potential borrower with negative bills to repay existing debt on the listed loans first and then to receive a CRB clearance certificate to indicate that the lender receives outstanding debt payments. A clearance certificate from one of Kenya's CRBs costs Ksh 2,200 (USD 22), or twenty times the M- Shwari's lowest credit limit of Ksh 100 (CBA, 2014).

Where loans are unpaid, registered lenders should notify CRB borrowers of non-repayment, leading to a failure to display their loans (CBK, 2014). If the borrower pays their loans, the list of loans is updated to reflect payments, which the CRB has kept for five years in Kenya. In the event that borrowers do not repay and default on the loan, the non-performing status will be maintained. Before taking another from most digital lenders, borrowers must pay back a loan. Borrowers who default on a digital loan cannot receive subsequent loans from the lender in default. Borrowers may find it more difficult to obtain loans from formal lenders, such as banks, who use CRB data in their credit decisions, due to the need that regulated institutions disclose nonperforming loans to CRBs (Velusamy, 2017).

According to KEPSA figures, up to 45 percent of digital credit institutions contribute to Kenya's GDP, although the business is fast shrinking and experiencing a number of issues (Banerjee et al., 2015). According to statistics, more than 2.2 million digital credit institutions have closed their doors by 2016. Every year, it causes 400,000 digital credit institutions to fail, with 80% of them dying before their second anniversary (World Bank, 2016). This study therefore sought to establish the determinants of digital credit repayment.

### 1.1.1 Digital Lending in Kenya

Digital credit is a type of digital banking product that requires little in-person interaction and relies on digital infrastructure. The solution relies on digital infrastructure to gather credit applications, analyze borrowers' creditworthiness, approve the credit, transfer funds and payment receipt. Digital credit products are those which depend, throughout or even part of the process, on digital infrastructure. Digital infrastructure employed for these products and their ease of operation contribute to significant demand in the industry (Velusamy, 2017).

Digital credit has four major properties. First, current digital access allows for loan eligibility. To get a loan, you don't need a bank account or a credit history. Borrowers must have existing mobile phone or mobile money service subscriptions, as well as social media accounts, to qualify for most goods. Second, lending choices are computerized and rely on non-traditional data. The digital providers take the position that all data is credit data. They employ various algorithms to assess the creditworthiness of consumers with no credit history (Kinyanzui, Achoki & Kiriri, 2018). All information is being utilized, including mobile phone usage, mobile payment, airtime use, and social media profile information. This is the manual decision-making process. Thirdly, the loans are immediately accessible. This is due to the automatic decision of the loan. If the lender has the right to a loan, the money is normally paid out within five minutes after the application. It differs from normal bank loans that take a long time to approve. Fourthly, the loans are short-term and high-risk in light of the target market. Since the items are offered to the unbanked people that lack credit and collateral, they are costly. It contributes to their short-term nature that the loans are taken out during exigencies or while the debtors await their next month's salary (Berg, Burg, Gombovii & Puri, 2018).

In Kenya, four business models are available for digital credit. Partnerships between banks or microfinance institutions and mobile network operators (MNOs) are the most popular and pioneering business model. MNOs provide credit algorithms based on information they obtain from knowing your customer's needs. They developed a system that determines creditworthiness based on the data they have on their consumers. Second, MNOs serve as channels for disbursing loans, collecting loans, and interacting with customers. Banks or digital credit lenders manage the accounts of their customers, provide funds for lending, and take on the high risk of lending. Safaricom M-Pesa and Commercial Bank of Africa (CBA) to provide M-Shwari, Safaricom M-

Pesa and Kenya Commercial Bank (KCB) to provide KCB-M-Pesa loans, and Airtel Money and Faulu Bank to provide Kopa chapaa loans are examples of such collaborations (Mugo, 2018).

Application-based digital credit is the second business model. This refers to businesses that make loans on their own without partnering with a digital credit lender. Borrowers must download an app and disclose their social media profiles to the lenders. The app tracks how much time people spend on their phones and using mobile money, as well as how much time they spend on social media. They can determine the creditworthiness of debtors using this information. Tala, Branch, and Saida loans are examples of such lenders in Kenya (Kiliswa & Bayat, 2014).

Peer to peer lending (p2p) is Kenya's third business model. This business model is not as common in the United States as it is in other areas of the globe. P2P lenders are a type of online marketplace that connects lenders and borrowers. They do not lend money, but they do make the process of lending easier. Zidisha and Kiva Loans are two such companies in Kenya. The last business model is a bank that provides digital services, which is uncommon. This resulted from the CBK issuing licenses to Mobile Virtual Network Operators (MVNO). Because banks are developing their own digital infrastructure, they do not require partnerships with mobile network operators. Equitel, for example, is a subsidiary of Equity Bank. The telecommunication infrastructure provided by Airtel Kenya is leased (Kiliswa & Bayat, 2014).

### 1.1.2 Determinants of Digital Credit Repayment

In the past, a number of academics have looked at digital credit repayment and non-repayment (default) as well as its determinants. Several elements have been identified as having an impact on digital credit repayment in several research. Interest rates, age, marital status, geography, high interest rates, insufficient loan sizes, poor assessment, lack of monitoring, and wrong customer selection are all considered to influence the likelihood of default. Muthoni (2016), on the other hand, divides the factors affecting repayment performance into three categories: individual/borrowers factors, loan factors, and institutional/lender aspects.

The age of the borrower, gender, level of education, business experience, household size, credit use experience, household income, non-business income, type of business activity, and amount of business investment are all factors to consider (Ochung, 2013). Individual factors have been found to have an impact on loan repayment in several studies. Business considerations, borrower's attitude toward their loans, other debt burden, amount of loan obtained, business experience, business formality, and family background, for example, are all factors affecting borrowers' ability to repay their loans, according to Moradi and Rafiei (2019). According to a study by Ochung (2013), there was a substantial association between individual borrowers' variables and loan repayment among Kenyan commercial bank customers. Njangiru, Maingi, and Muathe (2014) found statistically significant results regarding the effect of borrowers' characteristics on loan payback and sustainability. As a result of the high risk and high cost of borrowing, the study discovered that the rural borrower's repayment capacity has been reported to be high due to unpredictable income streams.

The loan size, payback length, collateral value, number of installments, and application expenses are only a few of the loan characteristics. Past research have proven the influence of loan factors on loan repayment (Meht, 2015). Shema (2019a) indicated that the loan repayment rate was substantially connected with loan amount, loan type, and previous loan experience, purpose of loan, educational level and kind of collateral supplied. Commercial banks should establish loan strategies that place a strong emphasis on these variables when making loans to their customers, according to the report. Furthermore, according to Kibosia (2012), loan defaults by SMEs have been steadily increasing, and a range of drivers, including interest rates, kind of loan, payback length, and economic conditions, have all contributed to loan defaults by SMEs.

Factors that may influence repayment of loans within financial institutions are known as lender/institutional features. All institutional and lender variables include the period between application and distribution of the loan, the interest rate, access to business information, access to loan training, cooperative membership and penalty for delayed meetings (Katakam et al., 2016). The poor analysis and monitoring of loans as well as the economic circumstances contributed, according to a study (Shema, 2018b), to the default of credit to SMEs. The credit risk management, employee training and the use of credit scoring in the validation of customer loans from SMEs should therefore be given more importance by banks. Korankye (2014), who argued that financial institutions have clear and effective credit polices and procedures that should be regularly evaluated, have also listed inadequate loan sizes, inappropriate evaluations, lack of monitoring, and incorrect customer selection as reasons for loan default.

## 1.2 Problem Statement

Many borrowers rely heavily on traditional debt to meet their start-up, cash flow, and investment needs, and credit is the most prevalent source of external capital for them (Nawai & Mohd Shariff, 2013). Despite the evident role of banks and other digital credit lenders, lending remains a time-consuming and difficult task, since numerous factors influence borrowers' repayment behavior. Poor loan payback is a major issue for most digital credit lending companies. According to statistics, loan default is a tragedy, and loan repayment is an unsolvable problem for the majority of digital lending companies (Hwarire, 2012).

Following the crises of 1986-1989, 1993-1994, and 1998, Kenya suffered credit problems that culminated in large bank collapses (37 bankrupt banks as of 1998) (Kithinji & Waweru, 2007; Ngugi, 2001). Non-Performing Loans (NPLs) were blamed for the majority of the crisis (NPLs). YEDF, for example, has an overdue debt of 77.8% of all loans disbursed (YEDF, 2009). The success of digital credit institutions is heavily on credit advanced management, which necessitates the reduction of loan default rates. Mugambi (2010) investigated the causes of loan defaults in the areas of co-operative bank finance in Nairobi, Kangemi and Kawangware and found that irregular income, poor governance and high competitiveness of well-established companies have hampered a lot of micro-enterprises. Moreover, other factors such as poor credit grant decisions of digital loan lenders leading to over burdening borrowers, poor debt collection methods leading to embarrassment of borrowers contribute to credit default. As a result, it is necessary to understand the aspects that influence the success of digital credit repayment.

Various studies have been done that are related to borrowers' behavioral patterns and digital credit repayment. Ngatia (2013) looked into the impact of mobile banking on consumer behavior among executive MBA students in Kenya: a case of United States International University-Nairobi (USIU); Mugo (2018) studied the effects of consumer purchase behaviour on the uptake of mortgages offered by banks in Nairobi; Muthoni (2016) assessed borrower's and business' factors causing microcredit default in Kenya: a comparative analysis of Microfinance Institutions and Financial Intermediaries; Ochung (2013) investigated the factors influencing loan repayment among commercial bank customers in Kenya: a case study of Barclays Bank Of Kenya, Nairobi County. These studies however, did not establish portfolio manager's perception of the determinants of digital credit repayment in Kenya. Thus, presenting a research gap that this study sought to fill.

## 1.3 Research Objectives

### 1.3.1 Main Objective of the Study

The study sought to establish portfolio manager's perception of the determinants of digital credit repayment in Kenya.

### 1.3.2 Specific Objectives of the Study

1. To determine the effect of individual/borrowers factors on digital credit repayment in Kenya.
2. To establish the effect of loan factors on digital credit repayment in Kenya.
3. To assess the effect of lender factors on digital credit repayment in Kenya.

## 1.4 Research Questions

1. To what extent do individual/borrowers factors affect digital credit repayment in Kenya?
2. How do loan factors affect digital credit repayment in Kenya?
3. What effect does lender factors have on digital credit repayment in Kenya?

## 1.5 Research Hypothesis

**$H_{01}$**: Individual/borrowers factors do not affect digital credit repayment in Kenya.

**$H_{02}$**: Loan factors do not affect digital credit repayment in Kenya.

**$H_{03}$**: Lender factors do not affect digital credit repayment in Kenya.

## 1.6 Scope of the Study

The study focused on portfolio manager's perception of the determinants of digital credit repayment in Kenya. The study specifically looked into the effect of individual/borrowers factors, loan factors and lender factors on digital credit repayment in Kenya. The study took 6 months.

## 1.7 Significance of the Study

### 1.7.1 Digital Lenders

The findings might enlighten them on the borrowers' behavioral patterns and their effects on repayment of credit. The digital lenders regulators might also obtain information on how to formulate policies that might help digital credit repayment.

### 1.7.2 Borrowers

The study might elucidate and demystify digital credit products among lenders and also the factors affecting their behavior patterns on repayment of the digital credit.

### 1.7.3 Policy/Regulators

The findings of the study might be of interest to regulators as they would get to know strategies to employ in managing digital credit in relation to borrowers' behavioral patterns and encourage digital lenders to take necessary measures to control occurrences of nonperforming loans. Further, the findings of this research might be helpful in strengthening of guidelines that helps in digital credit management in Kenya, while protecting the interest of the borrowers.

### 1.7.4 Researchers and Academicians

This study might also be helpful to other researches and academic institutions to learn about digital credit. This study might also be the centre piece idea to other students willing to pursue a research on a similar field. This is so because the final draft of the completed research might provide further areas of research.

## CHAPTER TWO
## LITERATURE REVIEW

### 2.1 Introduction

This chapter examines the literature on the factors that influence digital credit repayment in Kenya. It presents the essential points from a wide range of perspectives on the variables. The theoretical framework, empirical review, and conceptual framework are so organized in the chapter. The chapter also includes an overview of the evaluated literature and the knowledge gap that the study aims to solve.

### 2.2 Theoretical Literature

Various theories gave clear explanation on the digital credit repayment. A multi-theoretical approach was adopted to help identify the limits to the study generalizations. A theoretical framework specifies which key variables influence a phenomenon of interest and highlights the need to examine how those key variables might differ and under what circumstances. Some of the theories include prospect theory and theory of delegated monitoring of borrowers as discussed here below.

#### 2.2.1 Prospect Theory

This theory was first proposed by Kahneman (1979) as a logically rational alternative to the utility principle. The principle explains why people pick known alternatives rather than hazardous ones (alternatives with unknown outcomes). The algorithm is descriptive and seeks not ideal solutions but to predict the real world. In circumstances when people need to decide, one can determine how people pick between risky options (for example, in financial decisions) (Byrne, 2016). The idea describes how humans identify future dangers and benefits, starting with observable information (Bernheim & Sprenger, 2019).

The idea is strongly linked to the utility concept already described. In short, prospect theory assumes that the utility functions of investors are more affected by changes in the value of their portfolios than by the value itself. The source of profit is dividends, not valuation of assets (Glänzel & Scheuerle, 2016). The edition and assessment at two levels are instances of the theory described decision-making processes. The first is the organization of numerous decision-making probabilistic (experience-based) decisions (Barberis, Mukherjee & Wang, 2016). The second section explains how digital credit institutions' sensitivity to threats and their inability to disregard hidden costs drives people to conduct not in their best interests (Hoffmann et al., 2017).

The theory of prospects has made psychology a leader in economic study than any other approach (Ingersoll Jr, 2016). Faced with barriers, many economists continue to seek the planned utility model, but prospect theories have gained momentum in recent years and are unquestionably second among some traditional economists on the research programme (Julien, 2018). Prospect theory has a solid statistical base, like other psychologies, which makes it easy for economists to examine. As opposed to the theoris of anticipated value, the theory of the prospect is about how decisions in the presence of uncertainty (a prescriptive approach) are taken (a descriptive approach). In issuing a loan, the attributes of the borrower were considered as a determining factor for the digital credit return.

One of the criticisms of the prospects theory is that it lacks psychological explanations for the process it talks about. The criticism comes from other psychologists who note that factors such as human emotional and affective responses that are important in the decision-making process are absent in the model. In this study, this theory was crucial as it shows that borrowers and lender differently assess profits and losses with perceived gains that count higher than felt losses. Creditors who have a choice of two options, both equal as regards future gains, will choose the one with the highest potential gains. The certainty effect indicated that people favor certain results over likely ones, whereas the isolation effect indicated that people cancel comparable information while making a decision. This is comparable to the topic of the study, when the conditions are right for borrowers always reimburse their credit. Therefore, this theory is relevant and forms a basis on the effect of individual/borrowers factors and lender factors on digital credit repayment in Kenya.

### 2.2.2 Theory of Delegated Monitoring of Borrowers

Matthews and Thompson (2008) established the Delegated Borrowers Monitoring Theory, which is particularly relevant in the literature on bank life. The information periods for pre- and post-loan disbursement are collected in the context of a borrower monitoring bank. This process involves the review of credit claims, the review of credit scores of lenders and the regulation of contractual conditions. The theory is founded on the idea that most financial savers do not have the ability and know-how to assess the risk of a default on institutional lenders. It's one of digital credit's most important works (Gupta & Starmans, 2019). A bank's "monitoring" of a borrower involves collecting information both before and after the borrowing has been supplied, such as examining borrowers, analyzing the continued creditworthiness of the borrower and ensuring that the requestor complies with the contractual conditions. A bank now holds the customer's current account and is capable of tracking income and expense balance. For digital credit companies, this is particularly important and has to do with the function of the financial institution in the payment process (Mulwa, 2018).

As a prerequisite for digital lending expansion, financial performance was emphasized. In view of this, it is evident that additional study in this domain is very focused (Nikolaev, 2017). This is especially true because the banking business enjoys a highly competitive climate. Domestic banking has seen new competition, which allows banks, insurance institutions and cooperatives to significantly diversify as part of the financial reform and growing globalization (Awunyo-Vitor, 2018). They said that IT has provided numerous options, including as mobile banking, online banking, to produce new financial products and distribution channels, reducing the creative needs in traditional industry networks. Thus, the efficiency and proximity of financial institutions are essential factors in the collection of debt.

An alternative view on the role of delegated monitoring is that lenders exert greater efforts to monitor borrowers who are more likely to default (e.g. Gupta & Starmans, 2019). If this argument is true, MFIs will increase monitoring efforts only if they expect the default risk to increase; that is, there will be a negative correlation between MFI monitoring and the repayment of microloans. Anticipating this, greater monitoring efforts by MFIs may discourage crowds from lending. The research questions of this paper are, therefore, empirical in nature.

This idea is employed in this study as it helps to screen and determine the creditworthiness of applicants. This theory shows that a credit is employed for prudentially pricing a loan, and for the internal aggregate purposes of lending risk management. The theory gave insight into the elements that impact the repayment of digital loans in Kenya. Moreover, the theory forms a basis on the effect of loan factors on digital credit repayment in Kenya.

### 2.3 Empirical Review

Key empirical papers are discussed analytically to bring out the research gap in this study. An empirical review is done to clearly bring out any contradictions or inadequacies in the knowledge of the particular phenomena, or of relationships between constructs, which makes the study necessary. This section entails literature on the effect of individual/borrowers factors, loan factors and lender factors on digital credit repayment.

### 2.3.1 Individual/Borrowers Factors and Digital Credit Repayment

Character, capability, and capital are the main criteria that define a borrower's ability to repay a loan, according to Uddin (2020). In addition to other ways for assessing creditors, many financial organisations employ the 3Cs approach. His personality is vital when judging the desire to pay of a customer. In accordance with financing or credit management, customers should make the least efforts to honor their credit obligations. In practice, the moral dimension plays a major part in the judgment of credit. When assessing several features frequently associated with digital loans, individual/borrowers considerations have a major impact.

Katakam et al. (2016) revealed that the worth of borrowers was influenced favorably by their income, age, experience, and education. The financial components of entrepreneurs have been highly emphasized, whereas the employer's human capital side has been disregarded. Creditors of a higher socioeconomic class are more inclined to select a certain kind of digital lender that they think would satisfy their needs. Likewise, their age group would determine the credit repayment by such borrowers. The properties of younger borrowers in a lender may be different from those sought by elderly borrowers. Revenues, education and employment are other demographic features (Björkegren & Grissen, 2018).

Economists view competition to be good, and most theoretical models are competing perfectly. The obvious problem with competition is that borrowers take loans from various lenders simultaneously. The reimbursement of one lender's installments with a loan by another causes borrowers to get over-indebted and all too frequently results in a debt spiral and financial ruin. There will be no single lender to tighten up and maintain complete control until borrowers think they have several options. Cooperation amongst lenders can help address the problem. The credit agencies' establishment would assist programs in better communicating credit access information and credit history (Ravikumar, Murugan & Suhashini, 2019).

In addition, during problem-sensing and information searches, Uddin (2020) also found that women always dominate the search phases for "typical" women's products, like house furnishings, equipment and cereals. In the scene of information search for male products such as autos, TV settings and shredders, however, men were seen as more prevalent. As a consequence, gender was found to be a crucial influence element in information search and other critical borrower behaviour. Men are also known to choose the leading view, whereas women in general seek to absorb all the information available. In addition, women are viewed more subjectively, intuitively, fully and relationally, and men are viewed as processed in wiser, analytical, selective and item-specific ways (Ndege, 2017).

Age has culturally established standards of behavior and attitudes that affect our conception and way of life (Costa, Deb & Kubzansky, 2015). Age differences are relevant when it comes to purchasing decisions. Many marketers have now created a niche to focus on a certain demographic group for themselves. For instance, older customers are more likely than younger consumers to utilize digital medical or travel-related loans and to buy less clothes and furnishings than young people, but young people are spending more on films, soft drinks and quick meals (Velusamy, 2017). The stage of the life cycle is an age-like notion. People pass through the stages of their lives: individual, married, married, with kids, and retired children. During each of those phases, their demands are changed and will continue to change. Some people never marry, but lifetime needs vary (Owens et al., 2018). For mortgage dealers to be alert and adapt their communication and product offers to meet their demands at the moment is vital in these crucial stages in a client's life. In general, most marketing concentrated on married status. The numbers and types of households owning and/or purchasing certain products and, more especially, the benefits of targeting specific matrimonial status categories for the majority of products and services are of importance to marketers. The more a student is on average, the less likely it is to default, Kiliswa and Bayat (2014) found throughout his investigation. When a student with a GPA between 0.00 and 1.99 is checked for additional variables, it is three percentage points lower than a student with a GPA between 3.00 and 4.00. The findings are in line with those of Shema (2019b) who examined the factors impacting Nigerian poultry farmers' loan reimbursement defaults and found that the majority of farmers in the research area were trained. They also found that the education of farmers has a significant impact on the default for loan reimbursement.

The demographic categories for lending and payment services are connected to access to and repayment performance (Özşahin, Yurür, & Coşkun, 2018). As a consequence, the demographic characteristics of consumers are a key consideration that banks assess when they make loans. This means that demographics might reveal the probable risk level of a person when it comes to borrowing. The features of borrowers are linked to their lending value and that they are also interrelated (Rahman, Azma, Masud, Kaium & Ismail, 2020).

LindStrom (2019) has recognized demographic profiling as a significant component for credit workers to make decisions regarding the acceptability of their groups or people as a major factor in the advancement of credit and the following bank credit performance. Makimu (2017) agreed that bank customers in their entirety have demographic features, which give banks a competitive advantage or disadvantage in promoting lending and credit performance. Older, less likely, lower-income, lower educated and household customers are more likely to default or have problems serving their loans, for instance. Bank customers have an investment-able asset balance because of their lowered income and profits potential.

According to Lindstrom (2019), most banks favor more trained borrowers, who are better able than borrower with a low degree of education to speak with banks about their condition. Indeed, bank borrowers with a high education degree are more capable of handling banking records and regulations and rescheduling their loans should their ability to pay their credits be impaired.

Singh and Rana (2017) believe if all other conditions are kept same that banks would be more likely than younger to see elderly customers as loans. While the clients aged 35-44 will increase dramatically during the next decade, there will only be small variations in the number of people aged 45-55. In order to fully participate in the expanding growth of the market, retail banking companies should concentrate on the ages of 35 to 44, according to its analysis. In fact, banks probably gain from inequalities in the ages of borrowers. In particular, men borrowers are more likely than female borrowers to obtain high ratings. Rabecca, Atmaja and Safitri (2018) also found that women's companies had nearly twice that potential to be refused for finance even after adjusting changes in creditworthiness and other financial factors. Stereotyping in which a person is described as a target group and inferences are generated on the basis of the predicted characteristics of the group without conscious knowledge of the decision maker generates such consequences (Duffett & Foster, 2018).

Nadolnyak, Hartarska and Griffin (2019), who explicitly add the risk of default, evaluate the theoretical literature on the model of life-cycle consumption. Because borrowers with little income will be more likely to lose their employment and be unable to pay their loans, this model offers a higher possibility of default. A combination of an older client base and limited profits potential is ascribed to a higher bank loan failure. The aim of banks that profile their clients on the basis of demographic data is to optimize their customers' returns. Indeed, high reimbursement rates are closely associated with benefits for both the digital lender and the borrower. It helps digital lenders to lower their borrowers' interest rates, reduce credit financing costs and make it more accessible to more individuals (Rahman, Azma, Masud, Kaium & Ismail, 2020). Increased re-payment rates can also lower the loan subsidy dependence on the digital loan provider, increasing its profits over the long term. The adequacy of digital credit lenders' services for customers' requests are demonstrated by high repayment rates according to Singh and Rana (2017).

### 2.3.2 Loan Factors and Digital Credit Repayment

The rules and limits for making loans are determined by the features of the loan to the borrowers. According to Abankwah, Awunyo-Vitor and Seini (2016), the reasons for non-returns can be divided into three categories: the essential characteristics of creditors and their firms, which make it impossible for the loan to be reimbursed, the underlying characteristics and features of creditors and their businesses, which makes the payment unlikely (Moran, 2016). It is unlikely to be repaid due to the financial entity's attributes and the applicant's acceptance of the debt asset. Third, external factors such as the economic, political and trade characteristics of the work environment of the creditor constitute systemic threats (Muhammad, Bambale, Ibrahim & Sulaiman, 2019).

Many different types of loans are in use throughout the world but other aspects describe the features of the loan. The first of these measures is that there may be an increase in interest at preset intervals, which can be consistent for the whole duration of the loan or contract (Sharma, 2014). Second, they have the term: a set payback period, while other countries do not receive amortization, allow a whole balance to be reimbursed, or even allow negative depreciation at any time (Beyhaghi, Nguyen & Wald, 2019). There is also the payment amount available: the daily payment amount and the payment frequency. The amount paid may vary, or in certain circumstances, the creditor may raise or decrease the amount paid (Agarwal & Ben-David, 2018). Credit crisis, lending delays, management deficiencies, non-profitability of firms and government interference in program operations sponsored by the government are the main causes of a loan failure. Some common consequences of failure include the challenge of retrieving funds for other borrowers that other financial intermediaries do not make available to cope with demands of farmers and create mistrust (Addae-Korankye, 2014).

Following a comparative study by microfinance institutions and financial intermediary, Muthoni, Mutuku, and Kamau (2017) studied the consequences of the loans for microcredited default in Kenya. Loan characteristics among MFIs and FIs were found to be significant, with certain differences in the measures being investigated. The findings will be of use as a source of information for reference purposes for politicians, MFIs, small firms, academia and the general public. The results show that all financial intermediaries who manage money carefully assess creditors' traits, which have a substantial effect on loan repayment before providing these loans, are strongly emphasized by the government. The cumbersome bureaucratic procedures and circumstances that result in delaying government fund releases must be reduced. The government should empower sub-country officers to grant individual loans and increase the number of financial intermediaries to improve loan delivery.

Depending on the characteristics of the loan contract, the effects of monetary shocks via this income channel could improve or reduce the impact of other commuting channels. The income channel can even negate other pathways in severe circumstances, making monetary shock ineffective. In other words, the parameters of the loan contract can have an impact on the effectiveness of the monetary policy's lower zero and liquidity trap (Moran, 2016).

The terms for digital credit lending and payback performance, according to Fox, Bartholomae, Letkiewicz, and Montalto, (2017) are, for the majority of cases, affecting business and investment type for borrowers. In order to reduce risk, microfinance companies are often promoting lower loan sizes. If customers do not receive enough resources to meet their business requirements, they are more susceptible to several loans. This affects your payments and increases the risk of the loan. This is consistent with Velusamy's findings in 2017 that MFI loans are sometimes too little to have an impact on women's companies. This also coincides with Wonder et al. (2009), who suggested that the customer might be lavish in terms of long loan times without payment of the debt. For a longer period of time, clients who accept minor loans should not have to repay their debt. Because the most of customers are small companies who take small loans, the facts show that they need a short loan for regular recapitalisation.

The factors influencing the repayment of loans in Southeastern Nigeria have been explored in Oyeagocha and Chidebelu (2012). They assumed that the size of the loan was negative with the payback rate. This means that the lower the customers' payback percentage, the greater the institution's lending amount. The results of their regression opposed this idea greatly. The bigger the credit to customers, the higher would be the rate of refund. Because the amount payable was significantly more and if the loan had been made by a development organization with subsidized interest rates and limited expectations of repeat loans, these customers would be under pressure or wish to delay repayment.

Effective loan sizes satisfy the repayment capacity of borrowers and boost business (Crone & Finlay, 2012). If the quantity of a loan is sufficient for the desired purposes, the borrower's ability to refund will have a good effect. On the other hand, the predicted sign is negative in cases of excess and under funding. If the borderline's loan exceeds the loan requirements and can be processed, this will not be an advantage, but will be more burdensome and extra funds may be used for personal purposes. The loan amount has been proven to be negative in his study, and he believes that if the loan is too tiny, borrowers might be prompted to deduct the loan for other purposes, which leads to a loan default. In addition, the current study has a loan size variable to determine how it influences group loan repayment.

Cash flow determines the capacity of the borrower to repay, according to Norberg (2016). Short repayment intervals may not lead to creditors generating enough money to reimburse the credit, while longer repayment periods may be adverse if borrower cannot receive more credit until such time as the present debt is reimbursed. This can minimize the default rate, both shorter and longer payback periods.

### 2.3.3 Lender Factors and Digital Credit Repayment

The lenders are in favor of a two-year history, a strong management group, a targeted sector, market share development, a high cash flow and the ability to obtain short-term funding from a number of additional sources in addition to the loan for the assessment of a SME as stated by Carlson (2017). A small company owner must submit or complete a loan proposal to most lenders.

A thorough company strategy as well as precise corporate and personal financial paperwork should be contained in the package submitted to the potential creator. The creditor then evaluates the request for the loan based on a number of characteristics. The lender, for example, examines small enterprises' credit rating and seeks demonstrations that they can repay the loan, such as earnings or expected revenue (Chan, Hamdi, Hui & Jiang, 2020). The creditor will also evaluate its shareholding and the expertise and know-how needed to achieve its management efficiency.

Relating repayment performance to corporate features Owens, Barrés, Rizzi, Daz, Moore, Mckee, and Fischer (2018), say that the company earnings have major repercussions on credit returns. Chou (2019) additionally addresses whether default occurs randomly, is affected by unpredictable behavior or systematically influenced by the local production conditions or efficiency of the branch. Chou (2019) Their research in Grameen on outstanding loans supports the assumption that there are only modest geographical changes. The low default rate and planned manager compensation relate to rural electricity, road width, primary school amenities and commercial Bank density. Shema (2019) also has identified a correlation between increased returns and access to extra sources of finance, marketing and metropolitan areas.

In addition to group loans, lenders often apply dynamic incentives and social intermediation. When credit is extended and the new loans are allocated on previous reimbursement results, creditors are required upon to implement drastic incentives when they raise the amount granted to a certain borrower. As many lenders provide services or training beyond finance, they are referred to sometimes as social intermediation. These two key characteristics of the approach of microfinance have taken less care of the contrary of group loans (Costa, Deb & Kubzansky, 2015).

According to Ravikumar, Murugan, and Suhashini (2019), the most important aspect that encourages credit groups to repay is that they value the future loan. Credit rationing has a considerable positive effect on the performance of paybacks to a certain degree according to Crone and Finlay (2012). The longer a branch was open in a particular location the higher the credit default rate was found by Fox, Bartholomae, Letkiewicz and Montalto (2017). The potential for a reduction in the marginal profitability of new companies is explained by this feature. This could be due to the dynamic incentive decline, in the case of extended credit over time, especially if borrowers discover that credit to defaulting or late borrowers is not regularly rejected.

Murugesh (2017) suggested that loan defaults are the result of many bank factors associated with banks' strategies for risk management. Among the factors of these institutions are the tax procedures used in the credit risk assessment. Failure to monitor credit default, insider loans, a lack of educated staff and an absence of proactive credit recovery procedures. Credit granting is a trip based on the process used to assess and award a loan, according to Henning and Jordaan (2016). This process begins with the loan request, continues the credit sales acquisition and finishes fully with the payment of the debt. Risk has been taken into account by lending institutions in a variety of ways. The strategies include simple approaches to advanced ones, such as computer simulation models, like subjective or informal (Sebanakita, 2019).

Many digital credit lender judgments are based on the subjective risk opinions of decision-makers with respect to the expectation of payback by the borrower. As the lending institutions are both simple and economic, this method is often used in their decision-making (Björkegren & Grissen 2018). Value-to-risk has become the normal methodology at institutions with active enterprises. Other companies have similar policies in place. In view of the number of information already available on these platforms in the public domain, this policy is currently seldom being reviewed.

The inability of lending agency employees to keep close to their clients leads in a failure to supervise projects if customer information and the conditions of borrowers are not regularly updated (Costa, Deb & Kubzansky, 2015). If loans are not submitted before payment, seniors, credit officers and debtors will suffer a moral hazard. If loans are not provided before payment. That may involve loans to undertakings under their control or affiliation, and to personal acquaintances and family members. If the borrowers don't use the loaned funds for their purposes but rather are diverted to other personal uses, the borrowers will confront this difficulty.

The high loan default rate is the main reason for digital lending failure, and a major difficulty for all stakeholders is the problem of payback. According to Ndege (2017), the main causes of these events are the difficulty of the organisation, unfavorable selection, and moral hazard caused by knowledge asymmetry. It is because lenders cannot observe the behaviour, whether honest or dishonest, of their customers. The result of their loans may only be observed by lenders if consumers pay the debts or not. Through monitoring, business advisors and regular meetings, the loaner can therefore have a tight interaction with the borrower to minimize reimbursement concerns. The prime minister can also develop a compensation scheme for persons paying on time, such as reimbursement or discount.

### 2.3.4 Digital Credit Repayment

The borrower's ability to efficiently deliver its loan on and when the loan is due is referred to as a reimbursement. Imbuga (2014) states that payment performance refers to the total time loans paid as stated in the loan agreement, and the performance of repayment measures are based on the level of arrears. Godquin (2014) also alludes to the traditional binary variable performance monitoring, based on a subjective definition of what constitutes a timely payment. Creditors are typically compelled for monthly payments to repay their loans, typically within a few months after the loan is paid out. A late payment is called a criminal payment; a non-payment is called a default payment. It is called a late payment. Unfavorable circumstances affecting the repayment capacity of the borrower may lead to default on the loaned funds. Repayment delays have two worrying effects for digital credit lenders: the failure to refinance a large number of safe consumers and the loan-officers' collection of late payments, leading to a rise in the burden of the lender, without reimbursement for resources. Moreover, because a member is late, other members will be encouraged to postpone their payment and perhaps negotiate a last portion of the loan with the institution (Sungwacha et al., 2014).

To have a functioning financial system, the financial market must be prepared to repay. Because of the lack of the execution of repayments by third parties, many borrowers and lenders fail to offer credit contracts successfully. The financial health of credit providers because they hinder their objectives and put their money in jeopardy is compromised by repayment problems. In addition, low repayment rates damage the connections between SMEs and digital lenders without any interest in future financial transactions SMEs (Bassem, 2018). Digital lenders utilize debt collection strategies to address the problem of loan repayment. One of digital lenders' key objectives is the recovery of loans that enables them to refinance and reach additional customers. In order for institutions to remain relevant to finance, they have to be able to lend and recover money in order to have a beneficial effect on the economies of a country. The recovery of loans is a crucial activity for a digital credit lender. Digital lenders also monitor lenders to make sure they use loans and are in a position to repay them for the desired aim (Kiliswa & Bayat, 2014).

## 2.4 Summary of Literature Reviewed and Knowledge Gaps

The chapter looked into different literature on the determinants of digital credit repayment. The study looked at the effect of individual/borrowers factors, loan factors and lender factors on digital credit repayment. Theories that form a basis of the study were such as prospect theory, and theory of delegated monitoring of borrowers.

Several literature such as Ngatia (2013) looked into the impact of mobile banking on consumer behavior among executive MBA students in Kenya: a case of United States International University-Nairobi (USIU); Mugo (2018) studied the effects of consumer purchase behaviour on the uptake of mortgages offered by banks in Nairobi; Muthoni (2016) conducted a comparative analysis of Microfinance Institutions and Financial Intermediaries to determine the elements that cause microcredit default in Kenya. Ochung (2013) investigated the factors influencing loan repayment among commercial bank customers in Kenya: a case study of Barclays Bank Of Kenya, Nairobi County; Nitin (2015) investigated the factors influencing consumer purchasing decisions in Kenya's automotive industry: a case study of Toyota Kenya Customers; and Okumu (2015) investigated the factors influencing consumer behavior in the purchase of beauty products in Nakuru County. These researches, on the other hand, did not identify the factors that influence digital credit repayment. Table 2.1 summarizes the knowledge gaps identified in the literature review.

**Table 2. 1: Summary of Knowledge Gaps**

| Author | Topic | Methodology | Findings | Research gaps | Focus of the Study |
|---|---|---|---|---|---|
| Ngatia (2013) | Impact of mobile banking on consumer behavior among executive MBA students in Kenya: a case of United States International University-Nairobi (USIU) | The study adopted a cross-sectional descriptive research design | Mobile banking adoption was influenced by its attributes such as security, reliability, speed (efficiency), ease of use, accessibility, convenience | The study was limited to MBA students | The study established the perception of the determinants of digital credit repayment in Kenya |

| Author | Topic | Methodology | Findings | Research gaps | Focus of the Study |
|---|---|---|---|---|---|
| | | | and affordability | | |
| Mugo (2018) | Effects of consumer purchase behaviour on the uptake of mortgages offered by commercial banks in Nairobi | The study employed a descriptive research design | The study further revealed that there was a positive significant relationship between social-cultural factors and mortgage uptake decisions. . | The study focused on the uptake of mortgages | This study focused on digital credit repayment in Kenya |
| Muthoni (2016) | Assessing Borrower's and Business' Factors Causing Microcredit Default in Kenya: A Comparative Analysis of Microfinance Institutions and Financial Intermediaries | This research used a descriptive research design | The findings of the study indicated that two variables namely; borrower's characteristics and business characteristics were significant among MFIs and FIs but with some differences in the parameters measured for the two variables | The study specifically looks into Microfinance Institutions | This study looked into all the digital credit lenders in Kenya |
| Ochung (2013) | Factors Affecting Loan Repayment Among Customers Of Commercial Banks In Kenya: A Case Of Barclays Bank Of Kenya, Nairobi County | The research design used was descriptive statistics | The study also suggests that there is a strong link between individual borrowers' variables and | The study does not look into the borrowers' behavioral patterns | The study assessed the effect of lender factors on digital credit repayment in Kenya |

| Author | Topic | Methodology | Findings | Research gaps | Focus of the Study |
|---|---|---|---|---|---|
| | | | loan repayment among Kenyan commercial bank customers. The study also suggests that there is a substantial link between loan variables and loan payback among Kenyan commercial bank clients. Commercial banks should have mandated supervision of borrowers on loan utilization and repayment, according to the report. | | |
| Nitin (2015) | Factors Affecting Consumer Purchasing Decision In Kenya's Motor Industry: Case Of Toyota Kenya Customer | Descriptive research design was employed in the study. | The study showed that the economic considerations and procurement decisions had a favorable and significant link. | The study focuses on Kenya's Motor Industry. | The study determined the effect of loan factors on digital credit repayment in Kenya |
| Okumu (2015) | An investigation of factors influencing consumer behavior in | The descriptive research | The study found, in particular | The study is limited to the purchase of | The study established the |

| Author | Topic | Methodology | Findings | Research gaps | Focus of the Study |
|---|---|---|---|---|---|
| | purchase of beauty products in Nairobi | design was employed in this research. | among 18 - 25 years and 26 - 30 years, the fact that a bigger % of loan factors influenced the purchasing behavior of beauty goods. | beauty products | perception of the determinants of digital credit repayment in Kenya |
| Kibrom (2010) | Determinants of successful loan repayment performance of private borrowers in Development Bank of Ethiopia North Region | A descriptive research design was used | The study found that educational level of the borrowers, repayment period of the loan, availability of other source of income, sector, purpose of the loan and type of labour determine successful loan repayment performance of the borrowers positively and significantl. Other variables such as, gender and household size have positive sign, but are not statistically significant. | The study used a probit model. The study was further done in a different country. | The study established the perception of the determinants of digital credit repayment in Kenya |

| Author | Topic | Methodology | Findings | Research gaps | Focus of the Study |
|---|---|---|---|---|---|
| | | | Moreover, variables such as age, loan diversion, other source of credit show negative sign but not statistically significant. | | |
| Abukari (2017) | Factors Influencing Loan Repayment among Microenterprises in the Greater Accra Region: A Case Study of LaNkwantanang-Madina Municipality | The study used secondary quantitative data and primary qualitative data | The study found that in the Greater Accra region, borrowers with some level of formal education were less likely to repay their loans compared with borrowers without any form of education. It was also found that borrowers who obtained loans for the purposes of consumer goods were less likely to repay their loans. | To ensure triangulation of data, in-depth interviews with some purposively selected micro-entrepreneurs were conducted to further deepen the understanding of the factors that influence loan repayment of households. | The study established the perception of the determinants of digital credit repayment in Kenya |
| Njangiru, James and Muathe (2014) | Effect of Borrower'Characteristics to Government Funded Micro-Credit Initiatives in Murang'a County, Kenya. | The research adopted a cross sectional descriptive survey | The study found that due to problems of high risk and high cost of borrowing, uncertainty of | Qualitative data were analysed using Chi-square, Analysis of Variance and | The study determined the effect of individual factors on digital credit |

| Author | Topic | Methodology | Findings | Research gaps | Focus of the Study |
|---|---|---|---|---|---|
| | | research design | repayment capacity on the rural borrower has been reported high due to irregular income streams. Systems should be developed to ensure consistent incomes and expenditure to reduce/remove uncertainty. | Logit Regression Model. | repayment in Kenya |

## 2.5 Conceptual Framework

A conceptual framework is a figure showing the link between the variable dependent and the independent. The dependent variable in this study is the digital credit repayment, whereas the independent variables include: individual factors, loan factors and lender factors. The conceptual framework is as shown in Figure 2.1.

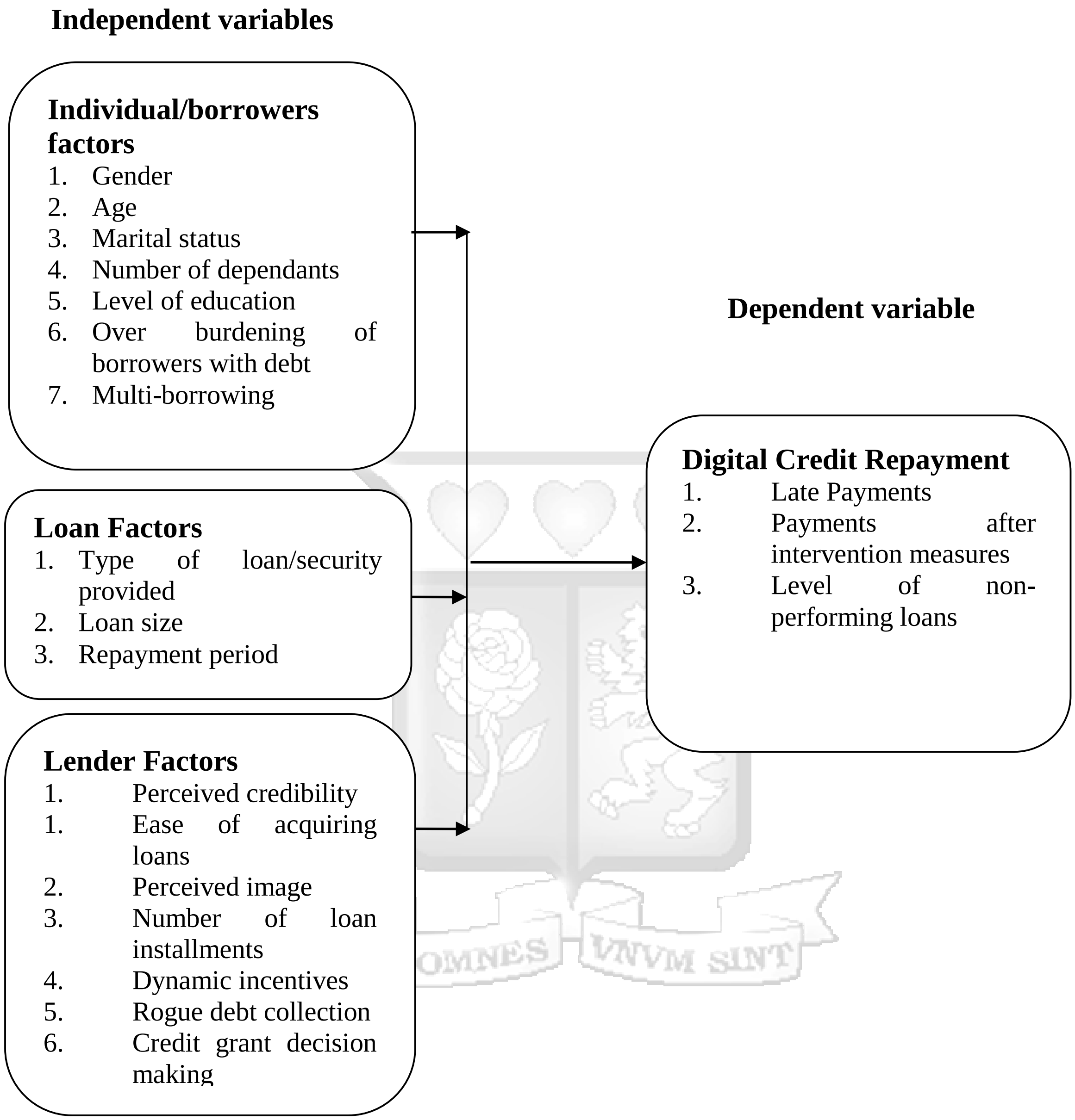


**Figure 2. 1: Conceptual Framework**

To determine the effect of individual/borrowers factors on digital credit repayment in Kenya, the study looked into how gender, age, marital status, number of dependants, level of education, over burdening of borrowers with debt, and multi-borrowing affect digital credit repayment. Moreover, to establish the effect of loan factors on digital credit repayment in Kenya, the study looked at the effect of loan type/security supplied, loan size, and repayment duration on digital credit repayment. In addition, to assess the effect of lender factors on digital credit repayment in Kenya, perceived credibility, ease of obtaining loans, perceived image, loan installment number, dynamic incentives, rogue debt collection, and credit grant decision making were used.

The digital credit repayment was the study's dependent variable. Late payments, payments after intervention efforts, and the amount of non-performing loans were all the factors used in the study to measure this variable.

### 2.5.1 Operationalization of the Variables

The study sought to establish portfolio manager's perception of the determinants of digital credit repayment in Kenya. Table 2.2 displays the operationalization of the variables.

**Table 2. 2: Operationalization of the Variables**

| **Objectives** | **Type of Variable** | **Indicator** | **Measuring of Indicators** | **Study informing operationalisation** |
|---|---|---|---|---|
| To determine the effect of individual/borrowers factors on digital credit repayment | Independent | Individual/borrowers factors | Gender<br>Age<br>Marital status<br>Number of dependants<br>Level of education | Uddin (2020) |
| To establish the effect of loan factors on digitacredit repayment | Independent | Loan factors | Type of loan/security provided<br>Loan size<br>Repayment period | Moradi and Rafiei (2019) |
| To assess the effect of lender factors on digital credit repayment | Independent | Lender factors | Perceived credibility<br>Ease of acquiring loans<br>Perceived image<br>Number of loan installments | Chan, Hamdi, Hui and Jiang (2020) |

| | | | | |
|---|---|---|---|---|
| | | | Dynamic incentives | |
| | Dependent | Digital credit repayment | Late Payments<br>Payments after intervention measures<br>Level of non-performing loans | Kinyanzui, Achoki and Kiriri (2018); Meht (2015) |

# CHAPTER THREE
# RESEARCH METHODOLOGY

## 3.1 Introduction

This chapter explains the design and the methods that were applied in this research for determining how borrowers' behavioral patterns affect digital credit repayment. The chapter covers research methodology used including research philosophy, research design, population and sampling, data collection instruments, data collection methods, data analysis, research quality which entails the validity, reliability and objectivity of the research, and finally ethical consideration.

## 3.2 Research Philosophy

A research philosophy is the set of common beliefs and agreements shared between scientists about how problems should be understood and addressed (Gorald, 2013). The paradigm that was suitable for this study was Pragmatism. For pragmatist knowledge claims and understanding arise out of actions, situations, and consequences rather than antecedent conditions in which there is a concern with applications of what works and solutions to problems (Ledford & Gast, 2018). In this case a pragmatist focused on multiple approaches to understand the problem. An abduction reasoning that uses induction and induction reasoning in order to permit the employment of qualitative and quantitative approaches in a single study is a pragmatic approach.

Bresler and Stake (2017) labeled these assumptions as forming a paradigm. Fletcher (2017) observes that the paradigm has the advantage of being flexible in its investigative techniques because it allows the use of both qualitative and quantitative techniques of gathering information. Qualitative research was used to enlighten the quantitative segment of research studies. The philosophy is further advanced by Kumar (2019) who notes that argue best paradigm for justification of mixed methods research use is pragmatism.

## 3.3 Research Design

A research design is the overall strategy that you choose to combine the many components of the study in the most cohesive and logical way so as to ensure that the investigation problem is effectively addressed (Gorard, 2013). A cross-sectional descriptive survey approach was used in this study to determine and describe the features of the variables of interest. This strategy made determining a sample size and gaining access to a population simple, reducing study time. The findings of a cross-sectional study's sample size are generalized to the population (Bryman & Bell, 2011). Descriptive studies describe features connected with the topic population in order to create an accurate picture of people, events, or circumstances. According to Kumar (2019), like the cross-sectional design, descriptive study design generalized the findings from the sampled population to the larger population.

### 3.4 Population and Sampling

The study targeted 7 credit digital lenders in Kenya (see in Appendix IV). The study's unit of analysis was the credit managers, credit analysts and account relationship managers. A study population refers to the total number of people included in the study's scope and whose characteristics the researcher is interested in (Ledford & Gast, 2018). It is a properly defined set of persons, services, items, events and residences under investigation. According to Bresler and Stake (2017), population refers to the total number of people, things, or events that a researcher needs to investigate. The target population is shown in Table 3.1.

**Table 3. 1: Target Population**

| | **Population** | **Percentage (%)** |
|---|---|---|
| Credit managers | 79 | 18.9 |
| Credit analysts | 196 | 47.0 |
| Account relationship managers | 142 | 34.1 |
| **Total** | **417** | **100.0** |

**Source: Researcher (2020)**

Sampling is a selection procedure in which a population subset is selected to represent the overall population (Fletcher, 2017). On the other hand, a sample is a sub-component of the population selected for the study. As the sample is larger, the more representative it becomes and therefore the study conclusions, the fundamental guideline for research is to use the largest possible sample. A stratified, proportionate random sample technique was used in the investigation. This sampling method had the advantage of reducing sample selection bias and ensuring that specific population groups were not overrepresented or underrepresented. The sample size was calculated using the Yamane (1967) formula, which is simple, scientific, and can be applied to a large population.

$$n = \frac{N}{1 + N(\varepsilon^3)}$$

$$n = \frac{417}{[1 + 417(0.05^3)]} = 204.2 \cong 204$$

The sample size of the study therefore was 204 respondents. The sampling ration was = 204/417=0.489 and this ratio was used for establishing the distribution of the respondents under the various categories.

**Table 3. 2: Sample Frame**

| Managers | Population | Ratio | Sample |
|---|---|---|---|
| Credit managers | 79 | 0.489 | 39 |
| Credit analysts | 196 | 0.489 | 96 |
| Account relationship managers | 142 | 0.489 | 69 |
| **Total** | **417** | | **204** |

**Source: Researcher (2020)**

### 3.5 Data Collection Methods

The study employed primary data obtained through the use of the questionnaires; use of the questionnaires was premised on the reality that they were suitable for a descriptive study as they were easy to administer, timely and convenient to the respondent. The questions were self-administered using a drop-and-pick method. Participants were also notified of the total confidentiality of the information provided by the researchers. After completion, the employee had received an envelope-labeled questionnaire and a theme of thesis to ensure secrecy inside the organization and safeguard the personnel or the person appointed by the company to coordinate the procedure from future victimization. The researcher then distributed the surveys to the individuals who had been chosen, working with them to ensure that respondents had adequate time to complete them. This made it possible to establish a friendly environment for the distribution and administration of the questionnaire. The questionnaire was distributed in accordance with the agreed-upon timetable.

### 3.6 Data Analysis

For simplicity of analysis, the data was sorted, categorized, and coded before being tabulated. The information was grouped and summarized based on common topics. The Statistical Package for Social Sciences (SPSS) was used to conduct the analysis (SPSS Version 25.0). The qualitative data from the open-ended questions was evaluated and presented in prose using conceptual content analysis. The data was analyzed using descriptive statistics. To profile sample characteristics and key patterns emerging from the data, mean and standard deviation were used. For ease of understanding and analysis, tables and other graphical presentations were employed to illustrate the data obtained. Principle component analysis (PCA) was used to do factor analysis. Factor analysis is a statistical process for determining correlations between many variables. This approach allowed a large number of associated variables to be condensed into a smaller number of factors.

The correlation matrices were also used for bivariate analysis in the study. Bivariate analysis was useful for testing simple hypotheses of association and assessing to what extent knowing and predicting a value for one variable (perhaps a dependent variable) gets easier when we know the value of the other variable (possibly the independent variable). For regressions, a categorical multivariate analysis strategy was applied. Moreover, a simple linear regression was adopted to give a more accurate prediction on the value of a dependent variable based on an independent variable. The multiple regression model gave us more of the information available from the simple analysis on which variable estimates the dependent variable more. The relevance of the independent variables on the dependent variable was determined using a regression model. The multiple regression model generally assumed the following equation;

$$\mathbf{Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon}$$

Where: -

$Y$= digital credit repayment

$\beta_0$=constant

$\beta_{1,}$ $\beta_{2,}$ and $\beta_3$ = regression coefficients

$X_1$= individual/borrowers factors

$X_2$= loan factors

$X_3$= lender factors

$\varepsilon$=Error Term

### 3.6.1 Diagnostics Tests

Normality, heteroscedasticity, and autocorrelation are all tested in this study. Normality is critical for understanding the distribution form and predicting dependent variable scores. Heteroscedasticity refers to a situation in which the dependent variable's variance varies throughout the data, as opposed to a situation in which the error term variation (homoscedasticity) V(j)=2for all j as assumed by Ordinary Least Squares (OLS). Heteroscedasticity hampers analysis since many approaches to regression analysis assume equal variation. Autocorrelation is the association of a temporal sequence with its own historical and future implications (Box, 2013). If the data is not random, the autocorrelation function can be used to diagnose non-randomness and to select an acceptable time series model.

This study assessed normality, heteroscedasticity, and serial correlation (autocorrelation) of regression residuals, as well as multicollinearity, using the Jarque-Bera test, which, unlike most other investigations, does not appear to exclude the null hypothesis when N is big (Jarque, 2011). Multicollinearity is a bad situation in which there are a lot of correlations between the independent variables.

Correlations between all pairs of independent variables are generated to test for multicollinearity. The model removed one of the two associated independent variables if some r is close to 1 or -1. Using the Variance Inflation Factor (VIF) is one method. The model's multicollinearity is assessed here. All VIFs would be 1 if there was no correlation between two independent variables. If the VIF for one of the variables is around or greater than 5, that variable has multicollinearity. In this situation, all such variables must be excluded from the regression model.

## 3.7 Research Quality

### 3.7.1 Validity of the Research Instrument

Gorard (2013) points out that the correctness and importance of the conclusions derived from the results of the investigation should be valid. One of the main reasons for conducting the pilot study is the validity of the questionnaire. The study relied on validity of content, which comprises extrapolating test findings to a wide range of objects identical to those in the test. The sample population's representativeness is a matter of content validity. The knowledge and skills of test items should be reflective of the broader field of information and competence, according to Meyers, Gamst and Guarino (2016). Expert assistance on the representation and relevance of the issues and ideas on the organization of research instruments were sought. This helped to improve the validity of the collected information. The content validity of the questionnaire was determined by requesting comments from the supervisor, teachers and other professionals on its appropriateness.

### 3.7.2 Reliability of the Research Instrument

On the other side, instrument reliability refers to the consistent generation of identical data by a research instrument under similar conditions. This is the extent to which it measures everything to be measured consistently (Wang, 2015). Reliability addresses the question of whether the results of a study are reproducible. Twelve questionnaires were provided to a pilot group of randomly chosen respondents from the target audience and their response was used to test the reliability of the tool. This represents 10% of the sample's overall size. For this study, all constructs should have a construct composite reliability coefficient (Cronbach alpha) of 0.7 or higher (Cronbach alpha) of 0.7 or above for all constructs is considered appropriate (Song, Coit, Feng & Peng, 2014). Cronbach's alpha (α) was used to determine the research instrument's reliability coefficient.

### 3.7.3 Objectivity of the Research

Table 3.3 indicates the operational definition of variables which includes their respective indicators, measurement, research design and type of statistical analysis.

**Table 3. 3: Objectivity of the Research**

| **Objectives** | **Variable** | **Indicators** | **Data analysis Techniques** | **Tool of Data Analysis** |
|---|---|---|---|---|
| To determine the effect of individual/borrowers factors on digital credit repayment | Individual/borrowers factors | Gender<br>Age<br>Marital status<br>Number of dependants<br>Level of education<br>Over burdening of borrowers with debt<br>Multi-borrowing | ➢ Descriptive statistics<br>➢ inferential statistics | ➢ Mean, frequency, standard deviation, and percentages<br>➢ Correlation and Regression analysis |
| To establish the effect of loan factors on digital credit repayment | Loan factors | Type of loan/security provided<br>Loan size<br>Repayment period | ➢ Descriptive statistics<br>➢ inferential statistics | ➢ Mean, frequency, standard deviation, and percentages |

| | | | | |
|---|---|---|---|---|
| | | | | ➢ Correlation and Regression analysis |
| To assess the effect of lender factors on digital credit repayment | Lender factors | Perceived credibility<br>Ease of acquiring loans<br>Perceived image<br>Number of loan installments<br>Dynamic incentives<br>Rogue debt collection<br>Credit grant decision making | ➢ Descriptive statistics<br>➢ inferential statistics | ➢ Mean, frequency, standard deviation, and percentages<br>➢ Correlation and Regression analysis |
| | Digital credit repayment | Late Payments<br>Payments after intervention measures<br>Level of non-performing loans | ➢ Descriptive statistics<br>➢ inferential statistics | ➢ Mean, frequency, standard deviation, and percentages<br>➢ Correlation and Regression analysis |

To find out how gender, age, marital status, number of dependants, and level of education affect digital credit repayment, the study looked into how gender, age, marital status, number of dependants, level of education, over burdening of borrowers with debt, and multi-borrowing affect digital credit repayment. Percentages and mean scores were employed as an analysis technique. The researchers employed descriptive statistics, bivariate analysis, and multivariate analysis in their study.

The influence of loan elements on digital credit repayment was investigated in the study, which looked at the effect of loan type/security supplied, loan size, and repayment duration on digital credit repayment. As an analysis technique, the study used percentages and mean scores. Descriptive statistics, bivariate analysis, and multivariate analysis were also used in the study.

In addition, the impact of lender factors on digital credit repayment was assessed using the following indicators: perceived credibility, ease of obtaining loans, perceived image, loan installment number, dynamic incentives, rogue debt collection, and credit grant decision making. As an analysis technique, the study used percentages and mean scores. Descriptive statistics, bivariate analysis, and multivariate analysis were also used in the study.

The digital credit repayment was the study's dependent variable. Late payments, payments after intervention efforts, and the amount of non-performing loans were all factors in the study. The mean scores were used to calculate this variable. Descriptive statistics, bivariate analysis, and multivariate analysis were also used in the study.

### 3.8 Ethical Considerations

The researcher observed the following norms of behavior in connection to the rights of people who become subjects of the study or are affected by it: To begin, the participants received a letter informing them of the study's purpose and the confidentiality of the information obtained, allowing them to give informed consent. Participants retained their right to withdraw or refuse to participate in some components of the study once consent was obtained, including the right to refuse to answer any question or set of questions and/or supply any data requested, as well as the right to have data they had provided removed. The researcher took great care to ensure that no one was forced to participate in the study, and he worked hard to get the information in the shortest period of time and with the fewest resources feasible. Second, quantitative research methodologies were employed to establish the impartiality, reliability, and independence of the researcher. Throughout the study, the researcher ensured that research ethics were followed. Participation in the study was totally voluntary. Privacy and confidentiality were also respected. The participants were informed of the study's objectives, and they were guaranteed that the information they provided would only be used for academic purposes.

## CHAPTER FOUR

## PRESENTATION OF RESEARCH FINDINGS

### 4.1 Introduction

The findings from the study's primary instrument are discussed in this chapter. It goes through the profiles of the respondents as well as their thoughts on the elements that influence borrowers' digital credit repayment behaviors. The researcher presented tables, pie charts, and graphs that summarized the respondents' collective reactions.

### 4.2 Sample Representation

Only 144 of the 204 questionnaires sent to credit managers, credit analysts, and account relationship managers were returned by the researcher. This resulted in a response rate of 70.6 percent, which is more than 50 percent and judged significant by Bresler and Stake (2017) for statistical analysis. This is as shown in Table 4.1.

**Table 4. 1: Sample Representation**

| | Number of informants | Percent |
|---|---|---|
| Response | 144 | 70.6 |
| Non-response | 56 | 29.4 |
| Total | 204 | 100.0 |

### 4.3 Demographic Analysis

This area allowed the researcher to see who was filling out the questionnaires, allowing them to determine whether the respondents were the ones they were looking for and whether the researcher was obtaining the information they needed. It also determines how well the sample represents the entire population. In this area, respondents were asked to provide background information such as their gender, age group, greatest level of education, and length of time they had worked in Kenya's Digital Credit Lending Sector. This data is presented in the form of graphs.

**Table 4. 2: Demographic Analysis Results**

| Gender | | |
|---|---|---|
| | Frequency | Percent |
| Male | 64 | 44.4 |
| Female | 80 | 55.6 |

| Age Bracket | | |
|---|---|---|
| | **Frequency** | **Percent** |
| 20-30 yrs | 11 | 7.6 |
| 31-40 yrs | 26 | 18.1 |
| 41-50 yrs | 37 | 25.7 |
| 51 – 60 yrs | 70 | 48.6 |
| **Highest Level of Education** | | |
| | **Frequency** | **Percent** |
| Certificate | 16 | 11.1 |
| Diploma | 34 | 23.6 |
| Undergraduate | 45 | 31.3 |
| Post Graduate | 49 | 34.0 |
| **Duration Working with the Digital Credit Lending Sector in Kenya** | | |
| | **Frequency** | **Percent** |
| 1-2 years | 43 | 29.9 |
| 3-4 years | 51 | 35.4 |
| Over 5 years | 50 | 34.7 |

The statistics show that females made up (80)55.6 percent of the respondents, while males made up (64) 44.4 percent. This means that the researcher took into account all respondents, regardless of gender, in order to gather trustworthy data on the subject at hand. The data also revealed that (70) 48.6% of the respondents were between the ages of 51 and 60, (37) 25.7 percent were between the ages of 41 and 50, (26) 18.1 percent were between the ages of 31 and 40, and (11) 7.6% were between the ages of 20 and 30. This demonstrates that the majority of the respondents were mature enough to cooperate in providing accurate information about the subject under investigation.

Furthermore, 49% of respondents had completed a postgraduate degree, 45.3% had completed an undergraduate degree, 34.6% had completed a diploma, and 16.1% had completed a certificate. This demonstrates that all of the respondents had a sufficient level of education to comprehend the surveys' questions. The findings also reveal that (51) 35.4 percent of respondents had worked in Kenya's digital credit lending sector for 3-4 years, (50) 34.7 percent for over 5 years, and (43) 29.9 percent for 1-2 years. This demonstrates that the majority of respondents had sufficient experience with Kenya's digital credit lending business to understand the company and provide credible and accurate information on the issue under investigation.

### 4.4 Descriptive Analysis

The descriptive analysis of the perception of portfolio managers on the determinants of digital credit repayment in Kenya is presented in this section. The goal of the study was to determine the impact of individual/borrowers, loan, and lender factors on digital credit repayment in Kenya. The results are provided in the subsections that follow.

#### 4.4.1 Individual/Borrowers Factors

The goal of the study was to see how individual/borrower factors affected digital credit repayment. The researcher wanted to determine how much individual and borrower factors influence digital credit repayment. Table 4.3 summarizes the findings.

**Table 4. 3: Effect of Individual/Borrowers' Factors on Digital Credit Repayment**

| | Frequency | Percent |
|---|---|---|
| Low extent | 12 | 8.3 |
| Moderate extent | 40 | 27.8 |
| Great extent | 40 | 27.8 |
| Very great extent | 52 | 36.1 |
| **Total** | **144** | **100.0** |

The findings show that (52) 36.1 percent of respondents said it was to a very great extent, (40) 27.8% said it was to a moderate amount, (40) 27.8% said it was to a great extent, and (12) 8.3 percent said it was to a low extent. This means that individual/borrower factors have a significant impact on digital credit repayment.

The respondents were also asked to indicate the extent to which individual/borrower factors influence digital credit repayment. The outcomes are shown in Table 4.4.

**Table 4. 4: Effect of Aspects of Individual/Borrowers' Factors on Digital Credit Repayment**

| | N | Mean | Median | Std. Dev. |
|---|---|---|---|---|
| Gender | 144 | 4.118 | 4 | 0.674 |
| Age | 144 | 2.924 | 3 | 0.853 |
| Marital status | 144 | 4.410 | 5 | 0.704 |

| | | | | |
|---|---|---|---|---|
| Number of dependants | 144 | 4.458 | 5 | 0.590 |
| Level of education | 144 | 4.257 | 4 | 0.645 |

The findings show that the number of dependants, as indicated by an average of 4.458; marital status, as indicated by an average of 4.410; level of education, as indicated by an average of 4.257; and gender, as indicated by an average of 4.118, all have a significant impact on digital credit repayment. The respondents also reported that age, as measured by an average of 2.924, had a moderate impact on digital credit repayment.

The respondents were also asked their thoughts on how individual/borrower factors influence digital credit repayment. They stated that they aid in determining whether a borrower's past record and economic prospects determine whether the borrower is likely to repay or not; they act as a guiding principle in credit appraisal to ensure that only those borrowers who require credit and are able to meet repayment obligations can access credit; and they predict whether a borrower is likely to repay or not based on an applicant's characteristics.

### 4.4.2 Loan Factors

The goal of the study was to determine the impact of loan parameters on digital credit repayment. The participants were asked to rate how much they believe loan factors influence digital credit repayment. Table 4.5 summarizes the findings.

**Table 4. 5: Effect of Loan Factors on Digital Credit Repayment**

| | **Frequency** | **Percent** |
|---|---|---|
| Low extent | 51 | 35.4 |
| Moderate extent | 27 | 18.8 |
| Great extent | 56 | 38.9 |
| Very great extent | 10 | 6.9 |
| **Total** | **144** | **100.0** |

As per the results, (56) 38.9% of the respondents indicated that loan factors affect digital credit repayment to a great extent, (51) 35.4% indicated to a low extent, (27) 18.8% indicated to a moderate extent while (10) 6.9% indicated to a very great extent. The findings implied that loan factors affect digital credit repayment to a great extent.

Moreover, the extent to which the aspects of loan factors affect digital credit repayment was sought. The outcome was as displayed on Table 4.6.

**Table 4. 6: Effect of Aspects of Loan Factors on Digital Credit Repayment**

| | N | Mean | Median | Std. Dev. |
|---|---|---|---|---|
| Type of loan/security provided | 144 | 3.861 | 4 | 0.958 |
| Loan size | 144 | 3.306 | 3 | 0.863 |
| Repayment period | 144 | 3.889 | 4 | 0.894 |

The results suggest that respondents indicated that repayment time (a mean score of 3.889) and type of loan/security given (a mean score of 3.861) have a significant impact on digital credit repayment. The findings also show that loan size, as measured by a mean score of 3.306, has a moderate impact on digital credit repayment.

The respondents also expressed their own thoughts on how loan parameters influence digital credit repayment. They stated that they identify the conditions and limits within which a lender will make loans to borrowers; shorter repayment periods may cause borrowers to not generate enough revenue to make loan repayments, whereas longer repayment periods may be disadvantageous to borrowers if they are unable to access further loans until the existing loan is paid back; and the amount of loan released is a factor.

### 4.4.3 Lender Factors

The goal of the study was to see how lender characteristics affected digital credit repayment. The goal of the research was to see how lender characteristics influence digital credit repayment. The results were displayed in Table 4.7.

**Table 4. 7: Effect of Lender Factors on Digital Credit Repayment**

| | Frequency | Percent |
|---|---|---|
| Moderate extent | 44 | 30.6 |
| Great extent | 45 | 31.3 |

| | | |
|---|---|---|
| Very great extent | 55 | 38.2 |
| **Total** | **144** | **100.0** |

According to the findings, lender characteristics affect digital credit repayment to a very great level for (55) 38.2 percent of respondents, a considerable extent for (45) 31.3 percent, and a moderate extent for (44) 30.6 percent. This implies that lender characteristics have a significant impact on digital credit repayment.

In addition, respondents were asked to describe the extent to which lender characteristics influence digital credit repayment. The outcome was as shown in Table 4.8.

**Table 4. 8: Effect of Aspects of Lender Factors on Digital Credit Repayment**

| | N | Mean | Median | Std. Dev. |
|---|---|---|---|---|
| Perceived credibility | 144 | 3.736 | 4 | 0.579 |
| Ease of acquiring loans | 144 | 4.160 | 4 | 0.644 |
| Perceived image | 144 | 3.889 | 3 | 0.489 |
| Number of loan installments | 144 | 2.451 | 2 | 0.884 |
| Dynamic incentives | 144 | 4.146 | 4 | 0.669 |

The results suggest that the ease of obtaining loans (mean score of 4.160), dynamic incentives (mean score of 4.146), perceived image (mean score of 3.889), and perceived credibility (mean score of 3.736) all have a significant impact on digital credit repayment. The study discovered that the number of loan installments, as measured by a mean score of 2.451, had a moderate impact on digital credit repayment.

The respondents were also asked to express their thoughts on how lender factors affect digital credit repayment. According to the respondents, they aid in the monitoring and early detection of difficulties that may occur as a result of non-repayment of loans, as well as the cooperation and coordination among various institutions that give additional support to help borrowers succeed.

### 4.4.4 Digital Credit Repayment

The research further sought to establish the trend of the various aspects of digital credit repayment for the last five years. The results were as shown in Table 4.9.

**Table 4. 9: Trend of Various Aspects of Digital Credit Repayment**

| | N | Mean | Median | Std. Dev. |
|---|---|---|---|---|
| Late Payments | 144 | 4.333 | 4 | 0.529 |
| Payments after intervention measures | 144 | 4.292 | 4 | 0.698 |
| Level of non-performing loans | 144 | 3.563 | 3 | 0.782 |

The findings revealed that late payments as demonstrated by an average score of 4.333; payments after intervention measures as demonstrated by an average score of 4.292; and level of non-performing loans as demonstrated by an average score of 3.563 had improved for the last five years.

## 4.5 Exploratory Factor Analysis

Based on the relationships between variables (in this case, questionnaire questions), exploratory factor analysis identifies the constructs – or factors – that underpin a dataset (Wang, 2015). The underlying constructs should be represented by the factors that explain the greatest proportion of variance among the variables. The tables show the proportion of each variable's variance that can be explained by the factors (e.g., the underlying latent continua).

### 4.5.1 Exploratory Factor Analysis for Individual/Borrowers Factors

Table 4.10 shows the Initial Eigenvalues where there is only one component which is greater than 1. This component explains 85.547% of the variance. Therefore, it can be concluded that there is only one factor.

**Table 4. 10: Total Variance Explained for Individual/Borrowers Factors**

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 4.277 | 85.547 | 85.547 | 4.277 | 85.547 | 85.547 |

| | | | |
|---|---|---|---|
| 2 | .322 | 6.436 | 91.983 |
| 3 | .219 | 4.379 | 96.362 |
| 4 | .116 | 2.321 | 98.683 |
| 5 | .066 | 1.317 | 100.000 |

Extraction Method: Principal Component Analysis.

Figure 4.1 shows a scree plot. This also shows that there is only one factor which is above 1.

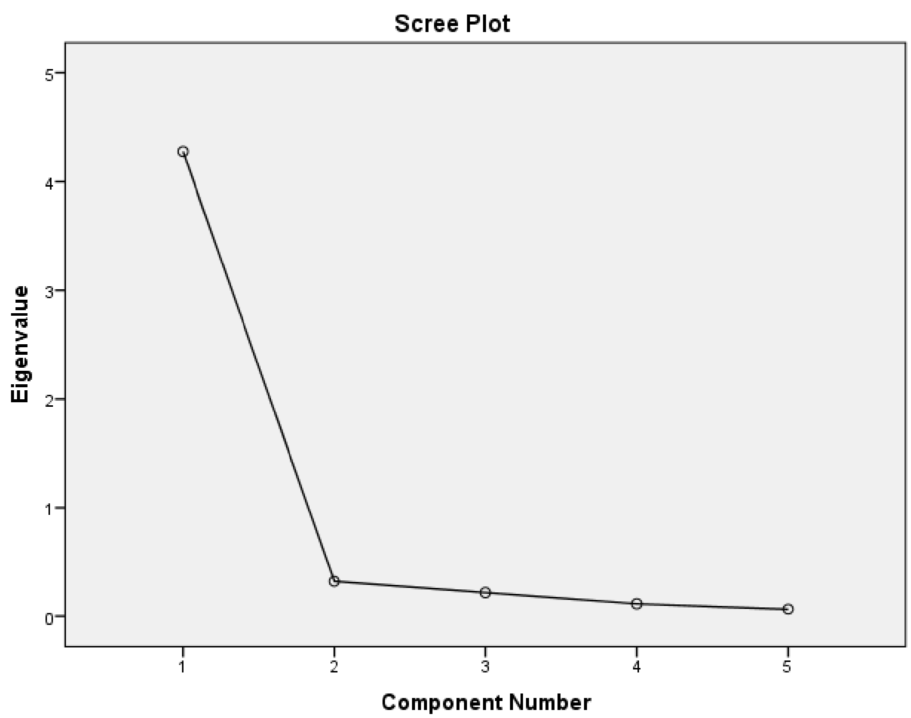


**Figure 4. 1: Scree Plot for Individual/Borrowers Factors**

The results in Table 4.11 helped us to figure out which variables fall under which extracted factor. Each of the five parameters was examined and ranked based on the proportion of variance it explained. Level of education (.966), age (.947), marital status (.938), gender (.911), and number of dependants (.858) all showed strong construct validity in the factor analysis because they all exceeded the prescribed factor loading criterion of 0.30 (Saunders, Lewis & Thornhill, 2012).

**Table 4. 11: Component Matrix for Individual/Borrowers Factors**

| | **Component** |
|---|---|
| | 1 |

| | |
|---|---|
| Level of education | .966 |
| Age | .947 |
| Marital status | .938 |
| Gender | .911 |
| Number of dependants | .858 |

Extraction Method: Principal Component Analysis.

1 component extracted.

### 4.5.2 Exploratory Factor Analysis for Loan Factors

The results in Table 4.12 reveal that there is only one component which is greater than 1 and explains 68.985% of the variance.

**Table 4. 12: Total Variance Explained for Loan Factors**

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 2.070 | 68.985 | 68.985 | 2.070 | 68.985 | 68.985 |
| 2 | .798 | 26.599 | 95.584 | | | |
| 3 | .132 | 4.416 | 100.000 | | | |

Extraction Method: Principal Component Analysis.

Figure 4.2 shows a scree plot. This also shows that there is only one factor which is above 1.

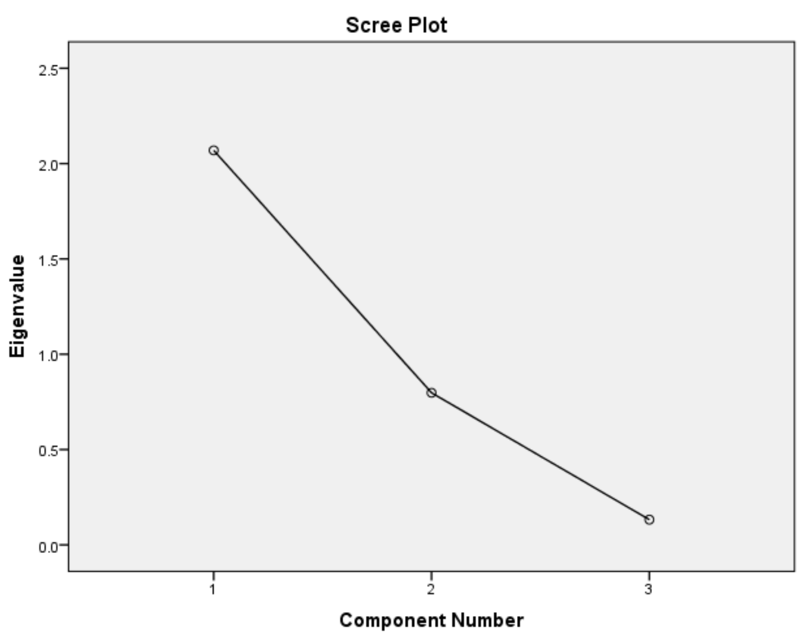


**Figure 4. 2: Scree Plot for Loan Factors**

The results made it possible to determine which variables fall under the extracted factor. Each of the three parameters was examined and ranked based on the proportion of variance it explained. The type of loan/security provided (.955), repayment period (.885), and loan size (.613) all showed strong construct validity, above the prescribed factor loading criterion of 0.30 (Saunders, Lewis & Thornhill, 2012).

**Table 4. 13: Component Matrix for Loan Factors**

| | **Component** |
|---|---|
| | 1 |
| Type of loan/security provided | .955 |
| Repayment period | .885 |
| Loan size | .613 |
| Extraction Method: Principal Component Analysis. | |
| a. 1 component extracted. | |

### 4.5.3 Exploratory Factor Analysis for Lender Factors

**The total variance explained by lender factors is shown in Table 4.12. According to the data, there is just one component that is bigger than 1 and accounts for 67.060 percent of the variation.**

**Table 4. 14: Total Variance Explained for Lender Factors**

| **Component** | **Initial Eigenvalues** | | | **Extraction Sums of Squared Loadings** | | |
|---|---|---|---|---|---|---|
| | **Total** | **% of Variance** | **Cumulative %** | **Total** | **% of Variance** | **Cumulative %** |
| 1 | 3.353 | 67.060 | 67.060 | 3.353 | 67.060 | 67.060 |
| 2 | .925 | 18.493 | 85.553 | | | |
| 3 | .474 | 9.481 | 95.034 | | | |
| 4 | .152 | 3.037 | 98.071 | | | |
| 5 | .096 | 1.929 | 100.000 | | | |
| Extraction Method: Principal Component Analysis. | | | | | | |

Figure 4.3 shows a scree plot. This also shows that there is only one factor which is above 1.

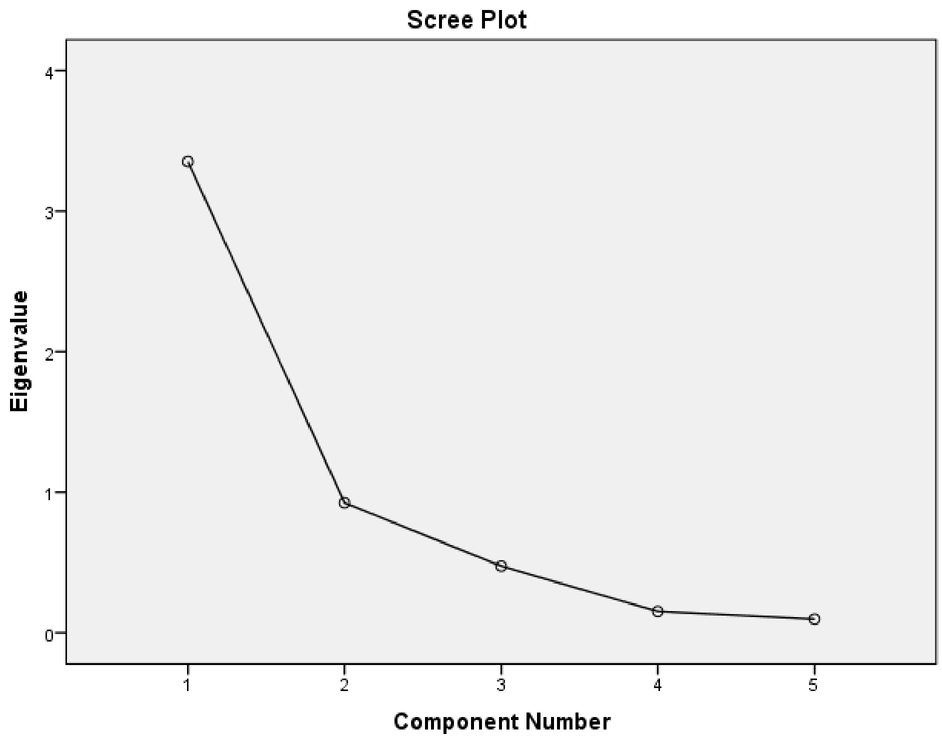


**Figure 4. 3: Scree Plot for Lender Factors**

The results made it possible to determine which variables fall under the extracted factor. Each of the five parameters was examined and ranked based on the proportion of variance it explained. Perceived credibility (.955), number of loan installments (.955), dynamic incentives (.872), perceived image (.787), and ease of acquiring loans (.386) all showed good construct validity, exceeding the 0.30 factor loading criteria (Saunders, Lewis & Thornhill, 2012).



**Table 4. 15: Component Matrix for Lender Factors**

| | **Component** |
|---|---|
| | **1** |
| Perceived credibility | .955 |
| Number of loan installments | .955 |
| Dynamic incentives | .872 |
| Perceived image | .787 |
| Ease of acquiring loans | .386 |
| Extraction Method: Principal Component Analysis. | |
| a.1 component extracted. | |

### 4.6 Bivariate Analysis

To determine the degrees of correlation between the variables, the researcher used a bivariate analysis. The Spearman rank correlation test was used, with a positive correlation value implying a positive link and a negative correlation value implying a negative or inverse association. The Pearson moment correlation data are shown in Table 4.16.

**Table 4. 16: Spearman Rank Correlation Test**

| | | | **Digital Credit Repayment** | **Borrowers Factors** | **Loan Factors** | **Lender Factors** |
|---|---|---|---|---|---|---|
| Spearman's rho | Digital Credit Repayment | Correlation Coefficient | 1.000 | .767** | -.133 | -.492** |
| | | Sig. (2-tailed) | . | .000 | .112 | .000 |
| | | N | 144 | 144 | 144 | 144 |
| | Borrowers Factors | Correlation Coefficient | .767** | 1.000 | -.185* | -.667** |
| | | Sig. (2-tailed) | .000 | . | .027 | .000 |
| | | N | 144 | 144 | 144 | 144 |
| | Loan Factors | Correlation Coefficient | -.133 | -.185* | 1.000 | .035 |
| | | Sig. (2-tailed) | .112 | .027 | . | .681 |
| | | N | 144 | 144 | 144 | 144 |
| | Lender Factors | Correlation Coefficient | -.492** | -.667** | .035 | 1.000 |

| | | | | | |
|---|---|---|---|---|---|
| | Sig. (2-tailed) | .000 | .000 | .681 | . |
| | N | 144 | 144 | 144 | 144 |

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

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

The correlation results between digital credit repayment and individual/borrowers characteristics show a positive coefficient of 0.767 with a p-value of 0.000, according to the analysis. It shows that the result is significant at 5% and that increasing the individual/borrowers factors will have a positive impact on digital credit repayment. The results of the association between loan factors and digital credit repayment show a negative coefficient of -0.133 and a p-value of 0.112, which was insignificant at = 5%.

The findings also demonstrate a negative relationship between lender variables and digital credit repayment, with a p-value of 0.000 and a correlation coefficient of -0.492. However, positive relationships imply that when the aforementioned component's practice is in place, the level of digital credit repayment rises, whereas negative associations imply that when the factor is in place, the level of digital credit repayment declines.

### 4.7 Multivariate Analysis

Individual/borrower factors, loan factors, and lender factors all had an impact on digital credit repayment in Kenya, according to a multivariate analysis. The results are shown in Table 4.17.

**Table 4. 17: Multivariate Analysis**

| **Model Summary for Individual/Borrowers Factors** | | | | |
|---|---|---|---|---|
| **Model** | **R** | **R Square** | **Adjusted R Square** | **Std. Error of the Estimate** |
| 1 | .792[a] | .627 | .624 | 1.05401 |

| **ANOVA Results for Individual/Borrowers Factors** | | | | | | |
|---|---|---|---|---|---|---|
| **Model** | | **Sum of Squares** | **df** | **Mean Square** | **F** | **Sig.** |
| 1 | Regression | 265.246 | 1 | 265.246 | 238.757 | .000[b] |
| | Residual | 157.754 | 142 | 1.111 | | |
| | **Total** | **423.000** | **143** | | | |

| Regression Coefficients for Individual/Borrowers Factors | | | | | | |
|---|---|---|---|---|---|---|
| **Model** | | **Unstandardized Coefficients** | | **Standardized Coefficients** | **t** | **Sig.** |
| | | **B** | **Std. Error** | **Beta** | | |
| 1 | (Constant) | -8.924 | 1.319 | | -6.764 | .000 |
| | Borrowers Factors | 1.058 | .068 | .792 | 15.452 | .000 |

| Model Summary for Loan Factors | | | | |
|---|---|---|---|---|
| **Model** | **R** | **R Square** | **Adjusted R Square** | **Std. Error of the Estimate** |
| 1 | .229[a] | .052 | .046 | 1.68021 |

| ANOVA Results for Loan Factors | | | | | | |
|---|---|---|---|---|---|---|
| **Model** | | **Sum of Squares** | **df** | **Mean Square** | **F** | **Sig.** |
| 1 | Regression | 22.118 | 1 | 22.118 | 7.835 | .006[b] |
| | Residual | 400.882 | 142 | 2.823 | | |
| | **Total** | **423.000** | **143** | | | |

| Regression Coefficients for Loan Factors | | | | | | |
|---|---|---|---|---|---|---|
| **Model** | | **Unstandardized Coefficients** | | **Standardized Coefficients** | **t** | **Sig.** |
| | | **B** | **Std. Error** | **Beta** | | |
| 1 | (Constant) | 15.180 | 1.352 | | 11.231 | .000 |
| | Loan Factors | -.334 | .119 | -.229 | -2.799 | .006 |

| Model Summary for Lender Factors | | | | |
|---|---|---|---|---|
| **Model** | **R** | **R Square** | **Adjusted R Square** | **Std. Error of the Estimate** |
| 1 | .457[a] | .209 | .203 | 1.53531 |

| ANOVA Results for Lender Factors | | | | | | |
|---|---|---|---|---|---|---|
| **Model** | | **Sum of Squares** | **df** | **Mean Square** | **F** | **Sig.** |
| 1 | Regression | 88.282 | 1 | 88.282 | 37.452 | .000 |
| | Residual | 334.718 | 142 | 2.357 | | |
| | **Total** | **423.000** | **143** | | | |

| Regression Coefficients for Lender Factors | | | | |
|---|---|---|---|---|
| **Model** | **Unstandardized Coefficients** | **Standardized Coefficients** | **t** | **Sig.** |

| | | B | Std. Error | Beta | | |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 23.58 | 1.992 | | 11.837 | 0.000 |
| | Lender Factors | 0.641 | 0.105 | 0.457 | 6.105 | 0.000 |

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .805[a] | .648 | .640 | 1.03194 |

**ANOVA**

| Model | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 273.913 | 3 | 91.304 | 85.739 | .000[b] |
| | Residual | 149.087 | 140 | 1.065 | | |
| | **Total** | **423.000** | **143** | | | |

**Regression Coefficients**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | -14.922 | 3.635 | | -4.105 | .000 |
| | Borrowers Factors | 1.196 | .095 | .895 | 12.582 | .000 |
| | Loan Factors | -.098 | .075 | -.067 | -1.305 | .194 |
| | Lender Factors | .235 | .098 | .167 | 2.393 | .018 |

To determine the impact of individual/borrower characteristics on digital credit repayment in Kenya, a simple regression analysis was used. The borrower factors model summary shows how well the regression line can account for the whole variation in the dependent variable (Digital credit repayment in Kenya). The results showed that borrower factors have a very high link with digital credit repayment in Kenya, with an r=0.792. Furthermore, the R2 (adjusted R-Square value) was 0.624, indicating that individual/borrower factors account for 62.4 percent of the variation in the dependent variable (Digital credit repayment in Kenya). This means that the other factors influencing digital credit repayment in Kenya accounted for 37.6 percent of the total. The overall model is statistically significant in predicting how individual/borrowers factors affect digital credit repayment in Kenya, with a p-value of 0.000, which is less than 0.05, according to the ANOVA results. At a 5% level of significance, the computed F was 238.757, which was more than F-critical (3.9077). The regression coefficients model demonstrated the proportion of the variance in the dependent variable that can be predicted by the independent variable. According to the data, if individual/borrower characteristics are held constant at zero, digital credit repayment in Kenya will be -8.924. Taking all other independent variables to zero, the data suggest that a unit increase in the individual/borrowers factors leads to a 1.058 rise in digital credit repayment in Kenya. Because the p-value (0.000) was less than 0.05, this variable was significant and therefore the null hypothesis that individual/borrowers factors do not affect digital credit repayment in Kenya was rejected. The regression model can be replaced with the following:

$\mathbf{Y}= -8.924+ 1.058\mathbf{X_1}$

Where;

$\mathbf{Y}$ = Digital credit repayment in Kenya

$\mathbf{X_1}$= individual/borrowers factors

In addition, a simple regression analysis was performed to determine the effect of loan parameters on digital credit repayment in Kenya. The loan factors model summary informs you about the regression line's capacity to account for the whole variation in the dependent variable (Digital credit repayment in Kenya). According to the research, r=0.229, indicating that loan parameters have a very strong link with digital credit payback in Kenya. The adjusted R-Square value (coefficient of determination) was 0.046, indicating that loan factors account for 4.6 percent of the variation in the dependent variable (Digital credit repayment in Kenya). This means that the other factors influencing digital credit repayment in Kenya were attributed to 95.4 percent of the time. Further, the p-value of 0.000, which was less than 0.05, indicating that the whole model is statistically significant in predicting how loan characteristics affect digital credit repayment in Kenya. The computed F of 7.835 was greater than the F-critical (3.9077), indicating that the whole model fit well. The regression coefficient section results revealed that if loan components were held constant at zero, digital credit repayment in Kenya would be 15.180. Taking all other independent variables to zero, the data suggest that a unit increase in loan factors results in a 0.334 drop in digital credit repayment in Kenya. The p-value (0.006) was less than 0.05, this variable was significant and therefore the null hypothesis that loan factors do not affect digital credit repayment in Kenya was rejected. The regression model can be replaced with the following:

**Y**= 15.180-0.334$\mathbf{X_2}$

Where;

**Y** = Digital credit repayment in Kenya

$\mathbf{X_2}$= loan factors

A simple regression analysis was also performed to determine the effect of lender characteristics on digital credit repayment in Kenya. The lender factor results in the model summary provide information on the regression line's capacity to account for the total variation in the dependent variable (Digital credit repayment in Kenya). According to the findings, r=0.457 indicated that lender factors have a very strong link with digital credit repayment in Kenya. The adjusted R-Square value (coefficient of determination) was 0.203, implying that lender factors explain 20.3 percent of the variation in the dependent variable (Digital credit repayment in Kenya). This means that the other factors influencing digital credit repayment in Kenya accounted for 79.7 percent of the total. Furthermore, the p-value from the ANOVA was 0.000, which is less than 0.05, indicating that the total model is statistically significant in predicting how lender characteristics affect digital credit repayment in Kenya. At the 5% level of significance, the computed F of 37.452 was more than the F-critical (3.9077). This implied that the whole model fit well. According to the results of the regression coefficients section, if lender factors were held constant at zero, digital credit repayment in Kenya would be 23.580. Taking all other independent variables to zero, the data suggest that a unit increase in the lender factors results in a 0.641 increase in digital credit repayment in Kenya. Because the p-value (0.000) was less than 0.05, this variable was significant and therefore the null hypothesis that lender factors do not affect digital credit repayment in Kenya was rejected. The regression model can be replaced with the following:

**Y**= 23.580+0.641$\mathbf{X_3}$

Where;

**Y** = Digital credit repayment in Kenya

**$X_3$**= lender factors

Furthermore, the researcher used a multiple regression analysis to assess the relationship between the effect of individual/borrowers factors, loan factors, and lender factors on digital credit repayment in Kenya. The model summary describes the regression line's capacity to account for the total variation in the dependent variable (Digital credit repayment in Kenya). The results showed that r=0.805, indicating that individual/borrowers factors, loan factors, and lender factors all had a very significant link with digital credit repayment in Kenya. The results also revealed that the adjusted R-Square value (coefficient of determination) is 0.640, indicating that the independent variables (individual/borrower characteristics, loan factors, and lender factors) explained 64.0 percent of the variation in the dependent variable (Digital credit repayment in Kenya). This implied that there are other factors influencing Digital credit repayment in Kenya, which accounted for 36.0 percent of the unexplained.

The ANOVA findings revealed that the p-value was 0.000, which was less than 0.05, indicating that the whole model is statistically significant in predicting how individual/borrowers factors, loan factors, and lender factors influence digital credit repayment in Kenya. At the 5% level of significance, the computed F was 85.739, which was more than the F-critical (2.6693). This meant that the overall model was a good match. As a result of the findings, there was a highly statistically significant association between individual/borrower characteristics, loan factors, lender factors, and digital credit repayment in Kenya.

The regression coefficient section's findings revealed that if all factors (individual/borrowers factors, loan factors, lender factors) were held constant at zero, digital credit repayment in Kenya would be -14.922. According to the study, a unit change in individual/borrower characteristics results in a 1.196 unit change in digital credit repayment in Kenya. Taking all other independent variables to zero, these findings suggested that a unit increase in the individual/borrowers factors will result in a 1.196 rise in digital credit repayment in Kenya. Because the p-value (0.000) was less than 0.05, this variable was significant and therefore the null hypothesis that individual/borrowers factors do not affect digital credit repayment in Kenya was rejected. As a result of these findings, individual/borrower variables are a strong predictor of digital credit payback in Kenya.

According to the study, a unit change in loan variables results in a -0.098 unit change in digital credit repayment in Kenya. Since $p=0.194>0.05$, the variable is statistically insignificant therefore the partial equilibrium interpretation does not apply. This variable was therefore insignificant and therefore the null hypothesis that loan factors do not affect digital credit repayment in Kenya was accepted. According to the research, a unit rise in lender variables will result in a 0.235 increase in digital credit payback in Kenya. The p-value (0.018) was less than 0.05, indicating that this variable was significant and therefore the null hypothesis that lender factors do not affect digital credit repayment in Kenya was rejected. This suggested that in Kenya, lender factors were a strong predictor of digital credit repayment. The regression model can be substituted using the statistical findings in Table 4.17 as follows:

$$\mathbf{Y = -14.922 + 1.196X_1 - 0.098X_2 + 0.235X_3}$$

Where; $X_1$= individual/borrowers factors

$X_2$= loan factors

$X_3$= lender factors

Overall, it was established that individual/borrowers factors had the greatest effect on the digital credit repayment in Kenya, followed by lender factors while loan factors had the least effect on the Digital credit repayment in Kenya.

# CHAPTER FIVE

# DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

## 5.1 Introduction

This chapter discusses the data findings, draws conclusions from the findings highlighted, and makes recommendations. The conclusions and recommendations are aimed at achieving the study's goal.

## 5.2 Discussions of the Findings

This section includes more literature reviews on the findings of each variable.

### 5.2.1 Effect of Individual/Borrowers Factors on Digital Credit Repayment

The study found that the individual/borrower factors have a significant impact on digital credit repayment, according to the study. The findings are consistent with those of Björkegren and Grissen (2018), who claim that individual/borrowers factors have a significant impact on the evaluation of various elements related with digital lending. The results were also in accordance with Uddin (2020) who stated that character, capability, and capital are the main criteria that define a borrower's ability to repay a loan. When determining a customer's desire to pay, his personality is crucial. Customers should make the least effort to honor their credit commitments, according to the financial or credit management. In practice, the moral aspect plays a significant role in credit judgment. When it comes to the evaluation of various characteristics related with digital lending, individual/borrowers factors are observed to have a significant impact. Borrowers accept many loans from different lenders at the same time, which is the obvious problem with competition. Ravikumar, Murugan and Suhashini (2019) asserts that borrowers get over-indebted as a result of paying one lender's payments with a loan from another, resulting in a debt spiral and, all too often, financial disaster. No single lender will be able to clamp down and maintain full discipline as long as borrowers believe they have several options. Cooperation among lenders may be able to assist alleviate the problem. The introduction of credit bureaus to better communicate information on credit access and borrowers' performance histories would help programs.

The study discovered that the number of dependants, marital status, degree of education, and gender all have a significant impact on digital credit repayment. This is in line with Costa, Deb and Kubzansky (2015) who noted that age brings with it culturally determined behavioral and attitudinal norms, which have an impact on our self-concept and way of life. When it comes to purchasing decisions, age disparities are important. Many marketers nowadays have carved out a niche for themselves in the marketplace by focusing on a specific demographic group. For example, elderly consumers are more likely to use digital loans for medical and travel-related products and purchase fewer clothes and home furnishings items than younger consumers, whereas teens spend more on movies, soft drinks, and fast food (Velusamy, 2017). These results also conform to Uddin (2020) who states that gender has thus been discovered as a component that has a significant impact on information search as well as other important borrower behavior characteristics, according to. Furthermore, Makimu (2017) agreed with the findings, stating that bank clients as a whole have demographic traits that put banks at a competitive advantage or disadvantage when it comes to advancing loans and loan performance. Customers who are older, less likely to be employed, have less household income, and have less education, for example, are more likely to default on their loans or have difficulty servicing them.

The study also discovered that age has a moderate impact on digital credit repayment. The study also found that age had a moderate impact on digital credit repayment. Björkegren and Grissen (2018) disagreed with the findings stating that the characteristics that younger borrowers are more likely to seek in a lender may differ from those that older borrowers seek. Most marketing has typically focused on marital status. Marketers are interested in the amount of and types of households who own/buy various products and more specifically, marketers have recognized the benefits of targeting specific marital status groupings for the majority of products and services.

These findings were also in agreement with Katakam et al. (2016) who found that borrowers' credit worthiness was influenced by their income, age, experience, and degree of education. Much emphasis has been placed on the financial aspects of entrepreneurs, while the human capital aspect of the entrepreneur has been overlooked. Borrowers from a higher social class are more likely to favor a specific sort of digital lender they believe would meet their needs. In his study, Kiliswa and Bayat (2014) discovered that the greater a student's grade point average, the less likely they are to default. Controlling for other variables, a student with a GPA between 0.00 and 1.99 is three percentage points more likely to default than a student with a GPA between 3.00 and 4.00. Furthermore, the findings are consistent with those of Shema (2019b), who investigated the factors impacting loan repayment default among Nigerian poultry farmers and discovered that the majority of the farmers in the research region were educated. They also discovered that the farmers' educational level had a substantial impact on loan repayment default. Lindstrom (2019) identified demographic profiling as a key factor influencing loan advance and subsequent loan performance across the banking sector because it provides credit officers with critical information about the group and individuals, allowing them to make informed decisions about the group or individual's suitability or otherwise.

### 5.2.2 Effect of Loan Factors on Digital Credit Repayment

The study discovered that loan parameters have a significant impact on digital credit repayment. Sharma (2014) agreed that there are many different forms of loans in use around the world, but the characteristics of the loan are usually explained by other aspects. The first is that both accumulate interest, which may be constant throughout the loan or contract's life and adjust at predetermined intervals; alternatively the interest rate may be greater or lower. Second, they released the term: that is, they have a predetermined repayment period, whereas others have no amortization, enable full repayment of any residual balance at any time, or even allow negative depreciation. They also have a payment amount and frequency: the daily payment amount and the payment frequency.

The findings also show that loan size has a moderate impact on digital credit repayment. The results are not in line with Agarwal and Ben-David (2018) noted that the amount paid per term may alter in specific circumstances, or the creditor may have the ability to increase or decrease the amount paid. This is consistent with the findings of Velusamy (2017) who found that MFI loans are sometimes too little to have an impact on enterprises. Crone and Finlay (2012) also affirm that effective loan sizes meet borrowers' repayment capabilities while also stimulating business. If the loan amount is sufficient for the intended reasons, it will have a beneficial impact on the borrower's ability to repay. Shema (2019b) agrees that if the loan amount exceeds what the borrower requires and can handle, it will be more of a burden than a benefit, and the extra funds may be used for personal purposes, putting repayment performance at risk.

The study found that the type of loan/security given have a great impact on digital credit repayment. The results are also in line with Fox, Bartholomae, Letkiewicz and Montalto (2017) who noted that loan contract characteristics can impact when the zero lower bound of monetary policy is successfully reached and when the economy is in the liquidity trap. This is also in line with Jumpah, Tetteh, and Adams (2018), who argue that the most important notion to understand when it comes to borrower behavior is that the average person with a certain income level is likely to repay a given amount of credit. Abankwah, Awunyo-Vitor, and Seini (2016) added that the reasons for non-repayment can be divided into three categories: the underlying characteristics of lenders and their companies that make it unlikely that the loan will be repaid; the financial entity's features and the applicant's appropriateness of the debt asset that makes it unlikely that the debt will be repaid; and external conditions such as the e-commerce environment that make it unlikely that the debt will be repaid.

Credit scarcity, delay in credit issuing periods, inadequate management, non-profitability of firms, and excessive government meddling in government-funded program activities, according to Addae-Korankye (2014), are the key causes of loan default. The difficulty to recover cash for other borrowers, the unavailability of other financial intermediaries in addressing the demands of farmers, and the creation of mistrust are some of the usual consequences of the default.

The study also discovered that the length of the repayment period has an impact on digital credit repayment. The outcome agrees with Fox, Bartholomae, Letkiewicz, and Montalto (2017) who stated that digital credit lending conditions and repayment performance affect the sort of business and type of investment for borrowers in most circumstances. Micro finance firms frequently promote lower loan sizes as a means of reducing risk. When clients are not provided with sufficient finances to meet their business demands, they are more likely to take out multiple loans. This has an impact on their payments and raises the loan's risks.



In addition, Wonder et al. (2009) suggested that a long loan time may cause the client to be lavish, resulting in the loan not being repaid. Clients who take out small loans should not have to pay back their debts over an extended period of time. According to the data, because the bulk of the clients are small business owners who take out small loans, they require a short loan time for regular recapitalization. Muthoni, Mutuku, and Kamau (2017) however disagrees with the findings that loan factors had the least effect on the Digital credit repayment in Kenya because they found that loan characteristics were shown to be important among MFIs and FIs with some variances in the metrics examined. They stated that the government places a heavy emphasis on all financial intermediaries managing money to carefully analyze borrowers' qualities that have a significant impact on loan repayment before granting these loans. The consequences of monetary shocks through this income channel may enhance or lessen the impact of other transmission channels, depending on loan contract parameters. In severe cases, the income channel may even completely counteract other routes, rendering the monetary shock ineffectual. Moran (2016) states that loan contract characteristics may have an impact on when monetary policy's zero lower bound is effectively reached and when the economy has entered the liquidity trap. The expected sign in the event of over and under finance, on the other hand, is negative.

### 5.2.3 Effect of Lender Factors on Digital Credit Repayment

The study discovered that lender factors have a significant impact on digital credit repayment. This is in line with Carlson (2017) who states that lenders prefer to see a two-year operating history, a stable management group, a desirable niche in the industry, a growth in market share, a strong cash flow, and the ability to obtain short-term financing from other sources as a supplement to the loan when evaluating a small business for a loan. The results suggest that the perceived image and perceived credibility have a significant impact on digital credit repayment. Chan, Hamdi, Hui, and Jiang (2020) agree that a full business strategy, as well as detailed corporate and personal financial statements, should be included in the package of materials submitted to a possible lender, according to. After that, the lender will assess the loan request based on a number of factors. The lender, for example, will look at the small business's credit rating and seek for evidence of its ability to repay the loan, such as past earnings or projected earnings.

The study found that dynamic incentives have a significant impact on digital credit repayment. The findings are in agreement with Costa, Deb and Kubzansky (2015) who affirm that lenders frequently use dynamic incentives and social intermediation in addition to group lending. When lenders raise the amount provided to a specific borrower when credit is extended and condition the allocation of new loans on previous repayment performance, they are called to deploy dynamic incentives. Because many lenders provide services or training that go beyond financial services, they are sometimes referred to as social intermediation. In addition, Björkegren and Grissen (2018) noted that unlike group lending, these two key characteristics of microfinance methodology have received little attention to far. Because it is both straightforward and economical, lending institutions frequently employ this strategy in their decision-making. Value-at-risk has become the conventional methodology for institutions with active trading businesses. Other businesses have similar procedures in place. Given how much information about these systems already exists in the public domain, there is little use in revisiting this strategy now. These findings are also consistent with Fox, Bartholomae, Letkiewicz, and Montalto (2017), who discovered that the longer a branch has been open in a certain location, the higher the loan default rate. This trait is explained by the possibility of new ventures' marginal profitability decreasing. This could also be attributed to the diminishing strength of dynamic incentives as credit is extended over time, particularly if borrowers notice that credit is not consistently refused to defaulting or late borrowers.

The findings reveal that the convenience of obtaining loans, functionality, perceived image, and perceived legitimacy all have a significant impact on digital credit repayment.

Shema (2019) also found a link between greater repayment performance and access to additional finance sources, market selling activities, and urban location. According to Murugesh (2017), various bank factors connected to risk management mechanisms in place were to blame for loan defaults. Tax methods utilized in credit risk assessment are among these institutions' factors. Negligence in loan default monitoring, insider loans, a lack of educated people, and passive credit collection methods. The study established that the ease of obtaining loans has a significant impact on digital credit repayment. This is in accordance with Henning and Jordaan (2016) who noted that credit awarding is a journey whose success is determined by the methodology used to evaluate and award the credit. This process begins with a credit application, continues with the purchase of credit sales, and concludes with the debt being entirely paid.

Moreover, other authors such as Owens, Barrès, Rizzi, Daz, Moore, Mckee, and Fischer (2018) link repayment performance to corporate characteristics, stating that the earnings of the firm had a significant impact on loan repayment. Chou (2019) also raises the topic of whether default is random, impacted by unpredictable behavior, or influenced systematically by area features that dictate local production conditions or branch level efficiency. Their research on overdue loans in Grameen backs up the premise that geographical variables have a limited impact. Rural electricity, road breadth, primary educational facilities, and commercial bank density are all linked to a low default rate and expected manager compensation.

### 5.3 Conclusion

Individual/borrower factors positively and significantly affect digital credit repayment in Kenya, according to the study ($\beta=0.792$, $p=.000<0.05$). According to the findings, digital credit lenders screen borrowers and pick good borrowers from problematic borrowers, as well as monitor borrowers to ensure that they use the loans for the intended purpose. This is necessary to ensure that the borrowers can repay their debts. The study also found that proper borrower inspection is critical in determining the character, ability to repay (capability), viability of the projects for which the loan is intended, and the amount to authorize.

The study also concluded a negative but significant association between loan parameters and digital credit repayment ($\beta$= -0.229, p=.006>0.05). According to the findings, when a loan is not given on time, it is more likely to be diverted to non-productive activities. Higher interest rates are also deducted to raise the loan amount, making it tougher to repay the principal.

In addition, the study concluded a negative but significant relationship between lender factors and digital credit repayment in Kenya ($\beta$= -0.457, p=.000<0.05). Before making a digital loan, the study found that lenders look at the borrower's credit score and look for evidence of their ability to repay the loan, such as prior wages or income estimates.

### 5.4 Contribution to Knowledge

The factors of digital credit repayment in Kenya were explored in this study. The majority of the empirical studies examined focused mostly on banks, with a handful finding a number of potential digital credit repayment factors. Furthermore, most of these research tended to use fairly restrictive definitions and conceptualizations of these determinants in particular. More case studies in this area are needed to address the question of causality more directly.

This study adds to the body of empirical literature by expanding the conceptualization of the link between individual/borrowers variables, loan factors, and lender factors and digital credit repayment, as well as presenting the relationship between them. This integrated model has important policy implications for improving digital credit repayment.

### 5.5 Recommendations of the Study

The recommendations based on the study's findings are included in this section.

#### 5.5.1 Recommendations to Policy

The substantial association between individual/borrowers factors and digital credit repayment has important policy implications, including the necessity to include borrowers' educational level in the credit institution's credit policy, and it should be given high priority before the credit is disbursed.

### 5.5.2 Recommendations to Practice

This study suggests that digital credit lenders alter the terms and conditions of their loans in order to prevent loan payback issues caused by lender factors. According to the findings, digital credit providers should require borrowers to be monitored for loan usage and payback. As a result of this oversight, digital credit lenders will be able to closely monitor the performance of their borrowers. Borrowers should also be trained before and after getting loans in areas such as business management, bookkeeping, and saving. Taking such steps will reduce the number of defaulters.

Digital credit lenders in Kenya are needed to develop loans for various types of borrowers in various income levels in Kenya. They should also devise payment methods that are beneficial to borrowers, including as payments in installments. Furthermore, Kenyan digital credit lenders should take more steps to perform broad market surveys so that they can better understand the regions where they can tap into and produce lending products that are relevant to market needs.

When building loan products for the Kenyan market, digital credit lenders should take into account borrowers' demographic factors such as age, gender, marital status, occupation, education, and income, according to the study. This is because demographic elements are important and measurable population data that aid in the identification of target markets, are easier to quantify, and are appropriate for psychographic and sociocultural research. Furthermore, individual/borrower factors have a significant impact on the evaluation of many qualities that are commonly connected with consumer behavior.

The study also suggests that digital credit lenders use efficient and effective credit risk management to ensure that loans are matched to borrowers' ability to repay, there is no or little insider lending, loan defaults are forecasted appropriately, and appropriate measures are taken to reduce them.

This study suggests that digital credit lenders in Kenya should invest more in the development of credit scoring systems, based on the findings. More client data, including personal and business information, should be included in the new systems. This will greatly minimize occurrences of digital credit default and hazards, resulting in a rise in digital credit lender payback in Kenya.

Furthermore, the report suggests that digital credit providers consider altering the typical repayment time for digital credit. Customers are less likely to fail if they are given enough time to repay their loans. However, the repayment duration should be fair to avoid liquidity issues for digital credit lenders. Better performance will arise from the ability of digital credit lenders to reclaim a high share of the digital credit.

Lenders must do a better job of reporting and clarifying key loan elements so that borrowers have a clear understanding of the loan's cost, payment due dates, and the repercussions of late repayment and default. Simple techniques such as declaring interest payments separately and in absolute - rather than percentage - terms, as well as offering brief descriptions of the terms and circumstances, according to experimental research, can enhance borrowing decisions and minimize default rates.

### 5.5.3 Recommendations to Extant Knowledge

The perceptions of portfolio manager's on the determinants of digital credit repayment in Kenya were explored in this study. The majority of the empirical studies examined focused mostly on banks, with a handful finding a number of potential digital credit repayment factors. Furthermore, most of these research tended to use fairly restrictive definitions and conceptualizations of these determinants in particular. More case studies in this area are needed to address the question of causality more directly.

This study adds to the body of empirical literature by expanding the conceptualization of the link between individual/borrowers variables, loan factors, and lender factors and digital credit repayment, as well as presenting the relationship between them. This integrated model has important policy implications for improving digital credit repayment.

### 5.5 Suggestions for Further Research

The goal of this study was to figure out what factors influence digital credit repayment in Kenya. The report advises that another study to be undertaken that focuses on different aspects other than the ones covered in the current study, as the components investigated accounted for just 64.0 percent . The report also proposes that a study on the effect of loan characteristics on performance of digital credit repayment should be done. A similar study on a different financial lending organization, such as SACCOs, MFIs, or banks, is also recommended by the study.

## 5.6 Limitations of the Study

The study ran into numerous obstacles that made it difficult to get the information it needed. The respondents in this study were hesitant to provide information, thinking that the information might be used to intimidate them or portray them in a poor light. The researcher managed this by bringing an introduction letter from the university, which assured them that the information they provided would be kept private and utilized solely for scholarly purposes.

Furthermore, the study's findings were constrained by the respondents' willingness to offer accurate, objective, and trustworthy data. The researcher double-checked the data for consistency and tested its trustworthiness.

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# APPENDICES

## Appendix I: Ethical Clearance Letter

## Appendix II: Letter of Introduction

Ole Sangale Rd, Madaraka Estate,
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Cell: +254 703 414/6/7, Twitter: @SBSKenya
**Email: info@sbs.ac.ke** or vist **www.sbs.strathmore.edu**

**Strathmore**
UNIVERSITY
**BUSINESS SCHOOL**

Monday, 19 October 2020

**RE: FACILITATION OF RESEARCH EVA WANGARI NDUNG'U MDF |102921|17**

This is to introduce Eva Wangari Ndung'u who is a Master of Science in Development Finance student at Strathmore University Business School, admission number MDF 102921/17. As part of our MDF Program, Eva is expected to do applied research and undertake a project. This is in partial fulfilment of the requirements of the MDF course. To this effect, she would like to request for appropriate data from your organization.

Eva is undertaking a research paper on "**DETERMINANTS OF DIGITAL CREDIT REPAYMENT IN KENYA.**" The information obtained from your organization shall be treated confidentially and shall be used for academic purposes only.

Our MDF seeks to establish links with industry, and one of these ways is by directing our research to areas that would be of direct use to industry. We would be glad to share our findings with you after the research, and we trust that you will find them of great interest and of practical value to your organization.

We appreciate your support and shall be willing to provide any further information if required.

Yours sincerely,

**Veronica Muniu,**
**Manager | Graduate Programmes, Strathmore University Business School**

**Appendix III: Research Questionnaire**

Kindly answer the following questions by writing a brief answer or ticking in the boxes provided.

**PART A: BACKGROUND INFORMATION**

1. Please indicate your gender:

   Female [ ] Male [ ]

2. Please Indicate your age bracket

   20-30 yrs [ ] 31-40 yrs [ ]

   41-50 yrs [ ] 51 – 60 yrs [ ]

3. Which is your highest level of education?

   Post Graduate [ ] Undergraduate [ ]

   Diploma [ ] Certificate [ ]

   Any other (specify)……………………………………………………………

4. For how many years have you worked with the digital credit lending sector in Kenya?

   1-2 years [ ] 3-4 years [ ] Over 5 years [ ]

**PART B: INDIVIDUAL/BORROWERS FACTORS**

5. To what extent do individual/borrowers factors affect digital credit repayment in Kenya?

   Very great extent [5] Moderate extent [3] Very low extent [1]

   Great extent [4] Low extent [2]

6. Please indicate the extent to which the following aspects of individual/borrowers factors affect digital credit repayment in Kenya. Using the Likert scale from 1-5; where 5= Very great extent, 4=Great extent, 3= Moderate extent, 2= Low extent and 1=Very low extent

| | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| Gender | | | | | |
| Age | | | | | |
| Marital status | | | | | |
| Number of dependants | | | | | |
| Level of education | | | | | |

7. In your own opinion, how do the above aspects of individual/borrowers factors affect digital credit repayment in Kenya?

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

**PART C: LOAN FACTORS**

8. To what extent do you think loan factors affect digital credit repayment in Kenya?

   Very great extent [5] Great extent [4]

   Moderate extent [3] Low extent [2]

   Very low extent [1]

9. Please indicate the extent to which the following aspects of loan factors affect digital credit repayment in Kenya. Using the Likert scale from 1-5; where 5= Very great extent, 4=Great extent, 3= Moderate extent, 2= Low extent and 1=Very low extent

| | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| Type of loan/security provided | | | | | |
| Loan size | | | | | |
| Repayment period | | | | | |

10. In your opinion, how do the above aspects of loan factors affect digital credit repayment in Kenya?

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

**PART D: LENDER FACTORS**

11. To what extent do lender factors affect digital credit repayment in Kenya?

    Very great extent [5] Moderate extent [3] Very low extent [1]

    Great extent [4] Low extent [2]

12. Please indicate the extent to which the following aspects of lender factors affect digital credit repayment in Kenya. Using the Likert scale from 1-5; where 5= Very great extent, 4=Great extent, 3= Moderate extent, 2= Low extent and 1=Very low extent

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Perceived credibility | | | | | |
| Ease of acquiring loans | | | | | |
| Perceived image | | | | | |
| Number of loan installments | | | | | |
| Dynamic incentives | | | | | |

13. In your opinion, how do the above aspects of lender factors affect digital credit repayment in Kenya?

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

**PART E: DIGITAL CREDIT REPAYMENT**

14. What is the trend of the following aspects of digital credit repayment in Kenya for the last five years? Where; 1= Greatly decreased, 2= Decreased, 3= Constant, 4= Improved and 5= Greatly Improved

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Late Payments | | | | | |
| Payments after intervention measures | | | | | |
| Level of non-performing loans | | | | | |

**Thank You for Your Participation**

**Appendix IV: List of Digital Credit Lenders**

| Digital Credit Product | Partners involved | Bank or nonbank lender |
|---|---|---|
| Branch | Branch | Nonbank |
| Equity Eazzy | Equity Bank | Bank |
| KCB M-Pesa | Safaricom, Kenya Commercial Bank (KCB) | Bank |
| M-Coop Cash | Co-operative Bank | Bank |
| M-Shwari | Safaricom, Commercial Bank of Africa (CBA) | Bank |
| Tala | Tala | Nonbank |
| Timiza | Airtel, Jumo | Nonbank |

**Appendix V: Timeline of Activities**

| ACTIVITY/ MONTH | MAR | APRIL | MAY | JUN | JUL | AUG | SEP |
|---|---|---|---|---|---|---|---|
| Choice of research title | | | | | | | |
| Developing the proposal | | | | | | | |
| Presenting the proposal | | | | | | | |
| Collection of data | | | | | | | |
| Analysis of data and writing report | | | | | | | |
| Presenting the draft Report for approval | | | | | | | |
| Making corrections and writing fair copy of the Report | | | | | | | |
| Submission of Report | | | | | | | |

## Appendix VI: Research Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION

Ref No: 936560

Date of Issue: 10/February/2021

**RESEARCH LICENSE**

This is to Certify that Miss.. Eva Ndung'u of Strathmore University, has been licensed to conduct research in Nairobi on the topic: DETERMINANTS OF DIGITAL CREDIT REPAYMENT IN KENYA for the period ending : 10/February/2022.

License No: NACOSTI/P/21/8938

936560

Applicant Identification Number

Director General

NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION

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