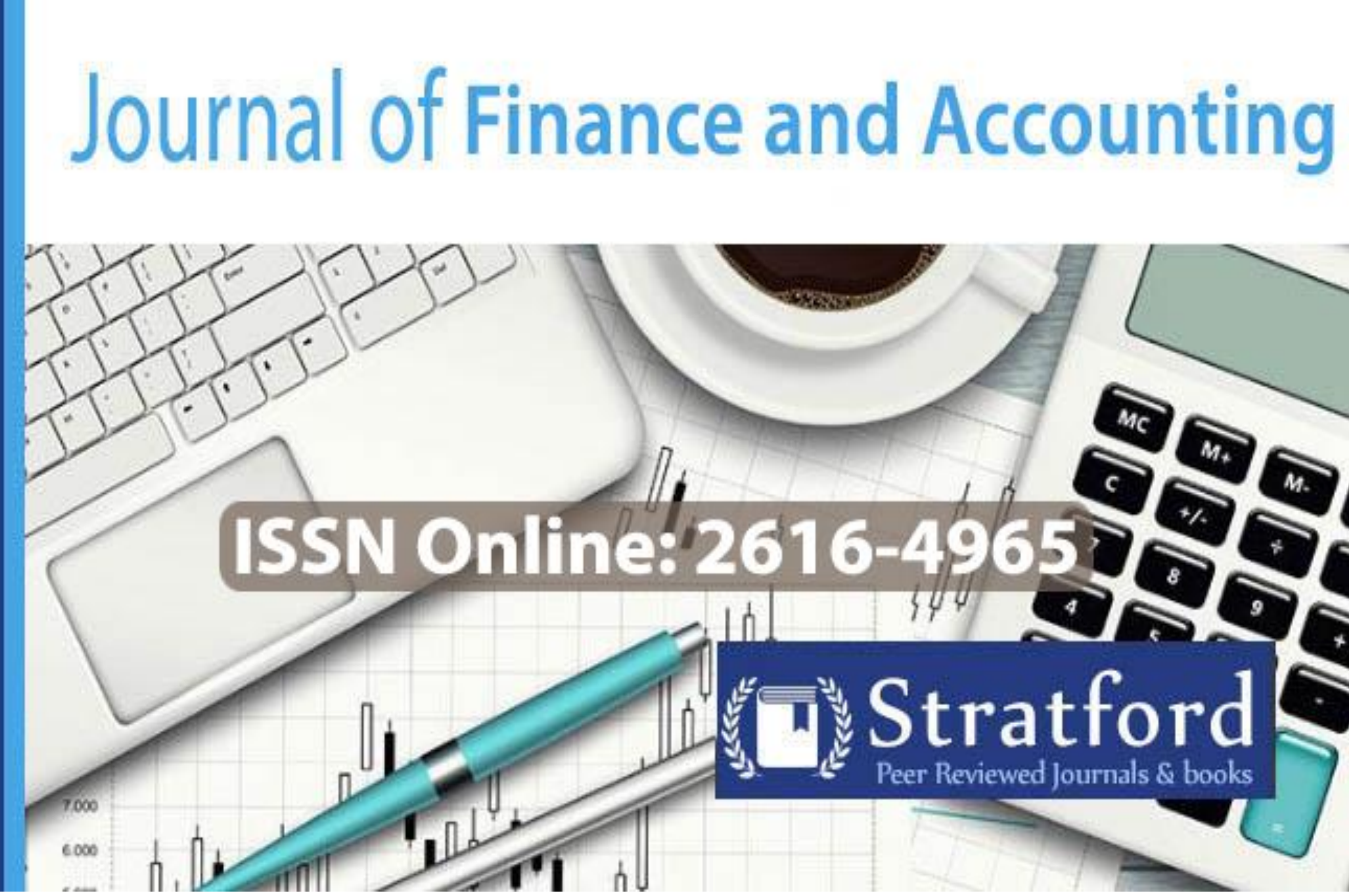

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ISSN: 2616-4965

Stratford Peer Reviewed Journals and Book Publishing
Journal of Finance and Accounting
Volume 8||Issue 8||Page 101-116 ||September||2024|
Email: info@stratfordjournals.org ISSN: 2616-4965

Credit Risk Management Practices and Profitability of Regulated Digital Credit Providers in Kenya

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How to cite this article: **Karanja, M., W. Wamugo L. (2024), Credit Risk Management Practices and Profitability of Regulated Digital Credit Providers in Kenya.** ***Journal of Finance and Accounting, 8*****(8) pp.101-116. https://doi.org/10.53819/81018102t3104**

Abstract

The profitability of digital credit providers in Kenya is a concern, as many firms lend unsecured personal loans, increasing credit risk. The decrease in loan amounts extended by these providers reflects lower profitability. The purpose of this study was to determine how credit risk management practices affect the profitability of Kenya's regulated digital credit providers. The specific objectives were to explore the effect of borrowers' screening, credit scoring, credit reminder practice, and credit risk control on profitability. The study focused on all 22 digital credit providers licensed and regulated by the Central Bank of Kenya as of January 2023. A census was necessary due to the small population. This study was based on the credit risk theory and the profit innovation theory. An explanatory research design with a quantitative methodology was used. Data was gathered using questionnaires. The data were analysed using descriptive statistics (mean, frequencies, standard deviation, and percentages) as well as inferential statistics (correlation and regression analyses). Before proceeding with inferential analysis, diagnostic tests such as normality, multicollinearity, heteroscedasticity, and autocorrelation were performed. The results were presented using tables, charts, and graphs. The study found that borrowers' screening had a significant positive impact on profitability ($\beta = 0.146$, $p < 0.05$). Credit scoring had a significant positive impact on profitability ($\beta = 0.327$, $p < 0.05$). Credit reminder had a significant beneficial effect on profitability ($\beta = 0.298$, $p < 0.05$). Credit risk control practices significantly increased profitability ($\beta = 0.357$, $p < 0.05$). The regression model accounted for 81.2% of profitability variation, and ANOVA confirmed the significance of credit risk management practices ($F = 42.204$, $p < 0.05$). All individual regression coefficients were positive and statistically significant, indicating a positive impact on profitability. The study concludes that digital credit providers improve their borrowers' screening processes, invest in sophisticated credit scoring techniques, optimize credit reminder practices, and strengthen credit risk management measures.

Keywords: *Credit Risk, Management Practices, Profitability, Regulated Digital, Credit Providers*

1.1 Background of the Study

Many countries' economies have been significantly impacted by digital credit. This is based on the ease with which credit is obtained, particularly by poor households and small businesses (Bull, 2019). Some financial technologies (Fintech) offer digital loans to farmers, thereby increasing financial inclusion. According to Bull (2019), this has a positive impact on the economy because financial inclusion is a key determinant of economic growth. The appeal of digital credit is that it can be tailored to the specific needs of users. It can also be delivered using machine-learning models, which are used to leverage alternative data such as electronic commerce, mobile phone activities, payments, and social media, without the need for human intervention. One of the primary benefits of digital credit is the ability to apply for and approve loans in a very short period of time. Often, no bank staff is required for the entire loan application, approval, and disbursement process (Pazarbasioglu et al., 2020). In Mexico, default rates among digital credit borrowers were close to 27.0% as of 2021. Digital credit providers faced significant credit risk when extending loans to their borrowers (Burlando, Kuhn, & Prina, 2021). Platform failures in China have recently raised concerns about rising credit losses in the financial technology (Fintech) sector. Therefore, risk management regulations for Fintech credit companies in some economies, including China, have been reviewed (Claessens, Frost, Turner, & Zhu, 2018). According to a previous poll, the following countries have strong credit policy frameworks and specific credit risk management criteria: The United Kingdom, France, Mexico, New Zealand, Spain, and the People's Republic of China. Digital credit has reached millions of low-income households in Africa, including Ghana, Zambia, and Tanzania (Bull, 2019). There have been calls for a closer look at digital lending practices in Tanzania and Kenya in response to emerging evidence of late loan repayments and defaults linked to digital credit (Kaffenberger, Totolo, & Soursourian, 2018). The Kenyan economy relies heavily on digital credit. In contrast to the traditional lending sector, which includes commercial banks, microfinance institutions, and savings and credit cooperative societies (SACCOS), digital credit platforms provide loans to both businesses and individuals.

Profitability is one of the measures used to evaluate a company's overall financial performance (Fatihudin&Mochklas, 2018). It is defined as an entity, enterprise, or concern's ability to generate profit (Tulsian, 2014). Profitability is measured using specific ratios like OPR, ROCE, GPR, ROI, NPR, ROA, ROE, and ROS (Rutkowska-Ziarko, 2015). In recent years, the profitability of Kenyan digital credit providers has been concerning. According to CBK data, the aggregate return on assets (ROA) for licensed digital credit providers decreased from 3.2% in 2019 to 1.8% in 2020, and then to 0.9% in 2021. Similarly, the return on equity (ROE) fell from 15.7% in 2019 to 8.3% in 2020, then 4.2% in 2021. Specific examples highlight the downward trend. Letshego Kenya Limited, a major digital credit provider, reported a 35.72% decrease in annual profits from 2021 to 2022 (Letshego Holdings Limited, 2022). Tala, another major player, saw its net profit margin decrease from 12% in 2019 to 5% in 2021, according to financial reports. High default rates contribute to a decrease in profitability. An empirical study conducted in Kenya discovered that approximately 90% of individuals blacklisted by credit reference bureaus were unable to repay digital credit (Johnen et al., 2021). This implies that digital credit platforms have higher default rates than conventional lending institutions such as commercial banks and SACCOs.

These trends aren't unique to Kenya. Despite a decade of operation, the digital lending industry in the United States has struggled to achieve long-term profitability. For example, in the first quarter of 2017, digital credit providers in the United States experienced net losses of $29.8 million (Turner). Similarly, Tanzania has reported high delinquencies among digital credit borrowers (Izaguirre, Kaffenberger, & Mazer, 2018). The declining profitability trends among digital credit providers in Kenya, combined with high default rates, emphasize the importance of proper credit risk management practices. This condition lays the groundwork for studies that seek to investigate the impact of credit risk management techniques on the profitability of these institutions, with the goal of identifying strategies that can reverse the downward trend and ensure the sector's long-term profitability.

To reduce the likelihood of loan defaults, digital credit providers should implement credit risk management strategies. This study focuses on four key practices: borrower screening, credit scoring, credit reminders, and credit risk management. Technological advancements and regulatory changes have shaped recent trends among Kenya's digital credit providers. Borrowers' screening practices have changed significantly in recent years. According to a report published by the Financial Sector Deepening Kenya (FSD Kenya, 2022), digital lenders are increasingly using a combination of traditional and alternative data to assess borrowers. Traditional data includes credit history obtained from Credit Reference Bureaus (CRBs), whereas alternative data includes mobile money transaction history and social media activity. However, CBK (CBK, 2023) stated that, despite these advancements, the effectiveness of current screening methods is still a concern, with non-performing loan rates for digital credit standing at 18.3% in 2022, compared to 14.2% for traditional banks. Credit scoring models are becoming more sophisticated. According to the Digital Lenders Association of Kenya (DLAK, 2023), 85% of its members use machine learning algorithms for credit scoring, up from 60% in 2020. These models use a broader set of data points, such as mobile money transactions and utility bill payments. However, a study by (KIPPRA, 2023) found that, while these new scoring methods increased loan approval rates, they did not significantly reduce default rates, which stood at 23% for digital loans in 2022.

According to a CAK survey (2022), digital lenders send 4-6 reminders per loan cycle, which 40% of borrowers consider excessive, prompting new CBK regulatory guidelines. Moreover, credit risk control has advanced, with 70% of licensed lenders using real-time data for credit limit adjustments, though smaller lenders continue to rely on traditional measures such as blacklisting. Despite these efforts, high default rates remain, indicating room for improvement. With digital credit providers playing an important role in Kenya's financial sector, offering products such as M-Shwari, M-Pesa, and Fuliza, it is critical to strike a balance between financial inclusion and responsible lending. By 2023, 22 licensed digital credit providers would operate in Kenya, with a focus on profitability and credit risk management strategies to improve sector sustainability.

1.2 Statement of the Problem

Digital credit providers have implemented measures to generate profits, such as imposing hidden late repayment charges (De Leon, 2021). However, digital credit providers in Kenya have experienced a decline in profitability, owing primarily to high delinquency rates (CGAP, 2022). For example, Letshego Kenya Limited reported a decrease in annual profits from Ksh 729.50 million on December 31, 2021 to Ksh 468.94 million on December 31, 2022 (Letshego Holdings Limited, 2022). It was also reported that between 2019 and 2021, Kenya Commercial Bank's disbursements on its digital platform (KCB Mpesa) dropped dramatically from Ksh 116.6 billion to Ksh 51.1 billion. The decline was also consistent in 2022 (Ksh 46.3 billion) and 2023 (Ksh 42.2 billion). Mshwari, another digital platform, saw a drop in digital credit. The platform reported a decrease in digital loans from Ksh 129.6 billion (FY 2019/2020) to Ksh 94.5 billion (FY 2020/2021) and Ksh 91.5 billion (FY 2022/2023). Since the profitability of digital credit providers has been steadily declining, so has the amount of digital loans given. Another issue that digital credit issuers have faced is high default rates. According to the findings of a related local study, digital credit borrowing accounted for approximately 90.0% of all cases of blacklisting, largely due to high default rates (Johnen et al., 2021).

According to statistics, the number of borrowers on digital credit platforms decreased from 2 million in 2019 to 600,000 in 2021, owing to negative listing by credit CRBs (KIPPRA, 2023).According to previous reports, poor borrower appraisal, light-touch credit assessment, measuring borrowers' willingness rather than their capacity to repay digital loans, and automated decision making are some of the key factors that cause default and, as a result, reduce the profitability of digital credit providers (De Leon, 2021). Despite the fact that the aforementioned elements are credit risk characteristics, the impact of credit risk management on digital credit provider profitability is unknown. Late payment penalties are responsible for their continued profitability (Gubbins & Totolo, 2020). As a result, digital lenders' core business activities have failed to increase profitability.

Previous studies have not provided sufficient empirical evidence on the relationship between profitability and credit risk management practices of digital credit providers. For example, Nthiga's (2021) study found that credit risk management practices influenced loan advancement by digital lending firms. The study, however, linked the stated practices to lending decisions rather than the profitability of digital credit companies. A related study found that credit risk management practices influenced financial performance but not profitability (Mudanya, Kadima, & Miroga, 2022). In addition, Ambuga (2022) investigated how manufacturing companies in Uasin Gishu County managed credit risk and performed financially. Despite the fact that the study found a strong link between credit risk management and financial outcomes, it did not specifically address profitability and was limited to a single county, limiting its applicability to the entire Kenyan digital lending sector. In addition, Masavu (2022) examines the relationship between prudent financial management and the financial performance of Kenya's MFIs. However, it emphasized strategies over specific practices and did not identify profitability as a key performance indicator. Lastly, Maina et al. (2021) examined the impact of online lending on Kenyan commercial bank performance. As a result, the purpose of this study was to address such knowledge gaps by conducting an empirical investigation into the credit risk management and profitability methods used by Kenya's licensed digital credit providers.

1.3 Objectives of the Study

1.3.1 General Objective

To determine the effect of credit risk management practices on profitability of regulated digital credit providers in Kenya.

1.3.2 Specific Objectives

i. To examine the effect of borrower's screening on profitability of regulated digital credit providers in Kenya
ii. To assess the effect of credit scoring on profitability of regulated digital credit providers in Kenya
iii. To analyse the effect of credit reminder practice on profitability of regulated digital credit providers in Kenya
iv. To examine the effect of credit risk control on profitability of regulated digital credit providers in Kenya

1.4 Research Hypotheses

H_{01}: There is no significant effect of borrower's screening on profitability of regulated digital credit providers in Kenya.

https://doi.org/10.53819/81018102t3104

H_{02}: There is no significant effect of credit scoring on profitability of regulated digital credit providers in Kenya.

H_{031}: There is no significant effect of credit reminder practice on profitability of regulated digital credit providers in Kenya.

H_{04}: There is no significant effect of credit risk control on profitability of regulated digital credit providers in Kenya.

2.0 Literature Review

This section covers literature review of applicable theories and relatable empirical studies on credit risk management practices and profitability. Those reviewed studies are summarized and research gaps tabulated. The final part of this chapter has a conceptual framework of research variables.

2.1 Theoretical Review

Both innovation theory of profits and credit risk theory are examined. These theories are also discussed where there is a clear demonstration of their application to credit risk management practices and profitability of digital credit providers respectively.

2.2.1 Credit Risk Theory

It was developed in the 1970s (Melton, 1974). It's also known as structural theory. According to Melton (1974), the transformation of a company's property is represented by a dispersion process with a static indicator, which results in a default event. The theory is based on the three quantitative dimensions used in risk assessment: form appraisal, incomplete information, and structural approaches. Credit risk is based on structural models that are specific to a particular issuer. In addition, the loss due to default is exogenously specific (Longstaff and Schwartz, 1995). According to the theory, liquidity risk is the one that typically leads to a significant increase in credit risks. This risk, combined with market risks, has the potential to cause large-scale financial firm collapses (Melton, 1974). It is critical to understand the fundamentals of credit risk. Default risk refers to a client's inability to fulfil financial obligations related to trading, lending, hedging, settlement, or other activities (Kovalová, Valášková & Adamko, 2015). The principles of credit risk theory are fundamentally important in improving our understanding of credit risk management practices. Given that the theory addresses the borrowers' propensity to default in repaying the loaned amount, digital credit providers can use this knowledge during borrower screening, credit scoring, and determining how effectively credit reminder practice and credit risk control can be conducted.

2.2.2 Innovation Theory of Profits

Schumpeter was the first to propose the profit-innovation theory. According to the theory, profits are the reward for an entrepreneur introducing new innovations into the economy. According to Śledzik (2013), entrepreneurship relies heavily on innovation. According to the theory, in order to make a profit, an entrepreneur must be innovative in terms of products or services. As such, the theory explains how economic profits are realized when entrepreneurs introduce successful innovations. This theory divides innovations into two categories: those that reduce production costs and those that increase demand. The first category of innovations includes new and cheaper techniques or production processes, as well as new raw material sources, among other things. The second set of innovations includes discovering new markets, designing new products, and introducing new products (Porter & Stern, 1999). Successful innovations, according to this theory, result in profits because they either allow for more sales at higher prices or cause expenses to fall below the price of the product prior to invention.

https://doi.org/10.53819/81018102t3104

However, it is important to note that the profits generated by a given innovation are likely to be depleted due to imitation and adoption by rival firms (Schumpeter, 1934).

Schumpeter's innovation theory of profits has been criticized on a variety of grounds. Critics argue that the theory fails to consider profit as a reward for taking risks. The innovation theory of profit has also failed to address the issue of uncertainty. According to Schumpeter, profit is a management reward, not uncertainty. The theory is also considered incomplete in explaining profit realization because it is limited to the entrepreneur's ability to innovate (Rohilla, n.d). The innovation theory can be used to explain the profitability of digital credit providers. This is based on the fact that these companies rely on innovation to extend credit facilities through digital platforms. Therefore, their profits are largely due to their innovative approach to reaching borrowers, lending loans to them, and tracking loan repayment via digital platforms. As a result, digital credit providers' innovations that make loans easier to obtain and more effective in reducing default are rewarded with profits.

2.2 Empirical Review

This part reviews literature on credit risk management strategies and reassesses its empirical findings (borrowers' screening, credit scoring, credit reminder practice, and credit risk control), and profitability of credit providers.

2.2.1 Borrowers' Screening and Profitability

A study by Gallo (2021) focused on the screening of borrowers particularly on the financial technology (Fintech) platforms. The study was concerned with examining misconduct of borrowers on the lending platform as well as comparing the Lending Club credit grade and the Fair Isaac Corporation (FICO) score. A mixed continuous model was engaged to determine the recovery rate of the loans that are not performing (NPLs). This procedure was aimed at assess the extent to which lack of screening (verification) impacted the performance of collections by lending firms. According to the study findings, it was clear that there existed a negative effect of the preliminary assessment on the identification of deceiving borrowers. The recovery rate of NPLs was also affected by platforms of Fintech not being able to screen and/or verify certain information, for example, data with regard to the borrowers' employment length and annual income. Consequently, the collection performance of the lenders was compromised. The study has, however, not made any attempts to link borrowers' screening to profitability. In the instance of the Mekelle, Ethiopia-based Dedebit Credit and Savings Institution (DECSI), Asgedom, Desta and Bahita(2015) examined elements that affected the performance of group loan repayment. An explanatory research design was incorporated. For the purpose of testing link between independent variables and success rate of loan repayment, Chi-square test was used. Regular visits of group members, and loan purpose had significant influence on loan repayment performance. This study supported earlier findings that in Ethiopia, screening of borrowers was among the elements that positively affected the performance of loan repayment. Apparently, however, the borrowers' screening was not linked to profitability. The study also failed to contextualize the aspect of digital credit providers in the country. A comparative analysis that focused on microfinance institutions (MFIs) as well as financial intermediaries (FIs) sought to assess both the business and borrowers' factors that led to microcredit default in Kenya (Muturi, 2016).The objective was to examine the causes of loan default in both financial intermediaries and MFIs. This study established that borrowers' and business characteristics were significant among microfinance institutions and financial intermediaries in Kenya. Consequently, it was recommended that screening of borrowers and businesses was crucial for the purpose of establishing the 'good' and 'bad' borrowers as well as be in a better position to make follow-ups on loan repayment. This study, however, was not specific on the aspect of borrowers' screening.

2.2.2 Credit Scoring and Profitability

An analysis of credit scoring via the usage of digital footprints was conducted in a research that centered on the increase of Fintech companies (Berg, Burg, Gombovic, & Puri, 2020). The outcome of the pertinent research pointed out the variables easily available from a digital footmark tallied with data scores from credit report bureau. The study also observed that a digital footprint affected the access to digital credit as well as reduced default rates. Nonetheless, the study fell short of illustrating credit scoring and its effect on profitability of credit providers on digital platforms. An empirical study by Gathu (2020) was curious to find out how alternative data helped with the Kenyan market's correct credit score assessment for digital wallet mobile lending. This research used a descriptive survey approach. This research exposed strong correspondence between credit score and transaction data. Yet, social network data did not significantly affect credit score. The increased transaction records by customers increased their credit score on the digital platform. Inasmuch as this study addressed credit scoring in the context of digital lending, there was no attempt of demonstrating the effect the said scoring had on the profitability of digital credit providers. A related study by Oira and Jagongo (2020) was centred on credit scoring and information sharing with regard to the commercial bank's performance in the country. The objective was to assess how commercial banks throughout the nation fared after implementing competitive information sharing and credit scoring. A descriptive research approach served as the compass for the investigation. In order to analyze the data, descriptive and inferential statistics were employed. Results showed that credit scoring significantly affected commercial banks performance. Consequently, it was suggested that the credit monitoring of credit reference bureaus (CRBs) ought to be improved with the view of generating more effective scores that can be relied upon when lending. Despite the study addressing credit scoring, it neither related it to profitability nor did it centre on digital credit providers in the country.

2.2.3 Credit Reminder Practice and Profitability

A study carried out by Campbell, Grant and Thorp (2022) was concerned with how the use of repayment reminders could possibly reduce the delinquency of credit card. The question addressed by the study was on the capability of digital repayment reminders to reduce the delinquency credit card. Such delinquency is considered to be costly. It emerged from the particular study that reminders surged repayment rates and subsequently the amounts repaid to a significant extent. The rise in repayment rates was 2.7% for the sampled respondents who had logged in and saw the reminders sent to them. Inasmuch as the study examined the credit repayment reminders on digital platforms, it fell short of linking them to profitability of the credit providers.

A related study what employed a randomized controlled trial evaluated the frequency of reminders and whether such frequency mattered in their effectiveness (Antinyan, Asatryan, Dai, & Wang, 2021). The objective was to scrutinize the effect of frequent reminders for payment of that was overdue. It was evident from the findings that weekly reminders were more likely to enhance tax compliancy in contrast to a one-off reminder. Yet, it was established that increasing the reminders to two text messages weekly diminished the effectiveness of such reminders. The study concluded that albeit the fact that frequent reminders were crucial triggers for human behaviour, these frequent reminders was only to a certain extent beyond which the effectiveness and efficiency of more reminders was bound to diminish. The apparent

https://doi.org/10.53819/81018102t3104

shortcoming of this study is that it did not establish nexus between the reminders and profitability, and also the study was not contextualized to digital credit providers.

Koki, Achoki and Kiriri (2018) studied association between commercial banks' operational efficiency and mobile credit in Kenya. The goal was to find out how the aforementioned institutions' operating efficiency was affected by mobile credit. This research made use of both primary and secondary resources. An analysis of multiple regressions was utilised. Results of the research showed that friendly reminders could be used to fast-track repayment of loans advanced to borrowers. The study, however, did not give much emphasis on credit reminders. On the same breadth, the study did not attempt to relate credit reminders to profitability. It also focused on commercial banks as opposed to digital credit providers.

2.2.4 Credit Risk Control and Profitability

Munangi and Sibindi (20202) looked at how credit risk affected the financial performance of South African banks. Results showed that credit risk is inversely related to financial performance. From an interpretive perspective, commercial banks' profitability declined as nonperforming loans (NPLs) rose. To reduce likelihood of bank collapse, this present study's recommendations focused on improving credit risk management. This study addressed credit risk but not the control of the said risk. The focus was on commercial banks as opposed to digital credit providers. Research among Nairobi County's micro and small businesses focused on digital credit borrowing and the associated financial risk (Ngulale, 2020). Determining management of credit risk with a particular interest in digital credit providers was among the specific objectives. Findings stipulated that credit risk management had a fixed notable correlation with financial aspect of risk exposure. However, the research did not specify how digital credit providers in Kenya's profitability were impacted by credit risk management. Additional empirical studies in this field examined commercial banks' financial performance and credit risk management (Wanjiru, 2017). The goal was to show how the mentioned financial institutions' financial performance was affected by their credit risk management measures. A study design based on descriptions was utilized. Findings revealed that commercial banks' financial performance was negatively and statistically significantly correlated with their credit risk management. Inasmuch as credit risk control was linked to financial performance (profitability is a parameter of financial performance), the study was not contextualized to digital credit providers; rather, it focused on commercial banks.

2.4 Conceptual Framework

It is expressed as a diagrammatic or narrative or both diagrammatic and narrative illustration of study variables and how they are perceived to associate with each other. Figure 2.1 shows the conceptual framework.

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Volume 8||Issue 8||Page 101-116 ||September||2024|
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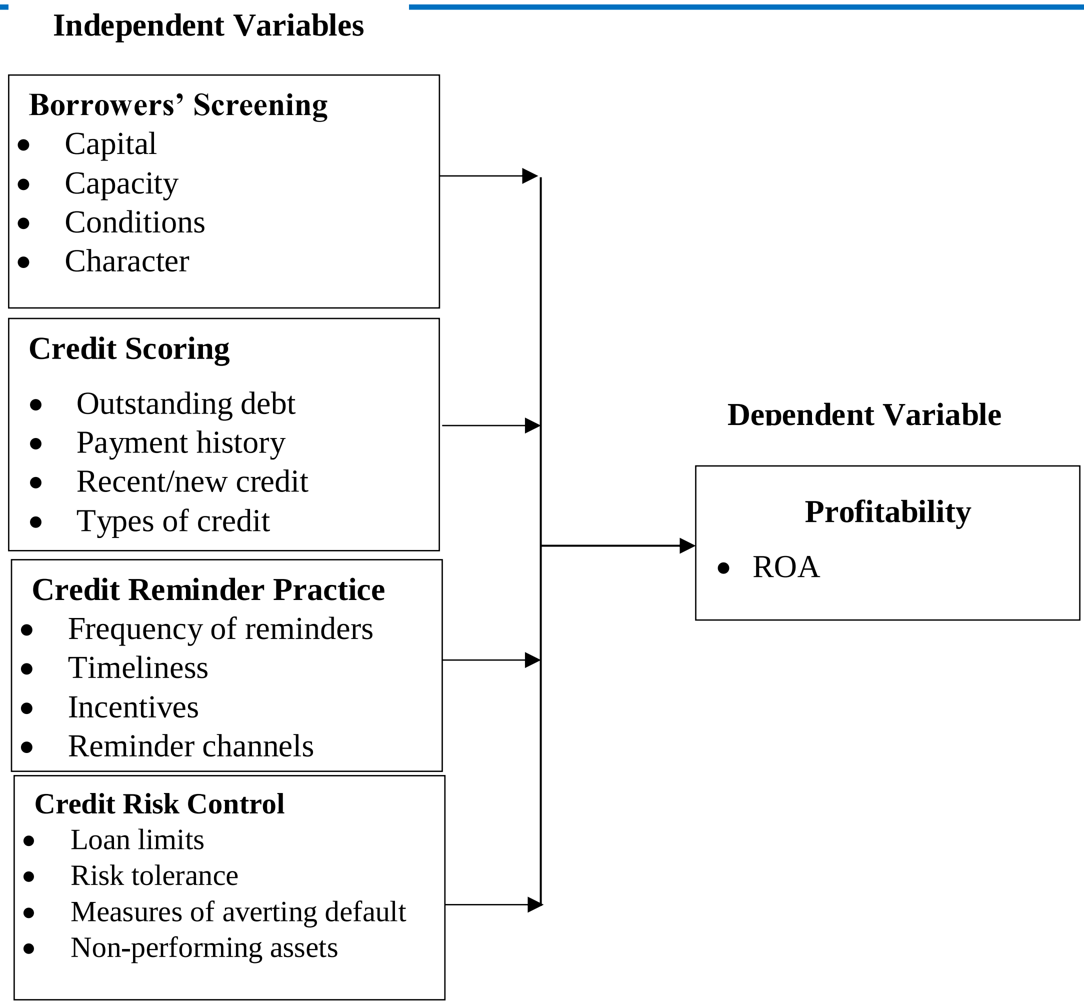

Figure 1: Conceptual Framework

3.0 Research Methodology

The research methodology section describes the study's approach, including key topics like the target population, research design, sampling design, and data collection instrument. An explanatory research design was used to examine the relationship between credit risk management practices and profitability among Kenya's regulated digital credit providers. Because the population was so small (44 credit and finance officers from 22 providers), a census approach was used. Structured questionnaires were used to collect data, with a drop-and-pick method using Google Forms. SPSS software was used to conduct data analysis, including descriptive and inferential statistics. Diagnostic tests were performed to ensure that statistical methods were appropriate, and multiple regression analysis was used to evaluate the relationship between the variables.

4.0 Results and Discussion

Data analysis, results and discussion are all covered in this section. Analysis was conducted using descriptive statistics and inferential statistics. Findings were explained using correlation, simple and multiple linear regression models. Tabular form was utilized to display findings.

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Journal of Finance and Accounting
Volume 8||Issue 8||Page 101-116 ||September||2024|
Email: info@stratfordjournals.org ISSN: 2616-4965

4.1 Diagnostics Tests

Validating certain assumptions is an integral part of doing conventional ordinary least squares to guarantee the results are genuine. The purpose of this test is to check for normality of the residual and that the model is free of autocorrelation, heteroscedasticity, and multicollinearity. Experiments were carried out and discussed based on this.

4.1.1 Normality Test

Table 1 gives findings of Shapiro-Wilk test, used to determine whether the model's output is normal. Analysis of the survey data revealed that the variables were normally distributed, as shown by their non-significant probability values. The presence of a probability value greater than 0.05 for the p-value indicates normalcy, unless otherwise stated (Table 1).

Table 1: Normality Test Results (Shapiro-Wilk Test)

Variable	Obs	W	V	z	Prob>z
Profitability	44	0.98721	2.456	2.103	0.007
Borrower's Screening	44	0.97234	5.312	3.876	0.000
Credit Scoring	44	0.98632	2.627	2.251	0.009
Credit Reminder Practice	44	0.95183	9.254	5.147	0.000
Credit Risk Control	44	0.98105	3.632	2.987	0.001

Table 1 shows that the Shapiro-Wilk test was performed to make sure results of normality test were correct. The results of the investigation showed that data was shared rather often. The significance threshold of less than 0.05 was used to back up this assertion using probability calculations. All of the variables above disprove the idea that they follow a normal distribution. The central limiting theorem, however, indicates that this follows normalcy when the observation is greater than 30.

4.1.2 Multicollinearity Test

To assess the degree of collinearity among model's explanatory variables, variance inflation factor (VIF) was utilised. For purpose of checking the model for multicollinearity, a margin of 10 was established and used in the study. Collinearity is considered severe when the VIF value is more than 10, and tolerable when the value is less than 10, as indicated in Table 2.

Table 2: Variance Inflation Factors Results

Variable	Tolerance	VIF
Borrower's Screening	0.488	2.051
Credit Scoring	0.483	2.07
Credit Reminder Practice	0.762	1.312
Credit Risk Control	0.512	1.952

Table 2 shows that the survey data points did not exhibit any substantial collinearity. According to the findings, the explanatory factors' VIF values (borrower screening = 2.051, credit scoring = 2.070, credit reminder practice = 1.312, and credit risk control = 1.952) were less than 10, show that the model was acceptable with collinearity and that the calculated parameters were not distorted.

4.1.3 Heteroscedasticity Test

Presence of heteroscedasticity in the model leads to inaccurate model estimate. In order to test if the model is devoid of residual variation of varying degrees and to evaluate the survey's null hypothesis, which is that the residuals are homoscedastic, experiment used the Breusch-Pagan appraisal technique. Findings in Table 3.

Table 3: Heteroscedasticity Test Results (Breusch-Pagan Test)

Test Statistic	Value
chi2(1)	0.23
Prob > chi2	0.9318

Based on the above table results, the constant residuals across all datasets, as held by the null hypothesis, was shown to be true. Outcome showed 0.9318 p-values, which is > 0.05 threshold significance. After taking this into account, the investigation's conclusion is deemed strong, and the heteroscedasticity problem was excluded.

4.2 Correlation Analysis

It was used to look at the factors' effects and how strong they were. Results in Table 4.

Table 4: Correlation Analysis

	Profitability	Borrower's Screening	Credit Scoring	Credit Reminder Practice	Credit Risk Control
Profitability	1.000				
Borrower's Screening	0.669	1.000			
	0.000				
Credit Scoring	0.766	0.648	1.000		
	0.000	0.000			
Credit Reminder Practice	0.635	0.294	0.439	1.000	
	0.000	0.053	0.003		
Credit Risk Control	0.770	0.628	0.599	0.422	1.000
	0.000	0.000	0.000	0.004	

Table 4 shows a bivariate Pearson effect of credit risk management practices on the profitability of licensed digital credit providers in Kenya, including borrower screening, credit scoring, credit reminder practice, and credit risk control. Borrower screening has a significant positive correlation with profitability ($r = 0.669$, $p < 0.05$). Profitability and credit scoring have a strong positive correlation ($r = 0.766$, $p < 0.05$). It suggests that the use of robust credit scoring techniques is linked to higher levels of profitability. The analysis of credit reminder practice shows a positive correlation with profitability ($r = 0.635$, $p = 0.000 < 0.05$). This suggests that effective credit reminder practices contribute to timely loan

Stratford Peer Reviewed Journals and Book Publishing
Journal of Finance and Accounting
Volume 8||Issue 8||Page 101-116 ||September||2024|
Email: info@stratfordjournals.org ISSN: 2616-4965

repayments, which improves profitability. Profitability and credit risk control show a strong positive correlation (r = 0.770, p < 0.05). This emphasizes the importance of comprehensive credit risk management measures in improving profitability. Thus, the correlation analysis demonstrates that borrower screening, credit scoring, credit reminder practices, and credit risk control practices are closely related to the profitability of licensed digital credit providers in Kenya.

4.3 Multiple Regression Analysis

Multiple linear regression analysis was adopted and findings outlined in Tables 5, 6 and 7.

Table 5: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.901a	0.812	0.793	0.20081

Table 5 gives summary of the model that examines effect of profitability and credit risk management practices, including borrower's screening, credit scoring, credit reminder practice and credit risk control practices. A strong association between the variables was noted. The coefficient of determination (R square = 0.812) reveals that 81.2% of the variation in profitability of licensed digital credit providers in Kenya may be explained by the adoption of these credit risk management practices. This indicates a substantial impact of these practices on profitability.

Table 6: ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.808	4	1.702	42.204	.000b
	Residual	1.573	39	0.04		
	Total	8.381	43			

Table 6 gives ANOVA. This table shows that adoption of credit risk management practices has a considerable influence on profitability of licensed digital credit providers in Kenya (F=42.204 and p-value=0.000<0.05).

Table 7: Regression Co-efficient

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	0.133	0.225		0.591	0.558
	Borrower's Screening	0.115	0.078	0.146	1.471	0.001
	Credit Scoring	0.281	0.086	0.327	3.275	0.002
	Credit Reminder Practice	0.258	0.069	0.298	3.747	0.001
	Credit Risk Control	0.304	0.083	0.357	3.685	0.001

Table 7 shows the regression coefficients. Borrower screening has a positive and statistically significant effect on digital credit providers' profitability (β = 0.146, p-value = 0.001 < 0.05). Suggesting that for every one standard deviation increase in borrower screening, profitability increases by 0.146 standard deviations, while other variables remain constant. Credit scoring has a positive and statistically significant effect on profitability (β = 0.327, p-value = 0.002 < 0.05). It shows that for every one standard deviation increase in credit scoring, profitability increases by 0.327 standard deviations, while other variables remain constant. Credit reminders have a positive and statistically significant effect on profitability (β = 0.298, p-value = 0.001 < 0.05). This means that for every one standard deviation increase in credit reminder practice, profitability rises by 0.298 standard deviations, while other variables remain constant. Lastly, credit risk control has a positive and statistically significant effect on profitability (β = 0.357, p-value = 0.001 < 0.05). Suggesting that for every one standard deviation increase in credit risk control, profitability increases by 0.357 standard deviations, while other variables remain constant. Credit risk control has the most significant impact on profitability (β = 0.357), followed by credit scoring (β = 0.327), credit reminder practice (β = 0.298), and borrower screening (β = 0.146).

5.0 Conclusions

Findings indicate that credit risk management practices have a significant impact on the profitability of Kenya's licensed digital credit providers. Borrower screening, credit scoring, credit reminders, and credit risk control all have a positive impact on the profitability of Kenya's regulated digital credit providers. The study concludes that, while borrower screening improves profitability, the effect is less pronounced than other practices. This suggests that, while screening is important, digital credit providers may need to improve their screening methods in order to achieve more significant profitability gains. Enhanced screening techniques, which may include alternative data sources, could result in better risk assessment and financial outcomes. This study concludes that credit scoring plays an important role in improving profitability. The strong positive effect suggests that more sophisticated and accurate credit scoring models can significantly improve the financial performance of digital credit providers. Investing in advanced credit scoring technologies and methodologies could result in significant returns for these organizations. In addition, credit reminder practices were found to be effective in increasing profitability. This suggests that well-designed and timely reminder systems can significantly increase loan repayment rates, benefiting the bottom line. To increase the effectiveness of their reminder strategies, digital credit providers should focus on optimizing them. Lastly, the study concludes that credit risk control is the most important factor in determining profitability among the practices examined. This highlights the critical need for comprehensive risk management strategies in the digital lending sector. Strong credit risk control measures are critical for maintaining financial stability and driving profitability in this industry.

6.0 Recommendations of the Study

Managers of Kenya's licensed digital credit providers, according to the report, should put money into extensive training programs for their employees so that they can better manage credit risk. Specifically, training should be offered in areas where the study noted potential for improvement.

These areas include advanced borrower screening techniques, sophisticated credit scoring models, effective credit reminder strategies, and robust credit risk control measures. Training on emerging technologies, data analytics, and regulatory compliance should be offered.

Organizational performance will improve with greater education in these areas since better loan performance and higher profits are the results of improved risk management techniques.

Digital credit providers, in collaboration with regulatory bodies, ought to review and update their credit risk management policies and stipulate clear guidelines for implementing best practices. It is essential that all employees be required to maintain a high level of competence in credit risk management. Regular assessments should then be conducted to ascertain they have understood concepts on risk assessment, credit scoring methodologies, effective reminder systems, and comprehensive risk control strategies.

The study advises management of digital credit providers to encourage a culture of proactive risk management among their staff. It is not just the implementation of risk management practices that ensures profitability, but rather the attitude and approach towards risk management that acts as a key driver of financial performance.

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