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Digital Credit Scoring Practices And Loan Performance In Commercial Banks In Nakuru County, Kenya

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ABSTRACT
Non-performing loans have been a monumental challenge to the banking sector for long and despite some commercial banks going digital loan delinquency has continued to be experienced. For example based on the CBK, bank supervision report, it was noted that, after adopting digital lending NCBA continued recording an increase in NPLs where it recorded an increase in gross NPLs by 262 percent to Ksh. 35.3 billion in 2022 from Ksh. 9.74 billion in 2014. From the CBK bank supervision report, it is clear that, the four early adopters of digital lending continued recording an increase in gross NPLs even after embracing financial technology in lending. Therefore the study sought to determine the effect of digital credit scoring practices on loan performance of commercial banks in Kenya. The study adopted descriptive design. The target population for this study consisted of the 29 commercial banks that are in operation within Nakuru County, Kenya. This study sampled 29 Nakuru County commercial banks. The survey censused Nakuru County's 29 commercial banks. Based on the CBK bank supervision report for the year 2022, the 29 Commercial Banks had a total of 61 branches operating within Nakuru County. Heads of credit departments for the 61 branches were the respondents to the study. This study sampled 29 Nakuru County commercial banks. The survey censused Nakuru County's 29 commercial banks. Heads of credit departments for the 61 branches were the respondents to the study. The data collection instrument was pretested in order to ensure their reliability and validity. Reliability was determined using the Cronbach alpha coefficient analysis. Data was analyzed using SPSS. Descriptive and inferential statistics studied data. Descriptive statistics included frequencies, percentages, means, and standard deviations. Multiple regression and Pearson product moment correlation coefficient were inferential statistics. Pearson product moment correlation coefficient was used to assess digital credit risk management strategies and commercial bank loan performance. Multiple regression analysis was utilized to investigate how digital credit risk management affects commercial bank loan performance. Null hypotheses were tested. In summary, the findings of the study revealed that, commercial banks verify the credit history of prospective borrowers when approving digital credit. It was also noted that the purpose of the loan is factored in before advancing digital credit facility. On the other hand, it was noted that first digital borrowers are approved within a short period of time. The study also revealed that borrowing frequency of digital loan borrowers is factored in before advancing digital credit facility. The study concluded that borrowing frequency of digital loan borrowers is factored in before advancing digital credit facility. Borrower loan repayment history was noted to be a critical factor before approving digital credit facility. It was discovered that it takes a short period to disburse digital credit once approval process is over. The study concluded that there was a moderate positive and statistically significant correlation between digital credit scoring practices on loan performance in Commercial Banks in Nakuru County, Kenya.
Key Words: *Digital Credit Scoring Practices, Loan Performance, Commercial Banks*

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I. INTRODUCTION

Digital credit scoring practices refer to the use of digital data and technology to assess the creditworthiness of individuals or businesses seeking loans or credit (Chakravorti & Palacios, 2017). Traditional credit scoring methods have relied on factors such as credit history, income, and employment status. However, with the proliferation of digital technology and the availability of vast amounts of data, financial institutions and alternative lenders have increasingly turned to digital credit scoring to enhance their risk assessment processes (World Bank Group, 2018) Traditional credit scoring models often rely on historical financial data, such as credit history, income, and employment records. In contrast, digital credit scoring leverages a broader range of data sources, often including digital footprints, online behavior, and alternative data points to evaluate an applicant's creditworthiness (De Roure & Hedley, 2018).

Digital credit scoring incorporates a diverse range of data points, including transaction history, online behavior, and social media activity (Cui & Li, 2019). This comprehensive data analysis allows lenders to gain a better understanding of an applicant's financial behavior and repayment capacity. As a result, lenders can make more accurate assessments of an applicant's creditworthiness, leading to better loan performance. One of the significant advantages of digital credit scoring is its potential to extend credit to underserved populations. By considering alternative data sources beyond traditional credit reports, lenders can evaluate the creditworthiness of individuals who lack a formal credit history. This promotes financial inclusion and provides opportunities for those who would otherwise be excluded from the lending process (Martinez-Jerez & Xie, 2017).

Digital credit scoring models continuously monitor borrower behavior and financial patterns. This real-time monitoring enables lenders to identify early warning signals of potential default. For example, sudden changes in spending habits or online activity may indicate financial distress, allowing lenders to take proactive measures to prevent defaults (Shen & Shi, 2020). Traditional credit scoring models often provide a static snapshot of an applicant's creditworthiness at a specific point in time. In contrast, digital credit scoring practices offer dynamic risk assessment by considering real-time data. This adaptability allows lenders to adjust credit limits, interest rates, or terms based on a borrower's evolving financial situation, thereby reducing the risk of default. Digital credit scoring can also contribute to better fraud detection. By analyzing various data sources, lenders can detect inconsistencies or irregularities that may indicate fraudulent activities. This helps mitigate the risk of lending to fraudulent applicants, ultimately improving loan performance (Restrepo, Sakkas & Seru, 2021)

In the United States, digital credit scoring practices have been widely adopted by commercial banks and alternative lenders. These practices involve leveraging alternative data sources, such as transaction history, online behavior, and social media activity, to assess the creditworthiness of borrowers. By incorporating a broader range of data, lenders can enhance their risk assessment capabilities, potentially leading to improved loan performance and better management of default risks. However, the use of alternative data sources and digital credit scoring in the U.S. has also raised concerns about privacy, data security, and potential bias in lending decisions. Regulatory frameworks, such as the Fair Credit Reporting Act (FCRA), play a significant role in shaping how digital credit scoring is conducted while ensuring fairness and consumer protection (CFPB (Consumer Financial Protection Bureau, 2020).

China has seen rapid growth in digital credit scoring practices, driven by the country's extensive digital economy and the availability of large volumes of consumer data. Digital credit scoring models in China often rely on data from e-commerce platforms, mobile payment systems, and other digital transactions (Huang & Ye, 2019). These practices have contributed to expanding access to credit for individuals who lack traditional credit histories, especially in underserved rural areas. The digital credit landscape in China is unique due to the prevalence of mobile payment platforms and the integration of financial and non-financial data. The Chinese government has also introduced regulatory measures to manage the use of alternative data and ensure responsible lending practices.

In South Africa, digital credit scoring practices have the potential to address the challenges of financial inclusion and access to credit. The country's diverse population and varying levels of financial infrastructure make digital credit scoring a valuable tool for assessing creditworthiness beyond traditional methods. Digital credit scoring practices in South Africa may involve analyzing transaction data, telecommunications records, and other alternative data sources. These practices enable lenders to evaluate the creditworthiness of individuals who may not have a formal credit history. However, like in other regions, concerns about data privacy, security, and potential bias remain important considerations in the implementation of digital credit scoring practices (Majeed, 2019).

Tanzania, like many other developing countries, has experienced a growth in mobile and digital technologies, particularly with the widespread use of mobile phones and mobile money services (Bank of Tanzania, 2021). This digital infrastructure provides an opportunity to leverage alternative data sources for credit scoring. Digital credit scoring practices could involve analyzing mobile money transaction history, telecommunications records, and other digital behavior to assess creditworthiness (Kavishe & Magesa, 2019). Digital credit scoring in Tanzania extend credit to individuals who have limited or no access to formal banking services. By analyzing alternative data sources, banks have been able to assess the creditworthiness of individuals who lack traditional credit histories, thereby promoting financial inclusion (Magesa & Aikaeli, 2018).

Kenya's commercial banks have embraced digital credit scoring as a means of enhancing risk assessment. By tapping into alternative data sources, such as mobile money transactions, e-commerce activities, and social media interactions, lenders gain a more comprehensive view of a borrower's financial behavior (Jack & Suri, 2014). This multifaceted approach contributes to a more accurate evaluation of credit risk, enabling banks to make informed lending decisions. As a result, loans are more precisely tailored to the borrower's capacity to repay, potentially leading to improved loan performance (Mulwa & Govender, 2017). A pivotal advantage of digital credit scoring is its potential to foster financial inclusion. Kenya's digital credit landscape has extended access to credit for previously underserved segments of the population. Individuals with limited or no formal credit history can now be assessed based on their digital footprints, bridging the gap between traditional banking systems and those on the fringes. (Tsofa, Asiki & Were, 2017). This inclusive approach not only empowers borrowers but also contributes to a more diversified loan portfolio for commercial banks (Central Bank of Kenya, 2021).

II. LITERATURE REVIEW

Asymmetric Information Theory

The study was guided by asymmetric information theory. The theory of asymmetric information was put forward by Akerlof and Spence in 1970s (Akerlof, 1970; Spence, 1973). Asymmetric information theory states that there is often an imbalance of information between sellers and buyers (between lenders and borrowers). According to the theory, one party in the lenders and borrowers relationship has more or better information than the other. Increased information asymmetry or uncertainty leads to borrowers relinquishing greater control rights to lenders (Garleanu & Zwiebel, 2009). In the context of digital lending by commercial banks, it is very likely that the borrowers have greater and better information regarding their collateral, industriousness, moral integrity and credit worthiness better than the commercial banks do. This is a case of information asymmetry which is potentially detrimental to banks since they may fail to accurately appraise the creditworthiness of prospective borrowers on digital platforms and thus failure to determine the best credit terms to apply to specific customers. There is therefore a higher possibility that commercial banks might end up lending out loans to customers on digital platforms with high degree of defaulting.

Effect of Digital Credit Scoring Practices and Loan Performance

Muthoni, Mwangi & Muathe (2020) carried out a study on credit management practices and loan performance of commercial banks in Kenya. The study found out that lending policy and debt collection policy had a positive significant effect on loan performance. However, client appraisal had no significant effect on loan performance of commercial banks in Kenya. Therefore, the study concluded that commercial banks' loan performance could be largely attributed to the efficiency of the credit management practices put in place at the institutions.

Gatimu (2014) assessed Key factors causing Kenyan microfinance loan defaults. The exam regressed the loan default against the initial loan appraisal process, to establish the effect. The findings established a significance difference between the loan defaulting and loan appraisal process, thus loan assessment affected default. Mohammad and Onni (2015) examined credit risk grading methodology and commercial bank loan performance in Bangladesh. The investigation showed, when credit officers pay key attention on evaluating borrowers the level of poorly performing loans is minimized. This signifies that when proper credit scoring system is put in place it decreases chances of loan defaults which ultimately lead to reduced loan loss provisions.

Bichanga and Aseyo (2013) studied the causes of loan default in micro finance institutions in Trans-Nzoia County in Kenya. From the outcome of the research the researcher noted that taking too long to score and disburse requested loans reduces borrowers' morale and such borrowers are likely not to pay in time. This was attributed to delays in the commencement of the intended projects by the borrowers some of which failed in totality.

Murunga (2017), researched on the impact of mobile-based lending process on loan performance in commercial banks. The researcher evaluated how loan appraisal process affect NPLs. The study observed that loan appraisal process was the most important element of mobile-based loans in respect of NPLs. The findings of the study indicate that the loan appraisal process had a substantial relationship with NPLs. The researcher recommended that commercial banks should have a comprehensive process of appraising loans advanced via mobile platform in order to enhance the mechanisms of assessing creditworthiness of prospective borrowers.

Niaz and Azimun (2015), studied credit risk grading model and loan performance of commercial banks in Bangladesh. The findings of the study revealed that, due to the increase in the number of poorly performing loan accounts and competition in the lending arena, majority of commercial banks have strongly focused on credit risk assessment where loan appraisal is the initial stage in the lending process. It was acknowledged that indeed bankers preferred sophisticated financial technologies in credit scoring with the object of assessing both the borrower's business and financial position.

Sufi and Qaisar (2015) examined credit risk management and loan performance in Pakistani microfinance institutions. This study examined client evaluation. Research showed that client appraisal process impacted significantly on the loan performance (LP). This implies that credit appraisal is one of the major aspects that digital lenders ought to factor when scoring borrowers in order to enhance the performance of loans.

Eid, Maltby and Talavera (2016) studied the impact of income rounding on loan performance in the Peer-to-Peer market. The study used data from Lending Club (LC), the largest online lender in the U.S, to analyze the consequences of income rounding in terms of loans performance. The researcher found that, rounding of income by a borrower indicated a bad outcome for a loan. Borrowers with a rounding tendency were more likely to default and less likely to prepay than borrowers with more accurate income reporting. Ampofo and Dartey-Baah (2016) studied the link between quality of work life and productivity of loan disbursement in Ghana. The finding indicated a significant positive impact of credit officers' quality of work life on productivity of loan disbursement.

III. METHODOLOGY

This survey research was descriptive. This study used descriptive research to identify the relationship between digital credit risk management techniques and loan performance in commercial banks in Nakuru County, which might be extrapolated to a wider range of people. The unit of analysis of this study included all commercial banks operating in Nakuru County, Kenya. Murunga (2017), describes target population as subjects or parties who share similar characteristics. The target population for this study consisted of the 29 commercial banks that are in operation within Nakuru County, Kenya. This study sampled 29 Nakuru County commercial banks. This study's small, well-defined population makes a census better. Thus, the survey censused Nakuru County's 29 commercial banks. Based on the CBK bank supervision report for the year 2022, the 29 Commercial Banks had a total of 61 branches operating within Nakuru County. Heads of credit departments for the 61 branches were the respondents to the study.

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IV. RESULTS

Response Rate

The study administered 61 questionnaires for data collection. However, 55 questionnaires were properly filled and returned. This represented 90% overall successful response rate.

Digital Credit Scoring Practices on loan Performance

Commercial bank credit department heads were asked about digital credit scoring and loan performance. Table 4.9 shows responses.

Table 1: Digital Credit Scoring Practices on loan Performance

	SA	A	U	D	SD	Mean	Std
Statement	%	%	%	%	%		
Commercial banks verify the credit history of prospective borrowers before approving digital credit.	26	47	17	10	0	3.887	0.907
Purpose of the loan is factored in before advancing digital credit facility.	37	45	13	5	0	4.113	0.870
First digital borrowers are approved within a short period of time.	55	42	3	0	0	4.516	0.565
The borrowing frequency of digital loan borrowers is factored in before advancing digital credit facility.	57	37	6	0	0	4.500	0.621
The borrower loan repayment history is a critical factor before approving digital credit facility.	39	44	11	6	0	4.145	0.866
Disbursement of credit on mobile platform takes short time once approved.	68	23	2	4	3	4.258	0.886

The results showed that, 73% of the credit officers agreed that commercial banks verify digital borrower's credit history before approving their credit request with 3.887 mean and 0.907 std. 82% agreed that the loan objective is considered before providing electronic credit with 4.113 mean and 0.870 Std. In addition, 97% of the credit officers agreed that first time digital borrower's loan requests got an approval within a short period of time with a mean of 4.516 and Std of 0.565. It was also noted that 94% of the officers agreed that the borrowing frequency of digital loan borrowers is factored in before advancing digital credit facility with a mean 4.500 and Std of 0.621. The study findings are in line with those of Aduda and Gitonga, (2011) who found that lenders analyze the borrowing history of digital loan borrowers to evaluate their creditworthiness. This assessment includes factors such as repayment patterns, credit utilization, and frequency of previous borrowings. Borrowers with a positive repayment history and a responsible borrowing frequency are more likely to be considered lower risk, making them eligible for favorable credit terms and higher loan amounts.

In addition, 83% of the respondents confirmed that while approving digital credit, the borrower loan repayment history is a critical factor 4.145 mean and 0.866 std. It was also noted that most of the credit officers in agreement that disbursement of credit on mobile platform takes short time once approved (mean=4.258, SD=0.886). The standard deviation ranged from 0.565 to 0.907 indicating that the dispersion of the respondents from the mean was minimal. The study findings are in line with those of Murunga, (2017) who found that lenders evaluate the borrower's loan repayment history to assess their creditworthiness. A strong repayment history with timely and consistent repayments indicates a responsible borrower who is likely to fulfill their future loan obligations. On the other hand, a poor repayment history, such as late or missed payments, can raise concerns about the borrower's reliability and increase the perceived risk.

Table 2: Loan Performance in Commercial Banks in Nakuru County, Kenya

Loan Performance	SA (%)	A (%)	N (%)	D (%)	SD (%)	Mean	Std.
Digital loans default rate is similar to other forms of loans.	15	5	2	60	18	4.403	0.778
Banks have significant bad debts occasioned by digital loans.	54	30	8	5	3	4.307	0.738
Commercial banks keep on restructuring digital loan terms in order to address non-performing loans.	38	38	4	11	9	4.145	0.807
Loan loss provisions on digital credit have increased in the recent past.	43	34	7	5	11	4.387	0.869
Commercial banks have been negatively impacted by the significant write offs of non-performing digital loans.	60	32	5	3	0	4.48	.731
Commercial banks have charged penalties on significant number of digital loan accounts in arrears.	58	32	10	0	0	4.44	.729

The findings of the study noted that, 78% of the heads of departments agreed that digital loans have a higher default rate, with a mean of 4.403 and standard deviation of 0.778. 84% of officers stated that banks have considerable digital loan-related bad debts with a mean score of 4.307 and standard deviation of 0.738. Most department heads also acknowledged that commercial banks restructure digital loan terms to address non-performing loans with a mean of 4.145 and standard deviation of 0.807. According to Ahmed and Malik, (2015) banks identify digital loans that have become non-performing, typically based on predefined criteria such as missed payments or extended delinquency. These loans are flagged for further evaluation to determine the appropriate restructuring options. Grinblatt, and Titman (2014) revealed that lenders must comply with applicable legal and regulatory frameworks when charging penalties on loans. There may be limitations on the maximum penalty amounts or requirements for clear disclosure of penalty terms to borrowers. It's important for lenders to ensure that their penalty practices aren't against the laid down regulations by the relevant authorities on the country.

It was agreed by 77% of the department heads that loan loss provisions on digital credit has increased in the recent past 4.387 mean, 0.869 standard deviation. However, most department heads indicated that commercial banks have suffered from considerable write-offs of badly performing digital loans with a mean score of 4.48 and standard deviation of 0.731. Commercial banks penalized a high proportion of digital loan accounts in arrears with a mean of 4.44 and standard deviation of 0.729. Suri and Bharadwaj (2018) revealed that before initiating loan restructuring, banks assess the borrower's financial situation to understand the reasons behind the loan default or non-performance. They review the borrower's financial records, income sources, debt burden, and other relevant factors to gain insights into the borrower's ability to repay the loan.

Correlation Analysis

Using Pearson correlation analysis, digital credit scoring processes and loan performance in Commercial Banks in Nakuru County, Kenya, were investigated. Table 3 shows the results.

Table 3: Digital Credit Scoring Practices and Loan Performance

		Loan Performance
Digital Credit Scoring	Pearson Correlation (r)	.443*
	Sig. (2-tailed)	.000
	N	55

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

As shown in Table 2, digital credit scoring methods and loan performance at Commercial Banks in Nakuru County, Kenya were moderately positive and statistically significant ($r = 0.443$; $p < 0.05$). Digital credit scoring improves loan performance in Nakuru County, Kenya commercial banks.

Overall Model

Table 4 shows the overall significant test results for the hypothesized research model

Table 4: Regression Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.038	.145		.260	.796
	Digital credit scoring practices	.596	.107	.548	5.578	.023

The interpretations of the findings indicated the following regression model.

$Y= \beta_0 + \beta_1 X_1$

Therefore,

$Y= 0.038 + 0.596X_1$

The intercept (β0) predicts 0.038 for commercial bank loan performance in Nakuru County, Kenya, when the four independent variables are maintained constant. Digital credit scoring procedures boost loan performance by 0.596 units, holding all other independent variables constant.

V. DISCUSSION

In summary, the findings of the study revealed that, commercial banks verify the credit history of prospective borrowers when approving digital credit. It was also noted that the purpose of the loan is factored in before advancing digital credit facility. On the other hand, it was noted that first digital borrowers are approved within a short period of time. The study also revealed that borrowing frequency of digital loan borrowers is factored in before advancing digital credit facility. Moreover, the borrower loan repayment history is a critical factor before approving digital credit facility. Disbursement of credit on mobile platform takes short time once approved. The study findings are in line with those of Aduda and Gitonga, (2011) who found that lenders analyze the borrowing history of digital loan borrowers to evaluate their creditworthiness. This assessment includes factors such as repayment patterns, credit utilization, and frequency of previous borrowings. Borrowers with a positive repayment history and a responsible borrowing frequency are more likely to be considered as lower risk, making them eligible for favorable credit terms and higher loan amounts. The study findings are also in line with those of Muriki (2017), who found that lenders evaluate the borrower's loan repayment history to assess their creditworthiness. A strong repayment history with timely and consistent repayments indicates a responsible borrower who is likely to fulfill their future loan obligations. On the other hand, a poor repayment history, such as late or missed payments, can raise concerns about the borrower's reliability and increase the perceived risk.

VI. CONCLUSIONS AND RECOMMENDATIONS

The study concluded that borrowing frequency of digital loan borrowers is factored in before advancing digital credit facility. Borrower loan repayment history was noted to be a critical factor before approving digital credit facility. It was discovered that it takes a short period to disburse digital credit once approval process is over. The study concluded that there was a moderate positive and statistically significant correlation between digital credit scoring practices on loan performance in Commercial Banks in Nakuru County, Kenya ($r = 0.443$; $p < 0.05$). It can therefore be concluded that, digital credit scoring enhances loan performance in Commercial Banks in Nakuru County, Kenya. From the findings and conclusions, the study recommended that, commercial banks should incorporate non-traditional data, such as mobile phone usage patterns, utility bill payments, and social media activities, to assess creditworthiness. This provides a more comprehensive view of a borrower's financial behavior. Further, the study also recommended that commercial banks should implement real-time monitoring of borrowers' credit profiles to identify any changes that may affect their creditworthiness. This allows banks to proactively manage potential risks and take timely actions, such as adjusting credit limits or interest rates. Moreover, commercial banks should establish partnerships with credit bureaus to access credit histories and share data on borrowers' repayment behavior. This enables a more holistic evaluation of creditworthiness and reduces the risk of lending to individuals with a history of defaults.

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