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Navigating Risk: A Deep Dive into Credit Risk Management Practices and Loan Performance in Kenya's Fintech Frontier

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ABSTRACT: This study aimed at evaluating how credit risk management practices affect the loan performance of Fintech companies in Kenya. In particular, the study determined how credit terms, credit analysis, and credit mitigation affected loan performance. The research design used for the study was descriptive with the responders being credit officers from the Fintech companies in Kenya. Descriptive and inferential statistics were used to examine the information gathered from 62 Fintech companies through a primary data study that relied on questionnaires for data collection. Data collected was analyzed using descriptive statistics that yield tables, charts, mean and standard deviation that gave meaning to the data collected. The regression equation revealed that the predictors were significant and explained the model at an R squared of 80.5% to yield the study findings that credit risk management play a critical role in determining how well Fintech companies in Kenya operate when it comes to borrowing money and expanding their loan portfolio.

KEYWORDS: Credit Risk Management, Loan Performance, Fintech Companies

1. INTRODUCTION

Due to low simplicity of use and the removal of adoption obstacles, Fintech services have grown more user-friendly globally. Additionally, they have offered enticing non-bank payment options that are extremely practical. WeChat Pay and Alipay run independently on a global scale (Blakstad & Allen, 2018). With sufficient access rights to banking platforms, these applications can independently operate as well as interface with conventional banks. In contrast to the access that poor sectors of the population have to loans through banks and savings groups, Fintechs provide loans utilizing smartphone apps in a way that is more convenient (Arslanian & Fischer, 2019). Millions of people who historically had no access to any financial services because of their unemployment have affordable options that offer safety, security, and convenience. Fintechs and mobile banking have changed the financial sector.

In the recent past Kenya has had a tremendous advancement of the Fintech industry many technological advancements in the financial sector have been realized. The Fintechs are offering channels for quick and instantaneous receipt of financial products allowing flexibility by letting customers browse a variety of product offerings on a single phone. Those who have signed up for mobile platforms can currently obtain higher credit by using and making more payments through platforms like Tala, Branch, KCB MPESA MCo-op Cash, M-Shwari, Eazzy loan, Timiza, and HF Whizz, among others.

More people have expressed concern about the growing over-indebtedness aided by digital credit applications than regarding payments via digital and mobile credit (Donovan & Park 2019; Singh 2018), including several former Fintechs boosters (Izaguirre et al. 2018). However, one of the main arguments in favor of mobile money's long-term advantages continues to be its potential role in building the basis for increased lending (Kaffenberger et al. 2018; McKinsey Global Institute 2016). Therefore, credit management practices are very revealing and now hunting the new and existing Fintechs in Kenya.

Credit risk management (CRM) is critical for financial firms because it is an essential component of the loan process. Risk management is critical for banking institutions' survival and growth (Poot, 2020). The systems, procedures, and practices used by organizations to assure fast client payment collection and lessen the chance of non-payment are referred to as credit risk management (Kalui & Kiawa, 2015). Decision-making procedures that aim to lessen exposures to the credit quality category and loan loss provisioning are included in policies for credit risk (Wanyoike & Ngahu, 2015). Ndwiga and Waithaka (2012) further noted that as a result, these financial organizations urgently require the development of better systems and procedures that will increase the visibility of future performance.

According to Nelson (2012), credit management is just the way a company handles its credit sales. Since it is impossible to have a zero credit, it is a requirement for any organization that deals with credit businesses. An organization with high levels of outstanding receivables with high aging will consequently incur higher finance costs to maintain the debts. If receivables end up being not collectable on time, then the company may have to resort to borrowing to finance urgent cash needs arising. The opportunity cost is the interest costs paid for borrowed funds (Wachira, 2017).

Rising credit risks in commercial banks in Africa, which began in the early twentieth century, have threatened the performance of loans in banks throughout the Sub-Saharan Region (Jean-Philippe, 2018). Similarly, credit risk management has gained prominence in recent years, especially in the aftermath of traumatic events and bank failures caused by rising non-performing loans (Bodo, 2018). According to a related study, 23% of outstanding loans in Nigeria, Angola, and Ghana's banking sectors were classified as nonperforming by 2017, up from 17% in 2015 (Nsobilla, 2015).

In Kenya, bank failures remain primarily responsible due to non-performing loans since 2009 (Nasieku, 2017). Due to poor credit management practices during the COVID-19 era, the portfolio at risk (PAR) of Kenyan banks recently increased from 12.7 percent in 2019 to 13.1% in 2020 (Central Bank of Kenya, 2020). When loans become non-performing, banks' risk portfolios grow, reducing Loan Performance (Bodo, 2018). Several studies have been conducted in Nepal (Kattel, 2017), Nigeria (Ogbol & Okallo, 2018), Kenya (Kinyua, 2017; Mbiti et al., 2018; Kariuki, 2017; Mutua, 2016), and Uganda on credit risk administration and portfolio performance in the banking sector (Serwadda, 2018).

Receiving loans has recently become a source of anxiety for small firms. According to Eurenius (2020), it is difficult for small businesses to meet the bank's loan requirements because small and growing firms frequently operate in new unexplored business areas, which is associated with higher risk. It is also believed that SMEs face greater difficulty in obtaining finance due to asymmetric knowledge, which occurs mostly than in larger and publicly traded enterprises. Due to limited and unpredictable information, banks find it difficult to obtain relevant information about small enterprises (Binks et al., 1992).

The Fintech sector is quickly growing on a global scale. In the first six months of 2015, Fintech companies received $4.8 billion in funding. The first half of 2018 saw a surge in global investment in Fintech firms, with an estimated $57.9 billion invested in these businesses (UN Capital Development Fund, 2018). According to the European Central Bank Report (2019), the banking sector expects Fintech entities to execute more transactions than traditional banks by 2023. The phenomenon's expansion is due to the reduction of entry costs and the cost of providing services, which has removed the entry barriers of Fintech that characterize the banking sector. Fintech have been successful in providing banking services to underbanked markets and all demographics with internet access. Most financial institutions use debt in various ways to influence the venture made in their benefits, which affects the return on value (Kamar & Ayuma, 2016). The obligation value sum has a huge impact on the speculation risk; the higher the obligation per value, the more dangerous it is (Altman & Sironi, 2019). For Fintechs appear to build risk, which can result in poor performance or results as the cost of overhauling the obligation can create beyond the ability to either reimburse because of internal issues, because of the helpless asset the executives or pay misfortune.

The Fin-Access Survey (2021) conducted by Kenya national bureau of Statistics (KNBS) sought to measure the extent to which households defaulted on existing loans in 12 months. Missing a repayment deadline, paying beyond the due date, or paying nothing at all were defaults. These indicators highlighted abilities to manage cash flow and have implications on profitability of credit providers. The Survey results indicate that 10.7 percent of those who reported to have borrowed, had defaulted (did not pay at all the loan borrowed.) Those who indicated to have paid late on any loan taken/outstanding in 12 months to the Survey period, was 38.2 percent. This indicates that credit risk has led to increase in loan default rates and non-performing digital loans amounts that are provided by Fintech firms. This case of high default rates among customers of the Fintechs have led to poor performance of the firms which in cases the Fintechs have be shut den due to financial performance and ability to continue running the credit offering businesses.

Numerous local studies have demonstrated a link between credit exposure management and Kenyan enterprise success. Majority of SACCOs employed credit analysis methodologies to analyze risks when disbursing cash, according to the Kimani (2018) study, which occurred in the context of SACCOs in Nairobi. Kiplimo and Kalio (2019) on the context of Microfinance Institutions (MFIs) in Baringo County established CRM practices influenced the loan performances of MFIs in Baringo County. Blythin and Cooten (2017) conducted research on the development of Fintech companies in Nairobi, Kenya. The investigation concentrated on capital adequacy, regulatory framework, and managerial talent. Wachira and Ondigo (2016) investigated the result of technological innovation on the monetary performance of Kenyan banks. Kiilu (2016) investigated the impact of Fintech companies on the financial performance of Kenyan commercial banks. Liquidity, regulatory framework, and credit financing were among the variables investigated. The implications of CRM on the loan performance Fintech companies have thus far received minimal research in Kenya. Hence, this surveys shows that loan default is a credit risk, which is affecting most Fintech companies in Kenya hence Credit Risk Management practices are undoubtedly one major area of concern in Fintech companies that has seen an unprecedented solution from leveraging big data with analytics. As a result, this study addressed this empirical gap. The primary objective for this investigation was to define the effects of credit risk management practices on the loan performance of Fintech companies in Kenya. The independent variables for the study were credit terms, credit analysis and credit mitigation.

2. LITERATURE REVIEW

This section deals with a review of empirical literature, which includes the current knowledge including substantive findings, as well as theoretical and methodological contributions to the topic of study.

2.1 Credit Terms and loan performance

Credit terms refer to the terms on which an institution extends credit to its users. The credit terms will outline the credit period as well as the interest rates. The credit period is the period over which the credit is granted. The lending era's length is being determined by credit risk, amount lend (Ross et al., 2018). Saparila and Wisanupong (2019) explore the Microfinance Repayment Performance of SMEs in Indonesia: Examining the Roles of Social Capital and Loan Credit Terms. Their study adds to the existing literature by arguing that social capital and credit terms can influence loan repayment performance indirectly through improved business performance.

According to the current literature, three types of loan design features play an important role in determining loan repayment performance (Henepola, 2022). The first set of requirements is an 'access' requirement, which includes maximum loan ceiling (loan size), interest rates, collateral size, and repayment schedules. The second is 'screening,' which is used to determine the qualifications and merits of borrowers. The third category includes 'incentives' given to borrowers, such as interest discounts given to those who make loan repayments on time (Ng'ang'a, 2017).

Sola (2021) investigated the connection between credit management techniques and loan performance in Nigerian microfinance banks. Using primary data, the impact of specific credit management techniques (credit term, client appraisal, and collection strategy) on loan performance at 180 microfinance institutions investigated. The data came from responses to a research questionnaire from a sample of credit managers/officers at banks. The ordinal logistic regression technique in SPSS is used to examine the correlations between variables (SPSS). According to the study, credit length has a positive but insignificant effect on loan performance.

Nannyonga (2019) discovered, for example, that delinquent credit repayments caused by a disproportionate ratio of loan amounts to collateral size and infrequent repayment schedules. Kakuru (2018) also found that when repayment periods are perceived as 'inflexible', SMEs would not apply for loans, whereas Mutesasira et al. (2017) found that shorter periods of repayment do not meet SMEs' long-term credit needs. Furthermore, Anderson (2019) found that interest rates have negative ties between them to the likelihood that borrowers will take repayment-friendly actions, whereas Amonoo et al. (2018) found that interest rates have a negative impact on credit demand and loan repayment. Similarly, Papias & Ganesan (2019) discovered that loan repayment defaults increased by interest rate charges.

A study by Onyeagocha (2020) demonstrated that the larger the loan given to clients, the higher the repayment rates. Although loan size and interest rates are still contentious issues, Ojiako et al. (2019) found that borrowers who received smaller loans paid a higher proportion than those who received larger loans; 'reasonable' loan size and interest rates as perceived by borrowers were more likely to induce larger investments with potentially higher absolute returns. Overall, these studies indicate that favorable credit terms features will increase many in access to credit while also motivating them to stick to repayment schedules.

Another study by Njeru and Wachira (2017) studied the efficiency of credit management system on loan performance of commercial banks in Kenya with descriptive research design employed. There were 86 people in the sample. That is, one credit manager and one credit officer from each of the 43 commercial banks registered with the Kenyan Central Bank as of this year. Because the target population was small, there was a census. A self-administered set of questions and the drop and pick method were used to collect data. There were both wide and sealed questions on the survey. Reliability made sure to use the test-retest methodology. While piloting was used to ensure the research instrument's validity. Data analysis occurred using frequencies, percentages and means. According to the findings of this study, credit terms have an impact on performance. Commercial banks should involve credit officers more because they are constantly receiving customer feedback. Management, on the other hand, is the policymaker and should be involved. Their dedication to the policy is also critical if it is to be successful; it turned out to have a significant impact on commercial bank performance.

On the other hand, Mabonga and Kimani (2017) investigated financial management practices and financial performance of microfinance institutions in Bungoma County, Kenya. A correlation survey served in the study. Self-administered surveys were used to collect primary data from SMEs' owners/managers and business partners. A hundred respondents were picked from a population of 150 SMEs using a simple random selection procedure. To determine the reliability of a survey instrument, the internal consistency items measured using the reliability coefficient. In this study, inferential statistics analyzed the research data. Correlation and regression analyses determined the relationship between variables. The study discovered that collateral, interest rate, and repayment time all have an impact on the financial performance of SMEs in Bungoma County.

Also, Muthama and Warui (2021) studied the Influence of lending terms on loan performance of microfinance institutions in Kisii County (Case Study; Kenya Women Microfinance Bank). According to the study, borrowers make suggestions on the type of loan standards. Kenya women Microfinance Bank must include credit officers and customers in the development of loan standards, as credit officers are the ones who deal with customers. As a result, borrowers' lending terms and conditions should incorporate a more comprehensive understanding of the best loan standards. The study recommended that women microfinance banks in Kenya provide friendly payment modes and terms during the credit period. To determine a specific customer's credit period, the credit period used the 5'cs model of client appraisal.

2.2 Credit analysis and loan performance

Fatemi (2010) states that financial analysis (quantitative analysis) and qualitative analysis are two components of the typical risk analysis process. Financial analysis consists of financial data analysis available to credit applicants, with annual financial statement analysis playing a central role in this context. However, there should be an overall standard requiring that the person in charge of the organizational unit providing the module for credit analysis when this module arrives to the credit officer managing the exposure confirm the assessment. Credit analysts perform the majority of financial analysis (Eldelshain, 2018).

Credit can be obtained for a variety of reasons, including bank mortgages (or home loans), vehicle purchase financing, credit card purchases, installment purchases, installment school fees, and so on. Credit loans and finances are at risk of default (Nafula, 2019). Credit providers typically collect a large amount of information on borrowers in order to understand their risk levels. Statistical predictive analytic techniques analyze or determine default risk levels in credits, finances, and loans.

Personal credit scores are typically calculated using data from credit reports obtained from third-party credit agencies and rating agencies. Credit ratings can reveal details about a person's financial background and current circumstances. It does not; specify what differentiates an "excellent" score from a "terrible" score. It does not, for example, inform you of the level of risk associated with the lending you are assessing (Mwisho, 2011). The problem is addressed by the internal credit scoring methods described on this page. Note that internal credit scoring techniques would be appropriate to loans of Fintech companies.

Credit risk profiling (financial risk profiling) as being part of credit analysis is critical. According to the Pareto principle, 10%-20% of lending segments may account for 80%-90% of credit defaults. For credit risk management, segment profiling can reveal valuable information. Lending institutions routinely collect a large amount of information about credit users (Kalu, 2018). Credit user (or borrower) data frequently consists of dozens or even hundreds of variables, involving both categorical and numerical data, as well as noisy data. The process of determining which variables or elements best summarize the segments profiling.

On the assessment and evaluation of Credit analysis in terms of risk measurement, numerous research projects remain carried out. On the other hand, various hazards fall into categories according to the harm they could potentially cause (Fuser et al., 2019). This assists management in categorizing risks that threaten the survival and existence of the business. According to Waweru and Kalani (2014), the expected loss and its likelihood have an inversely proportional relationship. Thus, some risks that may affect an organization include fire as well as earthquake. Other risks, such as interest rates, result in relatively minor challenges and losses.

Al-Tamimi and Al-Mazrooei (2017) claim the effectiveness of controls in place and risk analysis and assessment have a big impact on how well banks function in the United Arab Emirates. Banks in the United Arab Emirates (UAE) have actually documented down methodologies for assessing risk in terms of potential losses, severity, and likelihood of occurrence.

According to Fuser (2015), identifying and categorizing various risks based on potential damages is critical. According to the research, this will enable managers to categorize risks based on their magnitude and category. Overlook minor damage risks have in favor of risks that are more serious. According to the study, the amount anticipated from shortfalls and corporate value have negative and insignificant relationships. Fire risks, which occur infrequently, and foreign exchange risks are among the risks cited as causing high and unexpected damages. This necessitates the creation of risk-mitigation strategies (Drzik 2013). According to a BAI risk assessment survey, large banks have made major progress in risk measure implementation and development. These indicators are not only for risk management, but also for performance evaluation and price setting.

Often this micro - enterprises have credit terms that are tailored to the needs of their clients. Numerous studies conducted on credit risk and the various risks that affect lenders. In a report conducted in the United States by Prakash and Poudel (2018), a survey of 50 financial institutions took place. Both sources of data were used, and data examined using a linear regression. The investigation's findings showed that the best practice in financial institutions is default risk management, and the best practices were followed by more than 90% of the nation's private financial institutions. Effective credit risk management have gained more attention in recent years since inadequate credit policies continue to be the largest source of risk in the financial sector. The study concluded that credit risk ought to manage across the board, as well as in individual credit transactions.

Eurenius (2016) investigated the challenges faced by 65 small businesses in meeting the bank's requirements to receive a loan in her editorial in The Swedish Daily Newspaper. A moderately questionnaire was used, and the data was analyzed using proportions. According to the investigation, small and expanding rapidly businesses are more likely to operate in new, unexplored business areas, which are riskier. It argued that small and medium-sized enterprises (SMEs) face greater difficulties in obtaining debt due to a lack of information than significantly bigger and publicly traded companies. Due to limited and ambiguous information, banks have a challenging time obtaining valuable information about small businesses.

Omara (2017) conducted research in Uganda to examine the credit evaluation system and the payment of credit facilities in Kampala. Barclays was the subject of a case study. The study's findings indicated that Barclays Bank took longer than expected to score loans and that it charged commitment fees to both new and existing clients. For the study, a sample of 73 people had interviews. Using frequencies and tables to analyze the data, it turned out that Barclays Bank demanded security for loans above UGX 20 Million.

All forty-four industrial banks in the country of Africa were included in the study's population. Mutangili (2019) used the cause analysis technique to investigate the association between financial portfolio management tactics and the amount of loans for industrial banks. The research involved acquiring primary data and analyzing secondary data in order to achieve its goal. Participants self-administered questionnaires that served to collect the data. In order to validate the association that was the study's goal, statistical analysis was accustomed to confirm the character of the link between capital adequacy and the quantity of non-performing loans. The survey revealed that banking sector often examine their credit policies, which employees are made aware of through credit guidelines, regular coaching, regular meetings, and management. The survey also revealed that risk-adjusted return on capital and the linear probability model are the two main methods used by commercial banks in African countries to analyze credit risk.

According to Mwithi (2018), the amount of non-performing loans and the methods employed by minor finance institutions (MFIs) in Nyeri County to manage credit risk are related (NPLs). In order to collect primary data for the analysis, questionnaires given to forty-four respondents from elite MFIs at different levels of employment. The parametric technique for statistical analysis created by Spearman followed by being utilized to analyze the data. The study discovered that credit risk evaluation and management in MFIs were highly developed.

Gladys (2012) surveyed how credit risk management strategies affected how industrial banks in the Republic of Kenya assessed SMEs and the size of their nonperforming loans. Banks in the Republic of Kenya did a multivariate study utilizing a qualitative design on credit strategies that was distributed to the banks in order to investigate the association between capital adequacy and SME non-performing loans in Kenyan banks. According to the report, credit risk management and nonperforming loans have a bad relationship.

2.3 Credit mitigation and loan performance

Credit mitigation is a comprehensive method of preventing losses by examining the finance institution's capital as well as loan loss reserves. Monitoring credit risk enables an executive manager to establish potential customers who are likely to pose too much risk and exceed the risk tolerance set previously. The company can significantly improve overall performance and gain a competitive edge by implementing comprehensive credit risk management (Kagoyire & Shukla, 2018).

Financial institution regulatory bodies have traditionally focused their attention to risk concentration by credit intermediaries. The goal of a credit risk controller is to prevent financial companies from relying too heavily on a single borrower or group of lenders, not to tell them whom they can and cannot lend. Modern regulation and supervision restrictions typically state that a financial institution should not reinvest, grant large loans, or extend other financial assistance in excess of a certain proportion of its assets and reserves to any individual entity or related group of entities.

Globally in Vietnam, Nguyen (2016) studied Credit mitigation for loan products in Bank for Development and Investment. Interviews with officers and supervisors of the target bank were via email in the qualitative research. The study used secondary information derived from credible sources for instance case bank's yearly reports, local government laws, and worldwide banking standards, besides primary data from the interviews. Results indicated Credit mitigation was important in ensuring an improving loan performance in the bank. Because this study was conducted in Vietnam, a developed country, its findings are incapable of being applied to a developing country like Kenya.

In India, Jain and Sangeetha (2021) assessed whether Credit mitigation influences loan Performance of the top thirteen commercial banks. Additionally, the information gathered from individual bank annual reports and the Money Control website. Based on each bank in Indian banking sectors' market share, a study sample size of 13 banks from 2009 to 2018 were chosen, with seven private sector banks as well as six public sector banks. The top 13 Indian commercial banks had a significant and favorable association between their credit risk certification (CRC) and loan performance. The data obtained directly through the distribution of a questionnaire survey produced by the researcher via pilot test in which the researcher took research tools to certain Saudi Arabian bank loan managers. According to the study, credit risk management, as measured by covenants, collateral, credit rationing, and loan securitization, has a favorable effect on the profitability of Indian banks.

When institutions are implementing credit mitigation measures, they should always consider credit risk concentration. The exposure of a financial institution to a single group of potential customers is a risk concentration. This exposes the credit lending institution to a weakness in a specific group of applicants and increases the likelihood of multiple clients failing for pretty much the same reasons at the same time. Because most banking institutions' reporting systems do not generate such information, assessing financial institutions' exposure to various sectors of the economy is frequently difficult (Posnaya, 2018).

In Tanzania, Catherine (2020) examined whether Credit mitigation affects financial performance in Bank of Africa (U) Limited. The bank operates over 35 locations across the nation, with 21 in the central region and 14 in the north. The findings show a weak but favorable connection between debt management and the profitability of some institutions, particularly Bank of Africa (U) Limited.

Locally, a cross sectional study by Murigi and Thuo (2018) studied the correlation between Credit mitigation and monetary health of agricultural corporations cited at Kenya, Nairobi Securities Exchange (NSE). Additionally, the population was of 6 agricultural companies listed at Nairobi Securities Exchange Primary figures was obtained by survey, whereas secondary data was derived from financial statements of agricultural businesses. Agricultural firms listed on the Nairobi Securities Exchange's financial performance is significant to debt risk mitigation, according to the research. The earlier study employed a cross sectional research strategy, whereas this study used a qualitative research strategy. The findings of the study on agricultural firms are also not applicable to the assessment of private institutions in Kenya.

Bwire and Omagwa (2019) researched the connection between reducing credit risk and the financial viability of SACCOs in Nairobi County. As part of a descriptive research approach, the information gathered from 40 deposit-taking SACCOs. One hundred and twenty respondents answered the questionnaires from every deposit-taking SACCO in Nairobi City County using a purposeful sample strategy. Multiple linear regression, reliability test, and deviation assessment examined the data. The study found a considerable impact of Credit mitigation on profitability. The earlier examination occurred at SACCOs that took deposits, but this study took place in Fintech businesses.

Kithinji (2018) investigated Kenyan financial institutions' profit growth and credit corporate governance. His study sought to assess the level of default risk mitigation to banks performance. He gathered account information, loan amounts, and profit amounts from 2009 to 2015 for performance reasons. A regression analysis for the study found no relationship between the studied variables, such as revenues, borrowing levels, and advance level. As a result, the study concluded that commercial bank profitability levels were unrelated to credit levels and advances, and thus the remaining variables influenced profit levels. Given that it focused on Credit mitigation in commercial banks' fiscal viability, the study's findings highlight a significant knowledge gap.

In Kitui County, Wanjala (2020) looked at the connection between SACCO profits and debt management. During the research, descriptive research approach used in data collecting instruments were self-administered questionnaires that were employed to obtain primary data from SACCOs' management. Data examined, and the concurrent effect of objective study factors on dependent study variables studied. The researcher discovered a strong correlation between Credit mitigation and SACCOs' profitability in Kitui County.

Muigai and Maina (2018) also studied the effect of financial performance on the lending performance of Kenyan banks. This research used descriptive research approach. According to the Bank Supervisory Report 2017, the study population was all licensed and operating Kenyan commercial banks by year 2017. Credit officers and financial managers from commercial banks made up the observation unit. A census conducted on all 39 commercial banks, resulting in seventy-eight respondents. The investigation used both primary and additional information. Credit mitigation has significant positive link with Kenyan commercial banks' loan performance, according to the research.

3. RESEARCH METHODOLOGY

This study used a descriptive research method. Orodho (2018) describes a research design as the format, sketch or chart utilized to come up with responses to the investigation questions. Creswell (2018) affirmed that the objective of descriptive method of study is to put together information about the existing situation. The stress was on describing and not on pronouncing judgment or interpretation. The financial aspect was practical with the descriptive approach given that the aspects studied are qualitative in nature.

In order to set precise parameters for ensuring the population's discreteness, the study's population must be carefully chosen, clearly defined, and delimited (Robson, 2002). No sampling occurred because a census study took place. The target population of the study will consider in 62 Fintech companies in Kenya. Kenya Based Fintech Companies (2021) and Mwangi (2020) were the source of target population while the unit of analysis was the credit officers in the Fintech companies.

The study used structured questionnaires to gather data used for comparison about the effects of credit management practices in Fintech companies in Kenya. While the previous analysis took place at SACCOs that accepted deposits, this study is in Fintech businesses. The validity of the questionnaires was ensured through interviews with a subset of respondents. The Cronbach's alpha test was used to test for reliability of instruments.

The study used structured questionnaires to gather data, in comparisons with other Fintech companies in Kenya. The questionnaire had two parts, part one was to gather information about the respondents while part two was to obtain data about credit management practices and systems, and the management approaches of each of the Fintech Company. The quantitative data was evaluated using descriptive statistics on a 5-point Likert scale and a composite score, and the results reported as proportions, averages, statistical significance, and ratios. For ease of understanding and investigation, the data appears using tables and figures. Before summation, categorized, and organized into a table, the gathered statistics underwent checking for inclusion, unambiguity, reliability, and consistency. For simple student comprehension, the obtained data underwent analysis to produce statistical measurements like percentages. The assessment helped the investigator in drawing accurate conclusions on the study's topic, and a conclusion drawn from the effects of CRM in Fintech companies in Kenya. The study further analysed the collected data using multiple linear regression analysis and other statistical measures such as percentages for ease of interpretation of the study. The study made use of the multiple linear regression equation shown below for the aggregate scores collected from the questionnaires:

$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon$

Where;

x_1: Credit Terms

x_2: Credit Analysis

x_3: Credit Mitigation

Y: Loan Performance

β_0 Represent the respective Y intercept (*calculated from the equation*).

'β_1'…'β_3': Represent the slope/coefficients denoting the interaction between the explanatory variables and predicted variable (*calculated from the equation*).

'ε' Represents the error term (*calculated from the equation*

The regression coefficients indicated the relative significance of every of the explanatory variables within the forecast of the variable quantity. The sign of the coefficients represented the character of the effects (positive or negative) every variable has no the variable quantity. The goodness-of-fit live for the linear regression model (R square) provided a mensuration of the share of the variance within the variable quantity (Loan performance) that the three independent variables make a case for jointly. In addition, the researcher used the P-values for each coefficient to test the null hypothesis that the coefficient is equal to zero (has no effect) on the explained variable using a confidence level of 95%. A low p-value (< 0.05) indicated that the explanatory variable has no effect on the dependent variable thus; we should reject the null hypothesis**.**

Diagnostic tests have five major assumptions, which include linear relationship, multivariate normality, little or no multicollinearity, no heteroscedasticity and auto-correlation. Multicollinearity occurs when certain predictor variables in a regression model is connected with other predictor variables. One variable projects with some accuracy from the other (Sahu, 2013). The predictor is singular and irreversible in Perfect multicollinearity. Tolerance and VIF serve as tools in this study to test for multicollinearity. Tolerance is measured using initial linear regression analysis and calculates the effect of one independent variable on all other independent variables. VIF < 10 indicates the absence of multicollinearity; VIF > 10 indicates the presence of multicollinearity in the study sample.

In order to perform a linear regression analysis, the data must have little or no autocorrelation. When the residuals are dependent of one another, autocorrelation occurs, that is, when value of y(x+1) is dependent of value of y(x) (Russell, 2013). Although scatterplot serve as tool to search for autocorrelations, the Durbin-Watson test and Breusch–Godfrey test serve as tool to test the linear regression model for autocorrelation.

The Breusch-Godfrey test is a tool to test the null hypothesis that residuals are not linearly auto correlated. Although d may have values ranging from 0 to 4, values around 2 suggest that there is no autocorrelation. As a rule of thumb, values of 1.5 d 2.5 indicate that the data is devoid of autocorrelation; however, the Durbin-Watson test examines only linear autocorrelation and only between immediate neighbors, which are first order effects.

The variance of the error terms in a regression model for an independent variable is referred to as heteroscedasticity. If heteroscedasticity exists in the data, the assumption is broken since the variance varies depending on the values of the explanatory factors. Due to bias, this will render the OLS estimator inaccurate. Therefore, it is crucial to check for heteroscedasticity and take corrective action if it is. The Breusch-Pagan test and the White test are two examples of tests often applied to identify heteroscedasticities. The standard errors derived from the results of the regression are used in heteroscedasticity testing.

The assumption underlying linear regression includes the sensitivity of the regression to outlier effects. One of the fundamental presumptions of multiple linear regression is this one. Linear regression needs the relationship between the independent and dependent variables to be linear. With scatter plots, the linearity assumption is tested. The assumption suggests that the linear combination of the random variables should have a normal distribution. The best way to verify this assumption is with a histogram or Q-Q-Plot. With a goodness of fit test, such as the Kolmogorov-Smirnov test, normality is verified. A non-linear transformation (such as a log-transformation) may be able to resolve this problem when the data is not normally distributed.

4. DATA ANALYSIS AND DISCUSSION

The section is concerned with the dissemination and explanation of the research results in light of the investigation objectives. Statistical analysis, descriptive statistical analysis, and inferential analysis served to examine the data. Descriptive analysis served to assess the profile of Fintech businesses operating in Kenya. The research objectives of credit management practices on the loan performance were established using regression analysis, and the ANOVA test to compare the influence of credit management practices on loan performance of Fintech companies in Kenya.

4.1 Response Rate

Survey response rates appear as a proportion. It is determined by dividing the number of sent surveys by the total responses. In most cases, a survey return rate is of 50% or higher is excellent. A high return rate is most likely due to the respondent's great motive to complete the questionnaire or a strong connection between the researcher and the respondent (Phillips at el, 2017). Out of 62 questionnaires administered, the answered were 45. This translates to a return rate of 72.58 %.

4.2 Demographic Information

Demographic data is the study of a census's characteristics such as age, education, and gender. Demographic information is a statistical representation of socioeconomic information such as employment, education, income, and duration of service. The study employed the use of descriptive statistic as a preliminary measure before the actual analysis.

4.2.1 Gender of the Respondents

Respondents provide a gender indication. According to the results, 64% of respondents identified as male, while 36% identified as female.

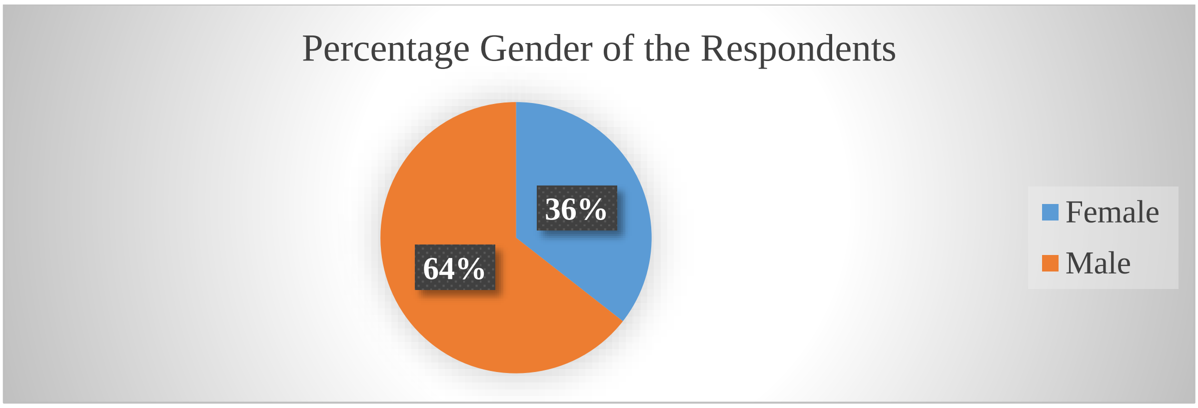

Figure 4.1: Gender of the Respondents

4.3.2 Age of the Respondents

According to the results, 27% of the respondents were between the ages of 18 and 25 years, 64% of the respondents were between the ages of 26 and 35 years, 9% of the respondents between the ages of 36 and 45 and there were no respondents between the age of 46 and 55 years and Over 55 years. This indicates that the majority of respondents were aged 26 to 35. This is as depicted in Figure 4.2.

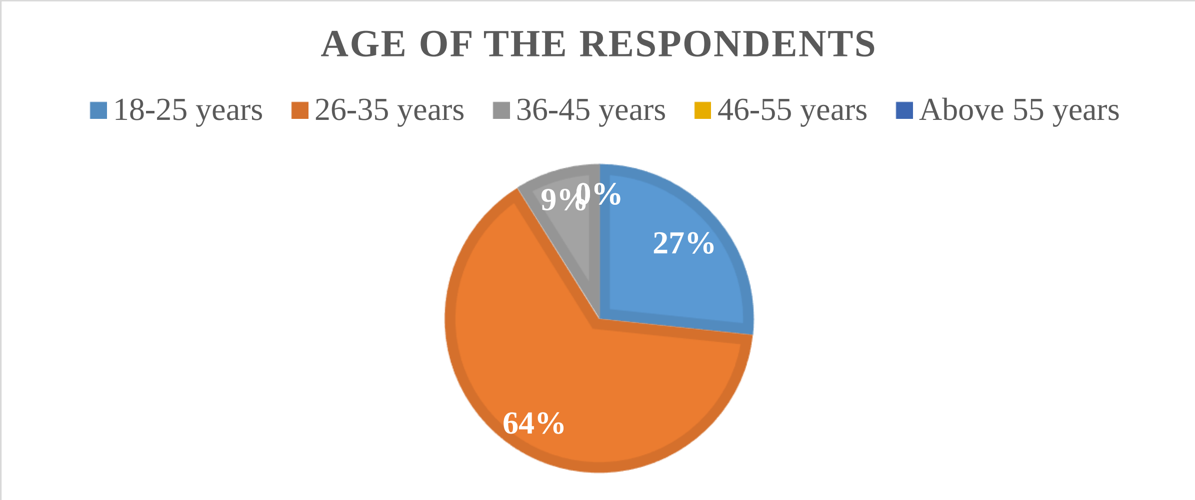

Figure 4.2: Age of the Respondents

4.2.3 Respondents' Level of Education

Respondent gave their status in their level of education. Figure 4.3 illustrates the study's findings. Per the findings, 2% of the participants is in have a Certificate in education level. 14% of respondents have diplomas, 69% of the respondents have bachelors, and 13% of respondents have post graduate and 2% of the respondents have other levels of education majorly professional certificates. This implies that the majority of respondents completed bachelor's degree

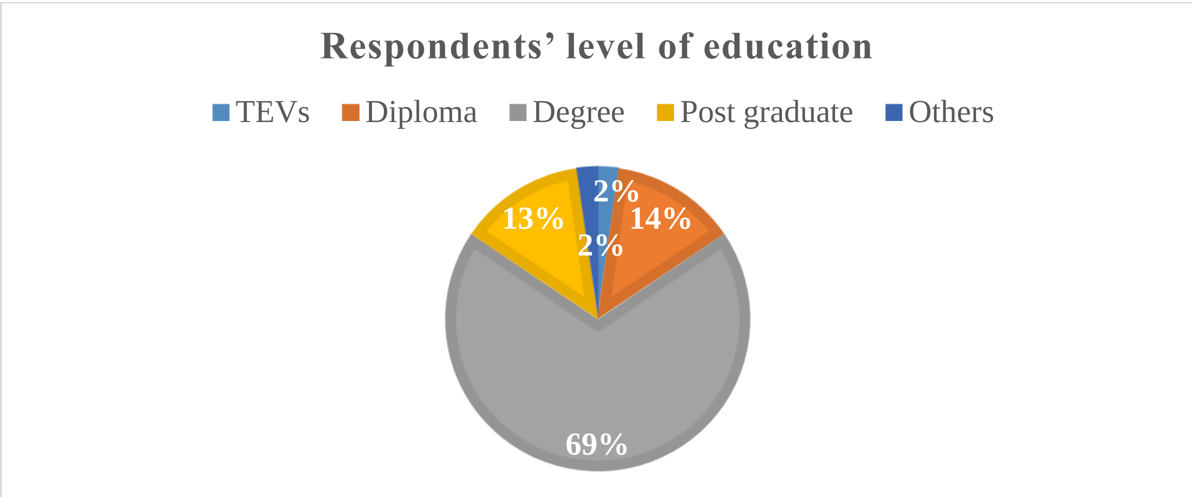

Figure 4.3: Respondents' Level of Education

4.2.4 Duration of Service

According to the findings, 9% of the respondents had been in service for less than a year, 13% of respondents between two and four years, 36% of the respondents were between five and seven years, 13% of the respondents were between eight and ten years, while 9% were more than ten years. The results are as depicted in Figure 4.4:

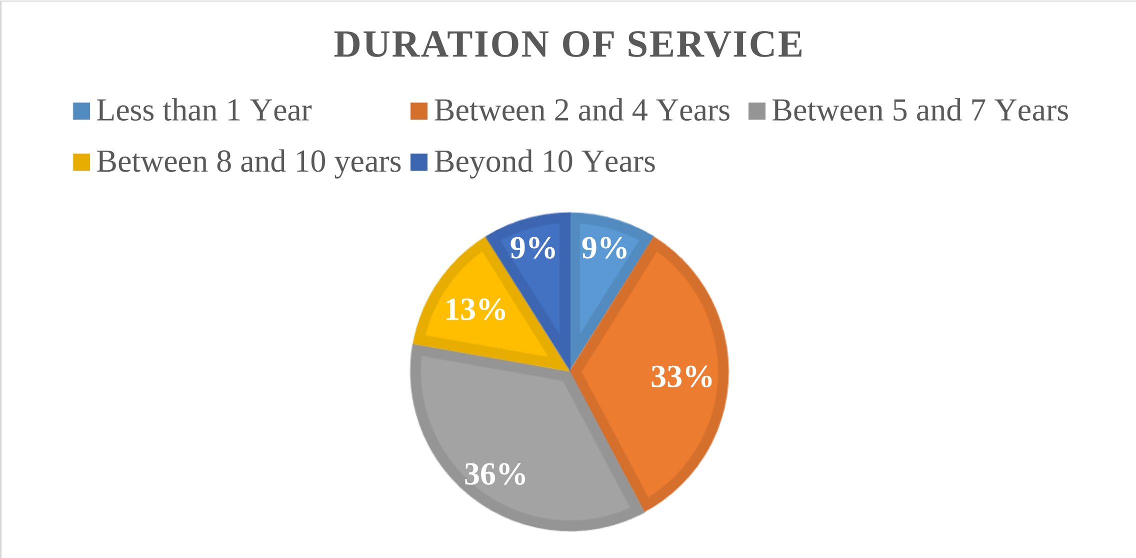

Figure 4.4: ***Duration of Service***

4.3 Study Variables

Quantitative data was obtained from closed questions as well as items measured on a 5-point Likert scale, with 1 representing strongly disagree, 2 representing disagree, 3 representing moderately agree, 4 representing agree, and 5 representing strongly agree. According to Ishtiaq, (2019) in his book review of Creswell's (2014) works, in a 5 scale Likert question, strongly agree is from 4.5 to 5.0, agree is from 3.5 to 4.5, moderately agree is from 2.5 to 3.5, disagree is from 1.5 to 2.5, and strongly disagree is from 0.5 to 1.5. Statements with standard deviations less than one imply agreement around the means, whereas statements with standard deviations greater than one imply variances in the mean.

4.3.1 Credit Terms and Loan Performance

The study set out to evaluate the influence of credit terms on loan performance in Fintech companies in Kenya. The research indicates that 49 % of the respondents agreed that the Fintech Companies has clearly stated its discount terms when offering loans. A mean of 3.2 resulted from that particular research which shows that a great number of respondents confirm that the Fintech companies states its credit terms to the customers. An 85% of the responses stated that the Fintech companies have a credit limit beyond which they cannot grant credit to the clients. The research further indicates that 87% of the respondents stated that they provide the credit period for the amount that is borrowed hence the borrowers are aware of the credit period before they get the loans. A mean of 3.711 resulted for this particular research indicating a higher mean, which shows that the Fintech companies shares the methods 0f payment of loans prior to offering the loan.

Table 4.1: ***Aspects Credit Terms***

No	Statement on Fintech Company:	1	2	3	4	5	Mean	Standard Deviation
1	The institution has clearly stated its discount terms	2	13	8	18	4	**3.200**	**1.087**
2	The company have a credit limit beyond which it cannot grant credit to the client	1	2	3	23	16	**4.133**	**0.884**
3	The borrower is aware of the credit period	1	5	0	20	19	**4.133**	**1.024**
4	The payment methods are shared prior to the loan	2	7	3	23	10	**3.711**	**1.108**

4.3.2 Credit analysis and Loan Performance

The study set out to assess the influence of Credit analysis on loan performance in Fintech companies in Kenya. Further analysis into the research also showed the extent to which Credit analysis had effect on loan performance in Fintech companies in Kenya. From the findings, 71 % of the population were certain the Fintech companies check the clients 'credit score before issuing a loan, a mean of 3.733 was obtained for this study.

Furthermore, 51% of the respondents were certain that the Fintech companies do not get the borrower's credit payment history from other financial organizations. A mean of 2.667 and standard deviation of 1.265 was obtained indicating almost half of the respondents were quite clear on the Fintech companies not obtaining credit payment history report from other former institutions this is due to the competitive nature of the credit lending companies they don't share their customers' history.

According to the research findings, 51% of people disagree with the claim that Fintech companies require loan applicants to provide collateral, such as legal charges over properties, to cover credit loss. A particular mean of 2.756 and standard deviation of 1.401 resulted from that research. Further investigations into the findings indicate that 69% of the researchers differ the statement that the Fintech companies assesses prevailing industrial and economic conditions facing the borrowers. A mean of 2.356 and standard deviation of 1.250 resulted from that research question. The findings are illustrated in the table 4.2:

Table 4.2: ***Aspects of Credit Analysis***

No	Statement on Fintech Company:	1	2	3	4	5	Mean	Standard Deviation
1	The firm checks the client's credit score before issuing a loan	4	5	4	18	14	**3.733**	**1.254**
2	Obtain credit payment history report of the borrower from other financial institutions	11	12	4	17	1	**2.667**	**1.265**
3	The company holds collateral such as legal charges over properties for loan applicants to cater for credit loss.	11	12	5	11	6	**2.756**	**1.401**
4	The company assesses prevailing industrial and economic conditions facing the borrower	12	19	4	6	4	**2.356**	**1.250**

4.3.3 Credit mitigation and Loan Performance

The study set out to ascertain the influence of Credit mitigation had on loan performance on Fintech companies in Kenya. According to the research risk mitigation is a component of Credit Risk Management Practices on loan performance in Fintech companies in Kenya. The study indicates that 38 % of those polled agreed with the statement that the Fintech companies' practices risk transfers to their respective loans insure their loan portfolio to reduce risk from defaults by clients. A mean of 3.089 and standard deviation of 1.244 resulted from this particular research. The research further indicates that 47% of those polled agreed with the statement that the Company uses a variety of clients and sectors for its credit facilities to spread out the risk of credit occurrence from funding its limited business activities. A certain mean of 3.156 and standard deviation of 1.192 arose for this particular research indicating a certain mean, which shows that the Fintech Companies diversify, extends credit facilities to a range of clients in diverse industries.

The research also indicates a 44% of the Fintech companies have known covenants with borrowers prior to the approval of the loan. A mean of 3.200 and standard deviation of 1.185 arose for the particular research. On the statement that the companies insure the loan portfolio to mitigate risk due to client defaults, a mean of 3.067 and standard deviation of 1.356 obtained for the research.

Table 4.3: ***Aspects of Credit Mitigation***

No	Statements on Credit mitigation Practices in Fintech Companies	1	2	3	4	5	Mean	Standard Deviation
1	The company practices risk transfers to their respective loans	5	6	16	11	6	**3.089**	**1.244**
2	The company diversifies its credit facilities to various clients in different sector to minimise credit risks occurrence from financing limited business activities	3	14	7	15	6	**3.156**	**1.192**
3	The company has known covenants with borrowers prior to the approval of the loan	3	12	10	13	7	**3.200**	**1.185**
4	The company insures the loan portfolio to mitigate risk due to client defaults	6	13	7	10	9	**3.067**	**1.356**

4.3.4 Credit risk management practices and loan performance

From the results, respondents concurred with a mean of 3.356 and standard deviation of 1.621 that the credit default rate had decreased due to the Company's strong credit management practices adopted. The participants responded that there is a lot to be done on delinquency rate where majority 49% of the respondents disagreed on the statement that there has been a decrease in delinquency rate in the company with diligent credit risk management practices as indicated by a mean of 2.800 and standard deviation of 1.628. The findings are illustrated in table 4.4:

Table 4.4: ***Aspects of Loan Performance***

No	Statements on Loan Performance among Fintech companies	1	2	3	4	5	Mean	Standard Deviation
1	The credit default rate had decreased due to the Company's strong credit risk management practices adopted	8	11	2	5	19	**3.356**	**1.621**
2	There has been an decrease in delinquency rate in the company with diligent credit risk management practices	16	6	5	7	11	**2.800**	**1.628**

4.4 Reliability Analysis

Reliability is a precise presentation of the total phenomenon under investigation; and if the results of a study achievable using a similar methodology, then the research instrument is reliable (Orodho, 2018). Cooper and Schindler (2001) define three types of reliability in exploratory studies: the extent to which a measurement remains the same when repeated; the stability of a measurement over time; and the similarity of measurements within a given time. This property of the instrument is stability. The results should be similar if we are dealing with a stable measure. A high degree of stability implies a high degree of reliability, implying that the results are repeatable. Orodho (2018) works by detecting a flaw in the test-retest method, which can render the instrument questionable to some extent.

The reliability of a summative rating scale made up of the variables (also referred to as items) specified is evaluated using Cronbach's alpha (Cronbach, 1951). The collection frequently referred to a test or battery. A scale is just the average of the scores for each individual item, with the scoring for statements that have negative correlations to the factor (like attitude) being measured being reversed. The raw item scores or the standardized item scores creates scales. The reliability α is defined as the square of the correlation between the measured scale and the underlying factor. If you think of a test as being composed of a random sample of items from a hypothetical domain of items designed to measure the same thing, α represents the expected correlation of one test with an alternative form containing the same number of items. The square root of α is the estimated correlation of a test with errorless true scores (Nunnally & Bernstein, 1994). In addition to reporting α, alpha generates the summative scale from the items (variables) specified and automatically reverses the sense of any when necessary. Specifying the reverse (varlist) option will override Stata's choice.

By calculating the internal consistency of a test or the average correlation of the items (variables) within the test, Cronbach's alpha evaluates reliability. The reliability test runs using Stata Alpha command. Internal consistency, or how closely related a group of items are to one another, is measured by Cronbach's alpha. The stability and consistency of the produced instrument are referred to as the instrument's reliability (Creswell, 2010). Alpha Cronbach (Creswell, 2010) represents the reliability level of the instrument. Pallant (2001) states Alpha Cronbach's value above 0.6 is high reliability and acceptable index (Nunnally & Bernstein, 1994). Whereas, the value of Alpha Cronbach is less than 0.6 considered low. Alpha Cronbach values in the range of 0.60 - 0.80 are moderate, but acceptable. While Alpha Cronbach in the ranges of 0.8 and up to 1.00 is, consider very good. From the data analyzed using Stata Cronbach's alpha is 0.6 hence, the data is reliable.

Table 4.5: ***Cronbach's Alpha Test***

```
Average interitem covariance:     .2505629
Number of items in the scale:            4
Scale reliability coefficient:      0.5541
```

4.5 Validity Analysis

In research, validity is determined by determining whether the research instruments the intended measure (Patton, 2002). Two experts and the supervisor had copies of the questionnaires and the study's objectives to determine whether or if the research equipment measured what it intended to measure (Oso & Onen, 2009). The Content Validity Index (CVI) was 0.7. The formulas used to calculate the CVI was Content Validity Ratio = (ne – N/2) / (N/2) where ne = number of SME panelists indicating "essential" and N = total number of SME panelists. According to Oso and Onen (2009), a minimum validity coefficient of 0.70 is acceptable. This indicates that the data collection instrument passed the validity test.

4.6 Residual analysis

Residuals are the discrepancies between the one-step anticipated output of the model and the measured output from the validation data set. The portion of the validation data that the model is unable to account for are residuals. Residual analysis, which examines differences between actual values and values the model predicts, assesses the reliability of a regression model. By visualizing the residuals and determining if the assumptions of linear regression models are true, the validity of linear regression models gets determined via residual plot analysis. The basic assumption of a linear regression model is that the residuals, also known as error terms, are independent and normally distributed. Using the Skewness Kurtosis test for normalcy, the residual hypotheses underwent scrutiny. Skewness is a metric for the asymmetry of a random variable's probability distribution around its mean. It displays the magnitude and skew direction. Kurtosis, on the other hand, shows how high and pointed the central peak is in comparison to a typical bell curve.

Table 4.6: ***Skewness Kurtosis Test for Normality***

```
. sktest residual
```

Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2) (joint)	Prob>chi2 (joint)
residual_t~s	45	0.7120	0.0521	4.08	0.1298

The test's results revealed the following findings: With 45 observations, the probability of skewness is 0.7120; skewness is asymptotically normally distributed (p-value of skewness > 0.05). Sktest displays the number of observations. Kurtosis has an asymptotically distributed distribution, according to Pr (Kurtosis) at 0.0521 (kurtosis p-value > 0.05). At the extreme least, chi (2) is 0.1298, above 0.05, indicating significance at a 5% level. The null hypothesis accepted as a result. Therefore, residuals have normal distribution as determined by the Skewness test for normality.

4.7 Diagnostics Test

Diagnostic tests took place to examine the main regression assumptions, which include linear relationship, multivariate normality, little or no multicollinearity, no heteroscedasticity and auto-correlation.

4.7.1 Multicollinearity test

This research employed tolerance and VIF to test multicollinearity. Tolerance is measured using initial linear regression analysis and calculates the effect of one independent variable on all other independent variables. VIF < 10 indicates the absence of multicollinearity; VIF > 10 indicates the presence of multicollinearity in the study sample.

The value for VIF starts at one and has no upper limit. A general rule of thumb for interpreting VIFs is as follows: A value of one indicates there is no correlation between a given explanatory variable and any other explanatory variables in the model. A value between 1 and 5 indicates moderate correlation between a given explanatory variable and other explanatory variables in the model, but this is often not severe enough to require attention. A value greater than 5 indicates potentially severe correlation between a given explanatory variable and other explanatory variables in the model. In this case, the coefficient estimates and p-values in the regression output are likely unreliable. The variables from this research had a VIF value of 1.01; this states that less correlation almost to nor correlation between the variables in the model. As demonstrated in table 4.7:

Table 4.7: ***Variance Inflation Factor (VIF) Test***

. vif

Variable	VIF	1/VIF
X2	1.01	0.986117
X1	1.01	0.990313
X3	1.00	0.995648
Mean VIF	1.01	

4.7.2 Heteroscedasticity test

If heteroscedasticity exists in the data, the assumption is broken since the variance varies depending on the values of the explanatory factors. Due to bias, this will render the OLS estimator inaccurate. Therefore, it is crucial to check for heteroscedasticity and take corrective action if it is. In this study, we will employ the Breusch-Pagan test, one of many tests that can assist detect heteroscedasticities. The Breusch-Pagan test aids in comparing the alternative hypothesis to the null hypothesis. The alternative hypothesis (heteroscedasticity) states that the error variances are a multiplicative function of one or more variables, as opposed to the null hypothesis, which states that the error variances are all equal (homoscedasticity).

Table 4.8: ***Breusch-Pagan Test for Heteroscedasticity***

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
          Ho: Constant variance
          Variables: fitted values of Y

          chi2(1)      =     1.81
          Prob > chi2  =   0.1788
```

The figure above shows that the probability value of the chi-square statistic is more than 0.05. Therefore, the null hypothesis of constant variance is accepted (alternative hypothesis) at a 5% level of significance. It implies there was no presence of heteroscedasticity in the residuals**.** If heteroscedasticity is present in the data, the variance differs across the values of the explanatory variables and violates the assumption. This will make the OLS estimator unreliable due to bias. In the case of this study, the results dictate that the data is reliable, the residuals are uniformly scattered and not biased.

4.8 Correlation Analysis

The association between two variables referred to as correlation. A strong or high positive correlation means that two or more variables have a strongly related, whereas a weak or low correlation indicates that the variables are barely related. A value of -1.00 indicates a perfect negative correlation, while +1.00 indicates a perfect positive correlation. A value of 0.00 indicates that no relationship exists between the variables being tested (Orodho, 2018). The Pearson R, also known as linear correlation, is the most commonly used type of correlation coefficient.

According to this methodology, the three variables are evaluated on at least interval scales. The coefficient decides by multiplying the product of the three variables' standard deviations by the covariance of the three variables. In this study, correlation employed to assess the relationships between the research variables. Pearson's correlation measures the strength of two variables' linear relationships. It goes from +1 to -1. A correlation of +1 indicates that the variables have a perfect linear relationship (Young, 2019). A correlation analysis was to find out how Credit Terms, Credit analysis, and Credit mitigation are correlated with loan performance. Table 9 below shows a there is a non-significant and positive correlation between Credit risk and loan performance ($r = 0.0403$, $P > 0.05$). Moti et al. (2012) agrees with the findings of this study, which are that credit terms do affect the performance of loans. Additionally, Credit analysis has non-significant negative correlation with loan performance ($r = -0.1715$, $P > 0.05$) while Credit analysis has a non-significant and positive correlation with Credit analysis ($r = 0.0984$, $P> 0.05$). However, the relationship between Credit mitigation and loan performance is a significant and strong positive correlation ($r = 0.8955$, $P< 0.05$) while the variable has non- significant and negative correlation with Credit risk ($r = -0.0101$, $P> 0.05$) and Credit analysis ($r = -0.0659$, $P > 0.05$). The results in the correlation matrix imply that the independent variable Credit mitigation is significant in enhancing performance of the loans and therefore if loan performance is accomplished, Fintech organizations should consider them. While Credit risk and Credit analysis are non-significant to the loan performance of Fintech companies in Kenya.

Table 4.9: ***Correlation Analysis***

	Loanpe~e	Credi~ms	Credi~is	Credit~n
Loanperfor~e	1.0000			
	45			
CreditTerms	0.0403	1.0000		
	0.7927			
	45	45		
CreditAnal~s	-0.1715	0.0984	1.0000	
	0.2601	0.5204		
	45	45	45	
CreditMiti~n	0.8955*	-0.0101	-0.0659	1.0000
	0.0000	0.9474	0.6673	
	45	45	45	45

4.9 Regression Analysis

The findings of regression analysis tests conducted using straightforward linear regression analysis are in this section. The p-values were used as the basis for making decisions about how to interpret the results because the regression was tested at a 95%

confidence level (α= 0.05). Results are significant when $p<0.05$, and results are insignificant when $p > 0.05$. Correlations, coefficients of determination, F Statistic values, and beta values are in account throughout the interpretation of the data and discussions that followed. R^2 showed how much of a change in the dependent variable is explained by changes in all of the independent variables. Additionally, the model proved more significant the higher the F-Statistic. By looking at the beta (β) sign, it was possible to determine whether the independent variable had a positive or negative impact on the dependent variable The R-value indicates the strength of the link between the variables, whereas t-values indicate the importance of individual variables. The coefficient of determination describes how much variation in the response variable can be explained by changes in the explanatory variables, or how much dissimilarity in the response variable (Loan performance in Fintech companies in Kenya) can be explained by all three explanatory variables (Credit risk, Credit analysis, and Credit mitigation).

Table 4.10: ***Regression Analysis Results***

```
. regress Y X1 X2 X3
```

Source	SS	df	MS
Model	87.8060971	3	29.268699
Residual	19.4939029	41	.475461045
Total	107.3	44	2.43863636

Number of obs	=	45
F(3, 41)	=	61.56
Prob > F	=	0.0000
R-squared	=	0.8183
Adj R-squared	=	0.8050
Root MSE	=	.68954

Y	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
X1	.1701444	.1866166	0.91	0.367	-.2067355	.5470243
X2	-.2255976	.1271402	-1.77	0.083	-.4823623	.0311672
X3	1.552363	.1165851	13.32	0.000	1.316914	1.787811
_cons	-1.774828	.8652938	-2.05	0.047	-3.522324	-.0273312

The model's r- squared (R^2) states that 81.83% of the independent variables explains the regression model while 18.17% caused by factors not included in the model. The adjusted r- squared of the regression model states that the three independent variables studied in this research, explain 80.50% of regression model. As a result, other factors not investigated in this study contribute 19.50% of the regression model. When determining how well the collected data are correlated We took into account the adjusted R-squared because; R-squared only works as intended in a simple linear regression model with one explanatory variable. The R-squared is adjusted in many regressions with several independent variables. The beta coefficients for the actual regression equation appear in this section. The emphasis is primarily on the "unstandardized coefficients," because this section contains both a y-intercept term (beta zero) and a slope term (beta one). The "standardized coefficients" are determined by rescaling the variables so that the y-intercept equals zero.

$\mathbf{Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \varepsilon}$ become:

Y= -1.7748+ 0.1701 Credit Terms - 0.2256 Credit Analysis +1.5524 Credit Mitigation

Taking all aspects into account (Credit risk, Credit analysis, and Credit mitigation), loan performance was -1.7748. Taking all other independent variables to zero, the data findings suggest that a unit increase in Credit risk leads to a 0.1701 rise in loan performance. A unit increase in Credit analysis equals a 0.2256 reduction in loan performance. A unit improvement in Credit mitigation results in a 1.5524 rise in loan performance. Credit risk and Credit analysis have p- values that are more than 0.05 hence they are not statistically significant in explaining loan performance. Credit mitigation is statistically significant in explaining loan performance, because its P value is less than 0.05.

ANOVA is a statistical method in which the variation in a set of observations divided into distinct components. The study used ANOVA to examine the consequences of the model. The null hypothesis states if the P- Value is greater than the level of significance the H_o is true hence accept the null hypothesis. While if the level of significance is greater than the P-Value reject the null hypothesis. Table 11 the P-value is 0.000 this is less than 0.05(5% level of significance) hence reject the null hypothesis this means that the model from the collected data is useful to be used in this research work.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

According to the authors of the study, credit risk management practices have a significant impact in Fintech companies in Kenya. The findings revealed that Fintech companies' credit terms have a non-significant positive effect on loan performance and thus the implication of this is that a more stringent companies Credit mitigation measures would less affect the loan performance.

Credit risk has a non-significant and positive relationship with loan performance this means that as much as the credit terms practices increase the loan performance but to extents that are significant to be considered much by the companies. The Fintech companies can still have the Credit risk practices such as having credit limits, making the borrowers be aware of their credit period also make the borrowers be aware of the payments method. These practices are not significant but still lead to an increase of the loan performance.

Based on the findings on the effect of Credit analysis on loan performance of Fintech companies in Kenya: the study concluded that credit risk has a non-significant negative relationship with loan performance Fintech Companies. This states the much the Fintech companies try to invest in analyzing the credit risk the end up having low loan performance and hence the companies should invest in other credit risk management practices that can improve on the loan performance.

Based on the findings, the study discovered a large and high correlation between loan performance and Credit mitigation in Fintech firms. Fintech companies in Kenya that follow good Credit mitigation practices such as diversification of credit facilities, transfer of credit risk, having covenants with borrowers before giving loans and also insuring their loan portfolio typically do better when it comes to loans than those who don't.

5.2 Recommendations

Based on the conclusion on the effects of credit risk management practices on loan performance of Fintech companies in Kenya Credit mitigation was significant in the model. Thus, the study recommended that all Fintech companies should create Credit mitigation practices on to improve on the loan. This will help to reduce the credit default rates and the delinquency rate of the Fintech companies.

Credit risk transfer, credit facilities to various clients in various sectors to minimize credit risks occurring from financing limited business activities. The Fintech companies should have known covenants with borrowers prior to the approval of the loan, and finally insurance of the loan portfolio to mitigate risk due to client defaults are some of the recommended activities for Credit mitigation.

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