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Evaluating Loan Performance in Kenya's Digital Lending Sector: The Role of Credit Risk Management

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

In Kenya, over 50% of loans from digital lending companies are defaulted by borrowers. These companies often assess borrowers' willingness, rather than their ability to repay loans, which contributes to high default rates and credit risk. The lack of collateral and ineffective credit risk management further exacerbates the problem, hindering the growth of digital lending firms. This study aimed to investigate the impact of risk identification, quantification, and measurement on loan performance in Kenyan digital lending companies. Anchored in modern portfolio theory, asymmetric information theory, and stewardship theory, the study has applied descriptive as well as analytical research design which incorporate correlational and explanatory research design. Data was collected from 108 digital firms using a census sampling technique and analyzed using SPSS version 20. The findings indicated that risk identification, quantification, and measurement positively impact loan performance. The study concluded that effective risk management, including detecting

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maximum probable losses and monitoring borrowers' cash flows, enhances loan performance. It recommended implementing a robust institutional framework for risk identification and ensuring timely communication of risks to management. The study also suggested that the Central Bank of Kenya should oversee the identification and planning for new risks by digital lending firms.

Keywords: Credit risk; digital lending; loan default; risk identification; risk managemen.

1. INTRODUCTION

Credit risk is the potential threat that financial institutions face when borrowers fail to meet their debt obligations [1]. Effective management of credit risk can enhance the financial performance of these institutions, as credit risk is considered the most significant factor affecting their performance [2]. Ekinci and Poyraz [2] emphasized that managing credit risk effectively is essential for the sustainability and profitability of financial institutions. Therefore, mitigating credit risk is crucial for achieving financial stability and success.

Credit analysis plays a vital role in ensuring the sustainability and financial performance of digital lending companies. Credit analysis involves assessing the risk associated with debt instruments offered by companies [3]. According to Njenga and Kavindah [4], credit analysis is essential because it improves the quality and efficiency of credit management, which in turn enhances the financial performance of lending institutions. Financial institutions conduct credit analysis to evaluate credit risk, thereby helping them avoid bankruptcy and improve decision-making processes. Uthayakumar et al. [5] also noted that credit analysis provides a robust framework for predicting bankruptcy, allowing financial institutions to classify borrowers into two categories: good credit and bad credit groups. This classification aids in identifying risky borrowers and mitigating potential losses, thereby promoting business sustainability [5].

Moreover, credit analysis is essential because it allows financial institutions to categorize consumers based on their creditworthiness [6]. This categorization helps in determining consumers' credit scores, which reflect their financial history [7]. Credit scores are instrumental in predicting the likelihood of bankruptcy, enabling financial institutions to make informed lending decisions.

Digital lending simplifies the loan application process for both lenders and borrowers [8]. It facilitates quick background checks and verifications, leading to a more efficient loan borrowing process. Digital lending companies can offer rapid decision-making, with some loans being processed within six hours due to technological advancements [9].

Loan performance is defined by the time taken by borrowers to repay their debts and is measured by the percentage of non-performing loans (NPLs) relative to total loans. Effective credit risk management, therefore, is crucial for digital lending companies to enhance liquidity and promote financial performance, driving the need to understand its effects on these companies in Kenya. [10].

Credit risk management involves preventing losses in an organization by controlling capital and loans, and it encompasses risk assessment, strategy development, client relationships, credit rationing, and collateral requirements [11],(Kidane, 2020). The credit management process includes several steps: identifying, measuring, monitoring, and controlling credit risk [12]. Effective credit risk management requires a suitable environment, a robust credit procedure, adequate administration with monitoring methods, and appropriate controls. Management must ensure that guidelines for managing credit risk are clear, well-communicated throughout the organization, and adhered to by all involved [13].

To ensure efficacy in credit risk management, organizations must understand credit risk at individual, customer, and portfolio levels. This involves identification, quantification, and measurement [14]. Risk identification entails screening, monitoring, and diagnosing organizational risks, which helps in recognizing threats that might impede goal achievement. It involves evaluating internal and external resources to establish risks and is crucial for pinpointing high-failure projects, enabling suitable risk responses [15].

Risk quantification measures risk by generating data to determine the best approach to manage corresponding risks. It helps prioritize risks and assess their potential impact on the organization [16]. Project managers use this to evaluate numerical risks that could cause significant harm.

Risk measurement, essential for predicting investment risk, aims to quantify potential losses from credit operations. As the amount of losses is uncertain, it is necessary to estimate them (Erika, 2015). Different projects encounter different issues over time, necessitating robust risk management systems to mitigate potential risks. Effective risk measurement helps avoid unforeseen challenges, making it a priority for project managers.

Tantri [17] defines loan performance as how well loan repayments align with scheduled repayment plans, typically measured by default rates. According to the Central Bank of Kenya, non-performing loans (NPLs) rose from 14.1% in December 2019 to 14.6% in March 2021. A loan becomes non-performing if no scheduled payments on principal or interest have been made for at least 90 days. Digital lending companies in Kenya face significant loan defaults, with over 50% of their loans defaulted by borrowers [18]. NPL rates in Kenya fluctuated from 13.8% in 2018, 14.1% in 2019, 13.9% in 2020, to 14.6% in 2021, and further increased to 14.9% in 2022. Various studies, such as those by Muigai and Mwangi [19,20], use NPLs to measure loan performance. Njenga and Kavindah [4] highlight worsening loan performance among digital lenders, noting a high default rate and potential future deterioration.

Kenya has seen a significant increase in digital lending companies, with approximately 108 currently operating, according to Njanja [21] and the Kenya Private Sector Alliance (KEPSA, 2021). These companies offer unsecured personal loans primarily via mobile phones, benefiting from widespread smartphone availability [22]. However, they charge high-interest rates due to the risks associated with unsecured lending [4]. Furthermore, digital lenders can now share information with credit reference bureaus (CRBs), enabling better assessment of potential clients' financial and loan histories in collaboration with banks. About 55% of Kenyans have obtained loans from digital lenders.

1.1 Research Problem

In emerging economies like Kenya, digital lending companies primarily focus on lending due to underdeveloped capital markets. However, lending poses significant challenges, as businesses and individuals often struggle to access credit due to strict conditions imposed by banks. Digital lending firms, in turn, face substantial losses from non-performing loans [23]. More than 50% of loans issued by digital lenders in Kenya are defaulted, and these companies typically assess borrowers' willingness rather than their ability to repay [18]. This exposure to credit risk threatens the financial stability of institutions. In 2021, over 15 digital lending companies in Kenya experienced a rise in non-performing loans, forcing some to close. The proportion of non-performing loans increased from 13.9% in 2020 to 14.6% in 2021, and then to 14.9% in 2022.Credit risk is a major factor affecting the profitability of financial institutions, as poor credit controls, including inadequate credit analysis of borrowers, increase credit risk [1,4]. While several studies have focused on the impact of credit risk analysis on banks' financial performance, there is limited research on digital lending companies in Kenya. This study aims to address this gap by examining the effect of credit risk on the financial performance of digital lending companies in Kenya.

1.2 Research Objective

The general objective of the study was to establish the effect of credit risk on loan performance of digital lending companies in Kenya and the specific objective were: to examine the effect of risk identification on the loan performance of digital lending companies in Kenya, to examine the effect of risk quantification on the loan performance of digital lending companies in Kenya and to examine the effect of risk measurement on the loan performance of digital lending companies in Kenya.

1.3 Research Hypothesis(es)

This study was guided by the following null and alternative hypothesis tested at 0.05 level of significance.

H_{01}: Risk identification does not have a significant effect on loan performance of digital lending companies in Kenya.

H_{A1}: Risk quantification and risk measurement have a significant effect on the loan performance of digital lending companies in Kenya.

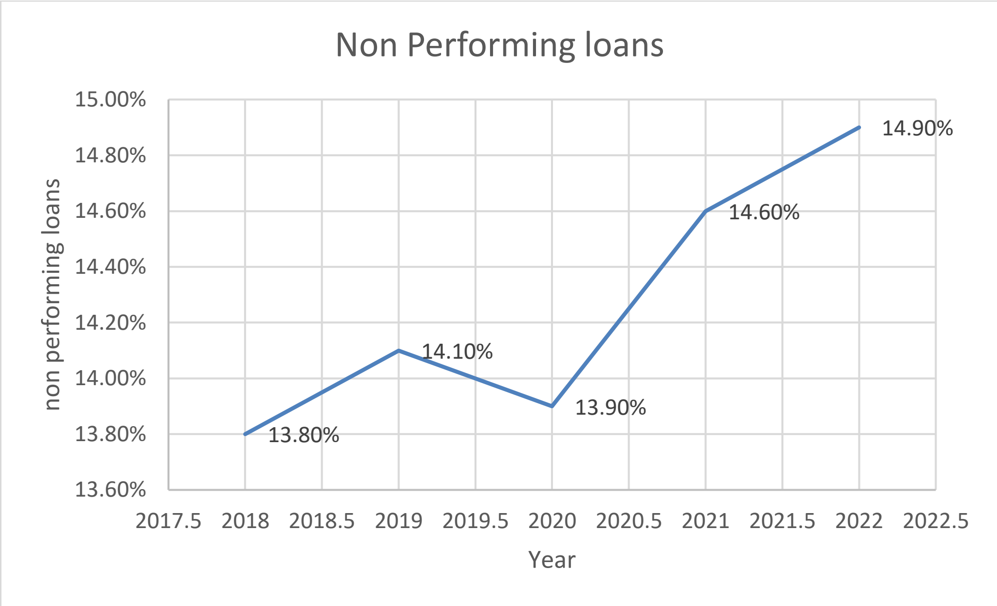

Fig. 1. Non performing loans of digital companies in Kenya

1.4 Justification of the Study

This study aims to provide valuable contributions to practitioners, policymakers, and scholars in the field of digital lending in Kenya. The findings are expected to help digital lending companies adopt and implement effective credit risk management strategies, enhancing financial performance and project success. The study's insights could guide regulators, such as the Central Bank of Kenya, in enforcing stringent measures to mitigate credit risks. This research is anticipated to provide valuable insights into credit risk management and loan performance within digital lending firms. Additionally, it aims to enhance the current understanding of how credit risk affects the financial performance of these companies and may serve as a resource for scholars pursuing related studies.

2. LITERATURE REVIEW

Impact of credit risk management practices on loan performance: This study explores three key theories relevant to the study on credit risk management in digital lending companies in Kenya: Modern Portfolio Theory, Asymmetric Information Theory, and Stewardship Theory.

Developed by Markowitz in 1952, Modern Portfolio Theory (MPT) offers a framework for maximizing investment returns while minimizing risk. It posits that asset prices fluctuate randomly and advocates for a portfolio approach to managing risk and return. Investors should diversify their portfolios to reduce risk and increase potential returns, rather than evaluating assets in isolation. According to DeLlano-Paz et al. [24], risk models are essential for managing credit exposures and mitigating financial performance impacts due to credit concentrations. MPT emphasizes that the risk and return of an asset should be assessed in the context of its contribution to the overall portfolio. Runting et al. [25] support this by suggesting that combining assets with negative or low positive correlations can reduce overall risk. Financial institutions often use MPT and associated risk models, such as the Value at Risk (VaR) model, to manage market and interest rate risks effectively. The theory's relevance to the present study lies in its application to portfolio diversification, risk management, and financial performance evaluation in digital lending.

Asymmetric Information Theory, as described by Turki [26], addresses the issue of uneven information distribution among market participants. This theory highlights the challenges arising when borrowers and lenders do not have access to the same information, leading to potential adverse selection and moral hazard. Zhou and Xu [27] suggest that lenders can mitigate these issues by acquiring comprehensive borrower information, such as credit history and cash flow evidence. Davis et al. [28] argue that reducing information asymmetry is crucial for minimizing non-performing assets

(NPA) and improving portfolio quality. The theory is pertinent to the current study because it underscores the importance of symmetric information in credit risk management and emphasizes the need for effective credit appraisal methods to enhance loan performance.

Stewardship Theory, articulated by Chrisman (2019), posits that organizational managers should act as stewards of the assets they oversee, aligning their personal goals with organizational objectives to maximize shareholder value. The theory advocates for managers to safeguard the organization's future and integrate their efforts with the firm's goals. Effective credit risk management is crucial for maintaining organizational performance and minimizing non-performing loans (NPLs). Managers are expected to leverage the stewardship theory to enhance loan performance and achieve organizational success. This theory's relevance to the study lies in its potential to guide managerial practices in digital lending companies, focusing on how stewardship can promote better credit risk management and overall financial performance. In summary, these theories provide a comprehensive understanding of different aspects of credit risk management. Modern Portfolio Theory offers insights into portfolio diversification and risk reduction, Asymmetric Information Theory highlights the importance of information symmetry for reducing adverse selection, and Stewardship Theory emphasizes the role of managers in enhancing organizational performance through effective credit risk management. Each theory contributes to a nuanced understanding of how digital lending companies in Kenya can optimize their credit risk management strategies.

Literature review explores empirical studies addressing the research objectives of credit risk identification, quantification, measurement, and assessment, and their impact on the financial performance of digital lending companies.

Maurishia (2021) examined the effect of credit risk management on loan performance in Ugandan commercial banks, specifically Tropical Bank. Utilizing a cross-sectional design and a survey of 80 respondents from four branches in Kampala, the study found a significant relationship between loan performance and risk identification, emphasizing that effective risk identification and control improve loan outcomes. Risk assessment, credit risk analysis, and management positively influence loan performance according to regression analysis.

Aboutorab et al. [29] investigated the suitability of risk identification techniques in a networked environment, emphasizing improvements needed for supply chain risk managers. The study, through a survey design, identified proactive techniques as crucial for effective risk identification in global supply chains.

Kalu et al [30] focused on credit risk management and the financial performance of microfinance institutions (MFIs) in Kampala. By analyzing primary data from questionnaires and secondary data from annual reports using frequencies and descriptive statistics, they found that credit risk identification and assessment had a strong positive association with financial performance, while risk monitoring and mitigation showed a moderate positive impact.

Aduda and Obondy [31] reviewed literature on credit risk management and the efficiency of savings and credit cooperative societies (SACCOs). Their desktop research indicated an impact of credit risk management on financial performance, though the relationship to SACCO efficiency remains inconclusive. Shang et al. [32] developed a credit risk identification method for clients based on rough set theory, addressing issues in EPC projects in China. Their model, tested with data from 120 companies, proposed improvements in credit risk identification by reducing redundant information and clarifying decision criteria. Mutembei and Gitonga [33] studied the effect of credit risk identification on loan repayment performance in SACCOs in Meru, Kenya. Using a correlation research design, they concluded that effective risk identification enhances loan repayment and recommended establishing clear risk reporting processes and staff training.

Kabutiei et al [34] explored the connection between risk assessment and project effectiveness within Kenya's National Irrigation Authority. Their study revealed a significant positive relationship, suggesting that improved risk identification practices enhance project performance. Fozia [35] investigated risk identification in the supply chain of Kenya's construction sector, specifically at ITS GOVINDA SONS (K) LIMITED. Regression analysis showed that risk identification methodologies explained 49.9% of the variation in supply chain performance.

Zhan and Su [36] conducted a comprehensive study on small micro-enterprise credit risk quantification. Utilizing logit regression and RAROC models, they recommended maintaining reasonable interest rates based on default risk levels to manage credit risk effectively. Jacobs (2018) examined asset price bubbles and credit risk capital quantification using sensitivity analysis and stress testing. The study found that traditional measures underestimated extreme credit losses, whereas the EHPCL measure provided a more accurate assessment. Lagat (2018) investigated the impact of risk evaluation on the performance of financial institutions. The study involved managers from various financial institutions and found a positive correlation between risk assessment and performance, suggesting that robust risk evaluation enhances overall performance. Jiao et al. [37] used the DEMATEL model and Bayesian network for risk quantification and analysis. Their approach improved the efficiency of risk analysis and highlighted the importance of coupled risk factors in system safety.

Mwangi and Muturi (2018) explored how credit risk management impacts loan repayment in Kenyan commercial banks. Their cross-sectional study showed significant positive connections between credit regulations, risk identification, and debt collection processes on loan repayment effectiveness. Agaba [38] studied credit risk management practices and loan performance in Ugandan commercial banks, finding strong correlations between credit risk management practices and loan performance. The study highlighted the need for specialized personnel to forecast and assess credit risks effectively. Ouma, Sang, and Kinoti [39] investigated the effect of risk analysis on project performance in Kenyan commercial banks, focusing on IT projects. They discovered that risk analysis significantly influenced project performance, with risk culture and project complexity playing moderating roles.

Kis et al. [40] used a model-based quantification approach to assess how new manufacturing technologies impact vaccine supply chains in Kenya. Their study demonstrated significant cost reductions and feasibility improvements through advanced manufacturing technologies. Chen et al (2020) developed a model for credit risk measurement and early warning for SMEs in China. Their updated KMV model provided stable prediction accuracy and highlighted that asset size impacts credit risk significantly. Wu [41] investigated credit risk measurement and decision analysis in the context of big data. The study highlighted the potential of big data to enhance risk measurement and transformation in the financial sector. Jingming et al. [42] focused on credit risk measurement for small and micro enterprises using an integrated algorithm combining Extreme Learning Machine and Good Point Set Adaptive Glowworm Swarm Optimization. Their model tailored credit risk measurement to the characteristics of small enterprises in a big data environment.

Nyong'o (2018) studied the relationship between credit risk management and non-performing loans in Kenyan commercial banks. The study found that robust credit risk management systems contribute to lower non-performing loans and improved credit assessment.

Muigai and Maina [43] explored the impact of credit risk management practices on the performance of Kenyan commercial banks. Their descriptive study showed a positive correlation between risk management practices and financial performance. Mutua [44] examined how risk management techniques affected core banking system projects in Kenyan banks. The study concluded that effective risk management positively impacted project performance, emphasizing the importance of thorough risk identification and analysis. This comprehensive review underscores the importance of credit risk management across various dimensions, highlighting its impact on financial performance in diverse contexts.

3. METHODOLOGY

A research design outlines a strategy for collecting and analyzing data, ensuring coherence within a study [45]. This study employed a descriptive research design to explore credit risk management and loan performance among digital lending companies in Kenya. The study applied descriptive as well as analytical research design which incorporate correlational and explanatory research design. Descriptive research design effectively addresses the how, where, what, and when of research questions, and accurately depicts the research problem. It was used here to describe and analyze the relationship between independent variables (risk identification, quantification, and measurement) and the dependent variable (loan performance).

The study focused on all digital lending companies in Kenya, totaling 108 as reported by the Kenya Private Sector Alliance (2021). Each company was represented by one participant, specifically a credit manager, leading to a total target population of 108. Given the manageable size, a census approach was utilized without sampling.

Data was collected using questionnaires and a reliable questionnaire yields the same results under consistent conditions. Validity refers to the extent to which a questionnaire measures what it claims to measure, a suitable method for gathering primary data due to their objectivity and ease of understanding. The questionnaires were divided into two sections: Section A covered demographics and job position, while Section B addressed the independent and dependent variables. Responses were measured on a 5-point Likert Scale, ranging from "Strongly disagree" to "Strongly agree," to ensure reliable and credible data.

3.1 Research Findings and Data Analysis

The study employed the "1drop and 1pick later" method for distributing and collecting questionnaires. This approach was chosen to ensure respondents had sufficient time to complete the questionnaires, thus enhancing the reliability and credibility of the study. After distribution, the questionnaires were collected two weeks later.

Upon collection, the researcher reviewed the completed questionnaires for errors and adherence to instructions. Data analysis was carried out using Statistical Package for Social Sciences (SPSS) Version 20, incorporating descriptive statistics, correlation analysis, and regression analysis. The findings were visually presented using pie charts, bar charts, and frequency distribution tables.

The regression model used was:

$$Y = \beta 0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon$$

Where:

Y= Loan performance
β0= Constant
β1 to β3 =Coefficients
X1 = risk identification
X2= risk quantification
X3 = risk measurement
ε =Error term.

3.2 Ethical Considerations

Before data collection, the researcher obtained approval from Kenyatta University Graduate School and ethical clearance from the Kenyatta University Ethics Review Committee (KUERC). A research permit was also secured from the National Commission for Science, Technology and Innovation (NACOSTI). Additionally, approval was sought from the Digital Lenders Association of Kenya to collect data from digital providers. Participants were given an informed consent form and an introduction letter to review and sign before agreeing to participate in the study.

Several diagnostic tests were conducted to ensure the validity of the regression assumptions:

Normality Test: To confirm if the residuals were normally distributed, the Shapiro-Wilk test was applied. A p-value > 0.05 indicated normal distribution, while a p-value < 0.05 suggested non-normality, leading to the rejection of the null hypothesis.

Multicollinearity: This test assessed the presence of high inter-correlations among independent variables. The Variance Inflation Factor (VIF) was used to measure multicollinearity severity. A VIF above 1 indicated some correlation, with values between 5 and 10 suggesting problematic multicollinearity.

Heteroscedasticity: To ensure constant variance of residuals, the Breusch-Pagan test was employed. A p-value < 0.05 indicated heteroscedasticity, suggesting that the assumption of constant variance was violated.

Autocorrelation: Refers to the correlation of a variable with itself over successive time intervals. In the context of regression analysis, it often pertains to the residuals (or error terms) from a regression model. The Durbin-Watson test was used to detect autocorrelation in the error terms. The test helps identify if there are sequential relationships in the residuals, which could affect model efficiency and standard error estimates.

These tests collectively ensured the robustness of the regression analysis, addressing potential issues related to data distribution, variable correlation, residual variance, and error term relationships.

4. RESULTS AND DISCUSSION

4.1 Response Rate

The number of queries that were submitted to credit managers of digital credit providers in Kenya were 108.

The outcomes revealed that 79.63% of the responders gave back their questionnaires fully filled while 20.37% never responded. Woolf and Edwards [46], indicated that response rate above 70% is considered extremely good. This infers that the response rate of 79.63 is extremely good for the investigation.

4.2 Descriptive Statistics

Descriptive Statistics on Risk Management and Loan Performance in Digital Credit Firms.

This study examines the descriptive statistics for both independent and dependent variables related to risk management practices and loan performance among digital credit firms in Kenya. The focus is on risk identification, risk quantification, and risk measurement, and how these factors influence loan performance.

The descriptive statistics for risk identification suggest that a majority of digital credit firms actively engage in identifying and mitigating credit risks. Specifically, 62.8% of respondents agreed that their firms identify credit risks and mitigate them, with an average response of 3.57 and a standard deviation of 1.24. This implies that most digital credit firms are proactive in managing credit risk. Additionally, 63.9% of respondents agreed that their firms check a client's credit history to identify credit risks, with an average response of 3.37 and a standard deviation of 1.48. This indicates that a substantial number of firms prioritize assessing client credit history before extending credit. Furthermore, 61.6% of respondents agreed that their firms keep updated financial records for clients to help identify potential risks, with an average response of 3.72 and a standard deviation of 1.18. This suggests that maintaining updated financial records is a common practice among digital credit firms to identify potential risks. Moreover, 80.2% of respondents agreed that their firms rely on credit information sharing to identify potential risks among clients, with an average response of 3.94 and a standard deviation of 1.16. This highlights the importance of credit information sharing as a tool for risk identification.

A significant majority, 76.7% of respondents, also agreed that their firms engage internal and external auditors to identify risks, with an average response of 3.91 and a standard deviation of 1.10. This demonstrates that engaging auditors is a key strategy for risk identification. When asked about the influence of credit risk identification on loan performance, 53% of respondents indicated that it has a great extent of influence, 22% indicated a very great extent, 20% indicated a moderate extent, and 5% indicated a little extent. These findings are consistent with previous studies, such as those by Mutembei and Gitonga [33] and Maurishia (2021), which highlight the impact of credit risk identification on loan performance. Descriptive statistics for risk quantification show that a majority of digital credit firms quantify their risk profiles. About 73.3% of respondents agreed that their firms quantify the company's risk profile, with a mean of 3.83 and a standard deviation of 1.29. This suggests that risk quantification is a widely practiced activity. Furthermore, 81.3% of respondents agreed that their firms apply Factor Analysis of Information Risk (FAIR) in quantifying risk, with a mean of 4.08 and a standard deviation of 1.14. This indicates a high level of agreement on the use of FAIR in risk quantification. Additionally, 76.7% of respondents agreed that brainstorming is an effective method of quantifying risk, with a mean of 3.88 and a standard deviation of 1.16. This shows that brainstorming is frequently used for risk quantification. Moreover, 67.4% of respondents agreed that their firms weigh and prioritize risk events and clients, with an average response of 3.50 and a standard deviation of 1.22. This suggests that prioritizing risk events is a common practice among digital credit firms.

Table 1. Response Rate

Response	Frequency	Percentage
Returned	86	79.63%
Unreturned	22	20.37%
Total	**108**	**100%**

A high percentage, 87.2%, of respondents agreed that sensitivity analysis is frequently used to quantify the amount of risk, with a mean of 4.08 and a standard deviation of 1.09. This further confirms the importance of sensitivity analysis in risk quantification. These findings align with those of Lagat (2018), who demonstrated a positive impact of risk assessment on the performance of financial institutions. When asked about the influence of risk quantification on loan performance, 81% of respondents indicated it has a great extent of influence, 7% indicated a moderate extent, and 5% indicated a little extent. This underscores the significant role of risk quantification in influencing loan performance.

Descriptive statistics for risk measurement indicate that digital credit firms employ various strategies to measure risk effectively. About 66.3% of respondents agreed that their firms can detect the number of times losses occur during a specific period, with an average response of 3.60 and a mean of 1.54. Similarly, 65.1% of respondents agreed that their firms review client loan repayment patterns, with an average response of 3.60 and a mean of 1.54. This suggests that reviewing repayment patterns is a common practice for risk measurement. Furthermore, 77.9% of respondents agreed that their firms can detect the maximum probable loss in each period, with an average response of 3.84 and a mean of 1.34. This shows that detecting maximum probable loss is an important aspect of risk measurement.

Additionally, 73.3% of respondents agreed that their firms can detect any risk of a downturn in the company, with an average response of 3.90 and a mean of 1.29. This highlights the emphasis on detecting downturn risks as part of risk measurement. Finally, 61.6% of respondents agreed that their firms constantly measure the borrowers’ cash flow, with an average response of 3.90 and a mean of 1.29. These findings are consistent with the study by Chen, Wang, and Wu (2020), which found that credit risk measurement significantly impacts loan performance. When asked about the influence of risk measurement on loan performance, 81% of respondents indicated it has a great extent of influence, 9% indicated a moderate extent, and 4% indicated a little extent.

The descriptive statistics for loan performance reveal that 58.2% of respondents disagreed that their firms have many non-performing loans, with an average response of 2.58 and a standard deviation of 1.67. However, 83.7% of respondents agreed that the abandoned loan rate is high, with an average response of 4.08 and a standard deviation of 1.16. This suggests that while non-performing loans are not widespread, abandoned loans are a significant issue. Additionally, 72.1% of respondents agreed that the average origination value was high, with an average response of 3.81 and a standard deviation of 1.27, and 72.1% agreed that the risk-adjusted return on capital was high, with an average response of 3.81 and a standard deviation of 1.18. This indicates that digital credit firms experience high origination values and risk-adjusted returns on capital. Data on the amount of loans issued by digital lending firms in Kenya show a fluctuating trend, with a notable decline in 2021, likely due to the COVID-19 pandemic. Similarly, the amount of loans defaulted followed a similar trend, with a decline in defaults in 2022 and 2023 after a peak in 2020 and 2021. The study's findings underscore the importance of effective risk management practices—risk identification, quantification, and measurement—in influencing loan performance among digital credit firms. By focusing on these areas, firms can enhance their ability to manage credit risk and improve loan performance outcomes.

4.3 Correlation Analysis

The study found a positive and significant association between risk identification and loan performance (r=0.523, p=0.000), indicating a moderately strong correlation. This supports Maurishia (2021) and Mutembei and Gitonga [33], who noted that effective risk identification and understanding credit risk positively impact loan repayment. Similarly, risk quantification showed a positive and significant correlation with loan performance (r=0.668, p=0.000), aligning with Lagat (2018) who highlighted its positive effect on financial institutions' performance. Additionally, risk management also had a positive and significant association with loan performance (r=0.523, p=0.000), consistent with Chen, Wang, and Wu (2020) who found that credit risk measurement affects loan performance.

Table 2. Correlation analysis

		loan performance	Risk identification	risk quantification	risk management
loan performance	Pearson Correlation	1			
	Sig. (2-tailed)				
risk identification	Pearson Correlation	.523**	1		
	Sig. (2-tailed)	0.000			
risk quantification	Pearson Correlation	.668**	.441**	1	
	Sig. (2-tailed)	0.000	0		
risk management	Pearson Correlation	.573**	.230*	.382**	1
	Sig. (2-tailed)	0.000	0.033	0	

Table 3. Regression analysis

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	-0.441	0.378		-1.166	0.247
risk identification	0.288	0.086	0.256	3.355	0.001
risk quantification	0.461	0.088	0.421	5.234	0.000
risk management	0.374	0.078	0.353	4.765	0.000

4.4 Regression Analysis

The regression analysis results demonstrate that the model effectively explains the study's phenomena, with an R-squared value of 0.617. This indicates that risk identification, quantification, and measurement account for 61.7% of the variations in loan performance. Agaba [38] supports this, highlighting a significant positive correlation between credit risk management procedures and loan performance. The model's overall statistical significance is confirmed by an F statistic of 44.1 and a p-value of 0.000, which is below the 0.05 significance threshold. Muigai and Maina [43] further reinforce these findings, noting that the financial performance of commercial banks in Kenya is significantly and positively related to risk measurement, lending requirements, credit management instruments, and loan recovery processes.

4.5 Model Summary

The study tested hypotheses regarding the impact of risk-related factors on loan performance in digital lending companies in Kenya.

Risk identification has a significant impact on loan performance. The results indicated a positive and significant relationship (β=0.228, p=0.001), leading to the rejection of the null hypothesis. This finding is consistent with the work of Maurishia (2021) and Mutembei and Gitonga [33], who demonstrated that effective risk identification positively influences loan performance and repayment.

Similarly, risk quantification also significantly affects loan performance. The analysis revealed a strong positive association (β=0.461, p=0.000), resulting in the rejection of the null hypothesis. This aligns with Lagat (2018), who found that risk assessment significantly enhances the performance of financial institutions.

Moreover, risk management significantly influences loan performance. The study identified a substantial positive relationship (β=0.374, p=0.001), which led to the rejection of the null hypothesis. This finding supports the conclusions of Chen, Wang, and Wu (2020), indicating that effective risk management improves loan performance [47-51].

Table 4. Model summary

Research Objective	Hypothesis	Rule	p-value	Results
To examine the effect of risk identification on the loan performance of digital lending companies in Kenya.	Risk identification does not have a significant effect on loan performance of digital lending companies in Kenya.	Reject H_0 if p value <0.05	P=0.000	The null hypothesis was **rejected**.
To examine the effect of risk quantification on the loan performance of digital lending companies in Kenya.	Risk quantification does not have a significant effect on loan performance of digital lending companies in Kenya.	Reject H_0 if p value <0.05	P=0.000	The null hypothesis was **rejected.**
To examine the effect of risk measurement on the loan performance of digital lending companies in Kenya.	Risk measurement does not have a significant effect on loan performance of digital lending companies in Kenya.	Reject H_0 if p value <0.05	P=0.000	The null hypothesis was **rejected.**

Source: Research Data (2023)

5. CONCLUSIONS

The study concluded that effective risk management significantly improves loan performance in digital lending firms. Specifically, risk identification is crucial; identifying risks early allows credit managers to analyze potential qualitative and quantitative impacts, leading to appropriate mitigation strategies. The study also found that risk quantification positively affects loan performance. Understanding risk sources more comprehensively through techniques like company brainstorming enhances performance by enabling firms to anticipate and prepare for potential losses. Additionally, risk measurement, particularly detecting the maximum probable loss and monitoring borrowers' cash flows, was shown to be essential in preventing loan defaults. This proactive approach helps digital lending firms avoid defaults, ultimately leading to better loan performance. The findings underscore the importance of comprehensive risk management practices in enhancing the financial stability and operational success of digital lending firms.

6. RECOMMENDATIONS

To prevent confusion between risk identification and other risk-related tasks, it is crucial to clearly define each risk. Practitioners and policymakers should assign a unique number to every identified risk. The study recommends that digital lending firms establish a robust institutional framework for effectively identifying risks associated with loans. Additionally, digital lending companies should ensure timely communication of identified risks to management.

The Central Bank of Kenya, as the regulator of digital lending firms, should ensure these firms are continuously identifying new risks and planning accordingly. Managers of digital lending firms should monitor emerging risks, address long-term risks through strategic risk action plans, and regularly reassess current risks to determine if conditions have changed.

Credit managers in digital lending firms should measure lending risks regularly and proactively, rather than reactively, to enhance loan performance. Firms should also be capable of detecting the maximum probable loss in each period.

The study's findings indicate that the R-squared value was not 100%, suggesting that some aspects of credit risk management were not covered. Future research should explore other credit risk management strategies, such as risk assessment and risk evaluation, and their impact on the loan performance of digital lending companies in Kenya.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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