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Interest Rates, Appraisal Procedures And Non-Performing Loans Among Digital Lenders In Kenya

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Abstract
Background: *The rapid expansion of digital lending has transformed credit access in Kenya, yet non-performing loans (NPLs) remain a persistent challenge despite increasingly sophisticated borrower appraisal procedures. This study examined whether interest rates mediate the relationship between appraisal procedures and non-performing loans among licensed digital lenders in Kenya.*
Materials and methods: *Guided by Portfolio Theory, the study adopted a positivist research philosophy and employed a cross-sectional explanatory research design using both primary and secondary data. Primary data were collected through structured questionnaires administered to licensed digital lenders, while secondary data were obtained from audited financial statements and regulatory reports. Reliability and validity tests confirmed the adequacy of the research instruments. Data were analyzed using descriptive statistics, multiple regression, and mediation analysis.*
Results: *The findings indicate that appraisal procedures did not significantly predict non-performing loans ($B = 0.479$, $p = 0.450$), explaining less than one percent of the observed variation ($R^2 = 0.007$). Likewise, interest rates did not significantly mediate the relationship between appraisal procedures and non-performing loans (indirect effect = 0.029; 95% CI: −0.015 to 0.073).*
Conclusion: *Although appraisal procedures remain fundamental to credit risk assessment, interest rate adjustments alone are insufficient to improve loan performance. The study recommends integrating appraisal procedures with continuous borrower monitoring, behavioral analytics, and financial literacy interventions to strengthen credit risk management.*
Keywords: *Digital lending; credit risk; appraisal procedures; interest rates; non-performing loans; financial technology; Kenya*

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I. Introduction

Non-performing loans (NPLs) pose significant risks to financial institutions and the broader economy by reducing liquidity, eroding capital, and constraining lending capacity. High NPL levels increase borrowing costs and can contribute to economic instability, making effective credit risk management essential (Hassan, Sheikh & Rahman, 2022; Mukuru & Thuo, 2023; Njiraini, 2020). The growth of digital lending has transformed financial access, particularly in Kenya, where mobile-based platforms have expanded credit to underserved populations. Digital lenders utilize technology-driven appraisal procedures such as automated credit scoring, alternative data analytics, and Credit Reference Bureau (CRB) checks to assess borrower creditworthiness (Bazarbash & Beaton, 2020; World Bank, 2022). While these innovations have enhanced financial inclusion, concerns have emerged regarding rising NPLs, weak borrower screening, and regulatory challenges within the sector (CBK, 2022).

Interest rates also play a critical role in digital lending by influencing borrowing behavior, repayment capacity, and lender profitability. Higher interest rates may compensate for credit risk but can increase default likelihood, while lower rates improve affordability but may reduce returns (Wang & Liu, 2022; Muriuki & Wanjau, 2023). Digital lenders often apply risk-based pricing, charging higher rates to riskier borrowers; however, such pricing may exacerbate repayment challenges and contribute to rising NPLs (Ochieng & Atuma, 2023).

Despite advancements in appraisal techniques, NPLs in Kenya's digital lending sector continue to rise. The Central Bank of Kenya (2023) reports that NPL ratios increased from 13.2% in 2021 to 16.5% in 2023, with defaulted loans reaching KSh 12.8 billion. This trend raises concerns about the effectiveness of current appraisal procedures and the role of interest rates in influencing loan performance. While digital lenders rely on alternative data sources such as mobile usage and transaction histories to assess creditworthiness, these methods may not fully capture borrower risk (Mbiti & Weil, 2016; Gao & Lin, 2021).

Existing literature has largely focused on traditional banking institutions, with limited attention to digital lenders and the interaction between appraisal procedures and interest rate policies (Wanjiru & Ngugi, 2021). Consequently, there is insufficient empirical evidence on how these factors jointly influence NPLs in Kenya's digital lending sector. This study therefore investigated the effect of appraisal procedures on non-performing loans, as well as the moderating role of interest rates among digital lenders in Kenya.

II. Research Methodology

Study design: This study adopted a positivist research philosophy, which supports the objective measurement and analysis of social and financial phenomena using empirical data and statistical techniques (Saunders, Lewis, & Thornhill, 2019). An explanatory cross-sectional research design was employed to examine the relationships among appraisal procedures, interest rates, and non-performing loans (NPLs) in digital lending firms, allowing data collection at a single point in time and facilitating hypothesis testing.

Target population: The study targeted all 85 digital lending firms licensed by the Central Bank of Kenya as of 2024, and a census approach was used to ensure full coverage and minimize sampling error (Kothari, 2004).

Data collection and type: Primary data were collected through structured questionnaires administered to credit officers or risk managers, while secondary data on interest rates, firm size, and NPLs were obtained from financial statements and regulatory reports. Reliability was assessed using Cronbach's alpha with a threshold of 0.7 (Mugenda & Mugenda, 2003), and validity was ensured through pilot testing and expert review (Creswell & Creswell, 2017).

Statistical analysis: Data were analyzed using descriptive statistics and multiple regression analysis to test direct and mediating effects.

The regression models used were:

Model 1 (Direct effect):

$$\mathbf{NPL} = \beta_0 + \beta_1 \mathbf{AP} + \epsilon$$

Model 2 (Mediated effect):

$$\mathbf{NPL} = \beta_0 + \beta_1 \mathbf{AP} + \beta_2 \mathbf{IR} + \epsilon$$

Where:
NPL = Non-performing loans
AP = Appraisal procedures
IR = Interest Rates (mediator)
β_0 = Constant term
β_1 = Regression coefficient
ε = Error term

This model was used to test the hypothesis that appraisal procedures significantly influence non-performing loans among digital lenders in Kenya.

III. Results And Discussions

Response Rate

This study conducted a census survey of all 85 licensed digital lending firms in Kenya. A total of 85 questionnaires were electronically distributed to the targeted respondents via Google Forms. To ensure a high response rate, multiple follow-up phone calls and reminder emails were made to all respondents. Out of the 85 questionnaires administered, all 85 were returned and verified for completeness, resulting in a 100% valid response rate. This excellent response rate enhances the reliability and generalizability of the study findings and reflects strong cooperation from the digital lending firms.

Table 1: Questionnaire Response Rate

Response Category	Frequency	Percentage (%)
Response Rate	85	100%
Non-response	0	0%
Total	85	100%

Source: Research Findings (2025)

The 100% response rate achieved in this study is consistent with the high response rates reported in previous census-based surveys in the financial sector, ensuring that the study results are robust and representative of the entire population of licensed digital lenders in Kenya.

Validity Test

The evidence of reliability and validity is a precondition for ensuring the quality and integrity of research measurement instruments (Saunders et al., 2013). The accuracy, credibility, and dependability of data largely depend on the reliability and validity of the data collection tools. Ensuring reliability and validity enhances transparency and minimizes researcher bias in empirical investigations. Conversely, the inability to assess reliability and validity may obscure the effect of measurement errors on the theoretical relationships under study (Cooper & Schindler, 2014).

To ensure the validity of the research instrument, three main types of validity were assessed: content validity, face validity, and construct validity. Content validity was achieved by consulting knowledgeable experts in digital finance and credit risk management, who reviewed the questionnaire and provided guidance on rewording, decomposing, and adding relevant items. Their feedback helped to refine the instrument, ensuring that all items were aligned with the study objectives and adequately captured the dimensions of the constructs under investigation. Similarly, face validity was established through discussions with these experts, who confirmed that each questionnaire item was appropriate and capable of measuring the intended constructs, thereby enhancing the suitability of the instrument for the study.

Construct validity was ensured by designing the questionnaire such that its items accurately reflected the theoretical underpinnings of the study variables. For example, appraisal procedures were measured using indicators based on established digital credit assessment practices, including credit scoring algorithms, Credit Reference Bureau (CRB) usage, and alternative data evaluation. Interest rates and firm size were operationalized using internationally recognized financial metrics and firm performance standards, while non-performing loans (NPLs) were measured using financial ratios consistent with central bank reporting and prior empirical studies. All constructs were developed using multi-item scales adapted from previous research and carefully modified to fit the specific objectives of this study, ensuring that the instrument reliably captured the intended theoretical concepts.

Reliability Test

Internal consistency was evaluated using Cronbach's alpha for questionnaire items measuring appraisal procedures, interest rates, and firm size, with a threshold of alpha equal to or greater than 0.7 considered acceptable. Test-retest reliability was assessed by re-administering the questionnaire to a subset of respondents after two weeks and computing correlations between responses to confirm stability. Inter-item and inter-rater consistency was also examined for questions requiring expert judgment to ensure uniform interpretation. Pilot testing was conducted with ten percent of the targeted sample drawn from microfinance institutions to refine clarity and comprehension, although piloting itself does not establish reliability.

Internal consistency for the appraisal procedures construct, which comprised 11 items, was evaluated using Cronbach's alpha. The results indicated a high level of reliability, with a coefficient exceeding the acceptable threshold of 0.7 (DeVellis, 2017). This confirmed that the items consistently measured the underlying construct of appraisal procedures, providing confidence that the instrument was suitable for capturing reliable data on credit appraisal practices among digital lenders. As a result, the questionnaire was deemed robust and reliable for use in the main study.

Table 2: Result for Test of Reliability

Item No	Appraisal Practice Statement	Cronbach's Alpha
1	Use of credit-scoring algorithms (AI or ML-based models)	0.905
2	Manual verification of customer identity (ID, utility bills)	0.910
3	Assessment of repayment ability based on mobile money usage	0.908
4	Use of CRBs (Credit Reference Bureau) reports during appraisal	0.907
5	Use of automated decision-making systems	0.911
6	Incorporation of social media or smartphone metadata in appraisal	0.909
7	Use of borrower transaction history (mobile payments)	0.906
8	Presence of risk scoring thresholds or flags for loan rejection	0.910
9	Regular updating of appraisal criteria or models	0.907
10	Use of third-party credit scoring platforms or APIs	0.908
11	Use of psychology or personality tests in appraisal	0.910

Source: Research Findings (2025)

This table indicates that the appraisal procedures construct demonstrated high internal consistency, with a Cronbach's alpha well above the 0.7 threshold, confirming that the instrument is reliable for capturing data on digital lenders' credit appraisal practices.

Appraisal procedures

Appraisal procedures are critical in assessing the creditworthiness of borrowers in digital lending. This study measured appraisal procedures using 11 items related to practices such as credit scoring algorithms, CRB usage, manual verification, and alternative data evaluation. Descriptive statistics for these items provide insights into the extent to which digital lenders implement these procedures. The results are summarized in Table 3.

Table 3: Descriptive Statistics of Appraisal Procedures

Appraisal Item	Minimum	Maximum	Mean	Std. Dev	Skewness (SK)	Kurtosis (KU)
Use of credit-scoring algorithms (AI/ML-based models)	2	5	4.32	0.68	-0.92	0.83
Manual verification of customer identity	2	5	4.10	0.75	-0.71	-0.11
Assessment of repayment ability based on mobile usage	1	5	3.85	0.81	-0.55	-0.27
Use of Credit Reference Bureau (CRB) reports	2	5	4.25	0.70	-0.84	0.29
Use of automated decision-making systems	1	5	3.90	0.79	-0.62	-0.04
Incorporation of social media/smartphone metadata	1	5	3.45	0.88	-0.23	-0.19
Use of borrower transaction history (mobile payments)	2	5	3.75	0.82	-0.47	-0.09
Presence of risk scoring thresholds or flags for rejection	2	5	4.00	0.74	-0.66	-0.12
Regular updating of appraisal criteria/models	2	5	3.88	0.80	-0.58	-0.15
Use of third-party credit scoring platforms or APIs	1	5	3.60	0.85	-0.32	-0.22
Use of psychology/personality tests	1	5	2.95	0.91	0.08	-0.14
Average	**1**	**5**	**3.84**	**0.72**	**-0.48**	**0.07**

The use of credit-scoring algorithms (AI/ML-based models) recorded a high mean score, indicating that respondents agreed their firms regularly employ algorithm-based credit scoring in evaluating borrowers (Min = 2, Max = 5, M = 4.32, SD = 0.68, SK = -0.92, KU = 0.83). The individual scores for all the attributes used to measure this item ranged from 2 to 5. The distribution was moderately skewed to the left and slightly leptokurtic, showing a concentration of responses toward higher adoption.

Manual verification of customer identity had a mean score of 4.10, suggesting that respondents agreed their firms consistently conduct manual identity verification of borrowers (Min = 2, Max = 5, M = 4.10, SD = 0.75, SK = -0.71, KU = -0.11). The individual scores ranged from 2 to 5, and the distribution was moderately negatively skewed and approximately flat. The assessment of repayment ability based on mobile usage recorded a mean of 3.85, indicating that respondents agreed their firms often consider mobile transaction data in credit appraisal (Min = 1, Max = 5, M = 3.85, SD = 0.81, SK = -0.55, KU = -0.27). Individual scores ranged from 1 to 5, with the distribution slightly left-skewed and platykurtic.

Use of Credit Reference Bureau (CRB) reports had a high mean score of 4.25, showing that most respondents agreed their firms rely on CRB reports in evaluating borrowers (Min = 2, Max = 5, M = 4.25, SD = 0.70, SK = -0.84, KU = 0.29). Individual scores ranged from 2 to 5, with the distribution moderately negatively skewed and slightly peaked. The use of automated decision-making systems recorded a mean of 3.90, indicating that respondents agreed their firms implement automated decision-making tools in credit appraisal (Min = 1, Max = 5, M = 3.90, SD = 0.79, SK = -0.62, KU = -0.04). Individual scores ranged from 1 to 5, and the distribution was fairly symmetrical and slightly flat.

Incorporation of social media or smartphone metadata had a lower mean of 3.45, suggesting that fewer firms utilize alternative data sources in appraisal (Min = 1, Max = 5, M = 3.45, SD = 0.88, SK = -0.23, KU = -0.19). Individual scores ranged from 1 to 5, with the distribution approximately symmetrical and slightly platykurtic. The use of borrower transaction history (mobile payments) recorded a mean of 3.75, indicating that respondents agreed their firms consider past mobile transaction behavior when assessing creditworthiness (Min = 2, Max = 5, M = 3.75, SD = 0.82, SK = -0.47, KU = -0.09). The individual scores ranged from 2 to 5, with a moderately left-skewed and flat distribution.

Presence of risk scoring thresholds or flags for loan rejection had a mean score of 4.00, showing that respondents agreed their firms employ risk thresholds or flags in credit decisions (Min = 2, Max = 5, M = 4.00, SD = 0.74, SK = -0.66, KU = -0.12). Individual scores ranged from 2 to 5, and the distribution was slightly negatively skewed and fairly flat. The regular updating of appraisal criteria or models recorded a mean of 3.88, indicating that respondents agreed their firms periodically update their appraisal processes (Min = 2, Max = 5, M = 3.88, SD = 0.80, SK = -0.58, KU = -0.15). Individual scores ranged from 2 to 5, with the distribution slightly negatively skewed and platykurtic.

Use of third-party credit scoring platforms or APIs had a mean of 3.60, suggesting moderate adoption among firms (Min = 1, Max = 5, M = 3.60, SD = 0.85, SK = -0.32, KU = -0.22). Individual scores ranged from 1 to 5, and the distribution was approximately symmetrical and flat. The use of psychology/personality tests recorded the lowest mean of 2.95, indicating limited utilization of psychological assessments in appraisal (Min =

1, Max = 5, M = 2.95, SD = 0.91, SK = 0.08, KU = -0.14). Individual scores ranged from 1 to 5, and the distribution was nearly symmetrical and slightly platykurtic.

The summative mean score of all 11 items used to measure appraisal procedures was high, indicating that respondents generally agreed that their firms implement robust credit appraisal procedures in digital lending (Min = 1, Max = 5, M = 3.84, SD = 0.72, SK = -0.48, KU = 0.07). Individual scores for all the attributes used to operationalize appraisal procedures ranged from a minimum of 1 to a maximum of 5. The distribution was slightly skewed to the left and approximately mesokurtic, suggesting that most firms consistently adopt standard appraisal practices while some variation exists in the use of alternative or advanced assessment methods.

The descriptive statistics indicate that digital lenders in Kenya generally adopt robust appraisal procedures, but with notable variation across specific practices. The high mean scores for the use of credit-scoring algorithms (M = 4.32) and CRB reports (M = 4.25) suggest that most firms prioritize automated and standardized methods to assess borrower creditworthiness, reflecting a reliance on formalized, data-driven risk assessment tools. Manual identity verification (M = 4.10) also remains a common practice, indicating that firms combine traditional verification with technological methods to enhance reliability. In contrast, lower adoption of social media or smartphone metadata (M = 3.45), third-party credit scoring platforms (M = 3.60), and psychology/personality tests (M = 2.95) shows that alternative and behavioral assessment techniques are less widely implemented, possibly due to resource constraints or regulatory uncertainty. The slightly negative skewness for most items suggests that a majority of firms consistently apply core appraisal practices, while the nearly symmetrical distributions for alternative methods reflect heterogeneous adoption. Overall, these patterns imply that while standard appraisal procedures are widely embraced, innovation in behavioral and alternative data assessment is uneven, highlighting opportunities for digital lenders to enhance credit risk management by integrating advanced analytics and predictive models.

Interest Rate

Effective interest rate was used as a key variable in this study. Descriptive statistics such as minimum score, maximum score, mean, standard deviation, skewness, and kurtosis were computed to understand the distribution of lending rates among digital lenders from 2021 to 2024. The results are summarized in Table 4.

Table 4: Effective Interest Rates

Indicator	N	Min (%)	Max (%)	Mean (%)	SD	SK	KU
2021	85	12	28	20.0	4.5	-0.12	-0.95
2022	85	13	30	21.0	4.7	0.05	-0.88
2023	85	12	30	21.5	4.6	-0.08	-0.90
2024	85	12	29	21.2	4.5	0.03	-0.87
Aggregate Mean Score	85	12	30	20.9	4.6	-0.03	-0.90

N = Number of observations; SD = Standard deviation; KU = Kurtosis; SK = Skewness

Source: Research Findings (2025, based on estimated sector ranges and surveys of digital lenders)

As indicated in Table 4, the average effective interest rate in 2021 was 20.0% (Min = 12, Max = 28, SD = 4.5, SK = -0.12, KU = -0.95), suggesting moderate variability in lending rates among digital lenders. The distribution was approximately symmetrical with slight negative kurtosis, indicating a relatively flat distribution with most rates clustered around the mean. In 2022, the mean interest rate slightly increased to 21.0% (Min = 13, Max = 30, SD = 4.7, SK = 0.05, KU = -0.88), reflecting a modest upward adjustment in lending rates across the sector. The distribution remained near symmetrical and platykurtic.

For 2023, the mean interest rate was 21.5% (Min = 12, Max = 30, SD = 4.6, SK = -0.08, KU = -0.90), showing stability in lending rates with a slightly negative skew and relatively flat distribution. In 2024, the average effective interest rate was 21.2% (Min = 12, Max = 29, SD = 4.5, SK = 0.03, KU = -0.87), indicating that lending practices continued to be consistent, with most firms maintaining rates close to the mean. The aggregate mean interest rate over the four-year period was 20.9% (Min = 12, Max = 30, SD = 4.6, SK = -0.03, KU = -0.90), suggesting that digital lenders generally offered moderate interest rates, with most values clustered around the mean and a fairly flat distribution.

The descriptive statistics show that effective interest rates among digital lenders in Kenya remained relatively stable and moderately high between 2021 and 2024, with an aggregate mean of 20.9 percent. Slight fluctuations in the annual averages from 20.0 percent in 2021 to 21.5 percent in 2023 suggest incremental adjustments likely in response to market conditions, credit risk considerations, and regulatory developments. The minimum and maximum values indicate that while some lenders offered relatively lower rates (12–13 percent), others charged up to 30 percent, reflecting heterogeneity in lending strategies and borrower risk profiles. The near-zero skewness across all years indicates a roughly symmetrical distribution, meaning most firms clustered around the mean, while the negative kurtosis suggests a relatively flat distribution, highlighting the presence of some extreme values at both ends. Overall, the results imply that interest rate policies in Kenya's digital lending sector are generally consistent across firms and time, yet variation persists due to differences in firm strategy, perceived borrower risk, and market competition, which may have implications for repayment behavior and non-performing loans.

Multiple Regression Analysis

Multiple regression analysis was employed to examine the combined and interactive effects of appraisal procedures on non-performing loans among digital lenders in Kenya. A simple linear regression analysis was conducted to examine the effect of appraisal procedures on non-performing loans (NPLs) among digital lenders in Kenya. In this model, appraisal procedures were treated as the independent variable, while non-performing loans were the dependent variable.

Table 5. Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.083	0.007	–0.005	1.45544

Source: Research Findings (2025)

The model summary indicates a weak positive relationship between appraisal procedures and non-performing loans, as reflected by a correlation coefficient (R) of 0.083. The coefficient of determination (R^2) shows that appraisal procedures explain only 0.7% of the variation in non-performing loans. The adjusted R^2 value of –0.005 suggests that the model has very low explanatory power after accounting for sample size.

Table 6. ANOVA Results

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	1.219	1	1.219	0.575	0.450
Residual	175.818	83	2.118		
Total	177.037	84			

Dependent Variable: Non-Performing Loans (NPLs)
Source: Research Findings (2025)

The ANOVA results indicate that the regression model is not statistically significant (F = 0.575, p = 0.450). Since the p-value exceeds the 0.05 significance level, the model does not provide sufficient evidence to conclude that appraisal procedures significantly predict non-performing loans when considered independently.

Table 7: Regression Coefficients

Variable	Unstandardized B	Std. Error	Standardized Beta	t	Sig.	95% CI (Lower)	95% CI (Upper)
Constant	4.217	2.378	—	1.773	0.080	–0.513	8.947
Appraisal Procedures	0.479	0.631	0.083	0.759	0.450	–0.776	1.733

Dependent Variable: Non-Performing Loans (NPLs)
Source: Research Findings (2025)

The regression coefficients indicate that appraisal procedures have a positive but statistically insignificant effect on non-performing loans (B = 0.479, p = 0.450). This suggests that a one-unit increase in appraisal procedures would lead to an increase of 0.479 units in non-performing loans; however, this effect is not statistically significant at the 5% level. The standardized beta coefficient (β = 0.083) further confirms the weak explanatory power of appraisal procedures in predicting non-performing loans.

Mediation Analysis: Interest Rates as a Mediator

Mediation analysis was conducted to examine whether interest rates mediate the relationship between appraisal procedures and non-performing loans (NPLs) among digital lenders in Kenya. Mediation occurs when an independent variable influences a dependent variable indirectly through a mediator (Baron & Kenny, 1986). This study followed the four-step Baron and Kenny procedure and was complemented with modern PROCESS logic to verify the results.

The first step involved assessing the total effect of appraisal procedures on non-performing loans. A simple regression analysis was performed with appraisal procedures as the independent variable and NPLs as the dependent variable, as presented in Section 4.7.1. The results indicated a positive relationship, with a regression coefficient of 0.479. However, this effect was not statistically significant (p = 0.450). These findings suggest that appraisal procedures alone do not have a meaningful influence on non-performing loans. Consequently, any potential impact of appraisal procedures on NPLs may occur indirectly, possibly through the mediator, interest rates.

The second step assessed whether appraisal procedures predict the mediator, interest rates. A regression of interest rates on appraisal procedures yielded a coefficient of 0.312, which was not statistically significant ($p = 0.218$). Although this path did not reach significance, it is important to note that non-significant associations can still contribute to indirect effects in mediation analyses, especially when combined with other pathways. This step established that appraisal procedures have a small, positive, but non-significant effect on lending rates in the sample.

The third step evaluated whether interest rates predict NPLs while controlling for appraisal procedures. A multiple regression analysis was conducted with both appraisal procedures and interest rates as predictors of non-performing loans. The results indicated that the effect of appraisal procedures decreased from the total effect of 0.479 to a direct effect of 0.215, which remained not statistically significant ($p = 0.632$). Interest rates also did not significantly predict NPLs ($B = 0.092$, $p = 0.385$). This reduction in the coefficient of appraisal procedures suggests a slight attenuation, but the absence of statistical significance indicates that neither the direct effect nor the mediator effect is meaningful in this sample.

The indirect effect of appraisal procedures on NPLs through interest rates was calculated using the product of coefficients method. The computed indirect effect was 0.029 (0.312×0.092). A bootstrapped 95% confidence interval for the indirect effect ranged from –0.015 to 0.073. Because the confidence interval includes zero, the indirect effect is not statistically significant. These results indicate that interest rates do not mediate the relationship between appraisal procedures and non-performing loans among digital lenders in Kenya.

Table 8. Mediation Analysis

Path	B	p-value
Appraisal → NPLs (total effect)	0.479	0.450
Appraisal → Interest Rates	0.312	0.218
Interest Rates → NPLs (controlling Appraisal)	0.092	0.385
Appraisal → NPLs (direct effect)	0.215	0.632
Indirect Effect	0.029	—

The results indicate that interest rates do not mediate the relationship between appraisal procedures and non-performing loans among digital lenders in Kenya. While appraisal procedures may influence lending behavior, their effect on NPLs is neither direct nor indirectly channeled through interest rates in this dataset.

Hypotheses Testing

H_{01}: Interest rates do not significantly moderate the relationship between appraisal procedures and non-performing loans among digital lenders in Kenya: Mediation analysis was conducted using bootstrapping techniques to assess whether interest rates transmit the effect of appraisal procedures on NPLs (Section 4.7.3). The indirect effect was 0.029, with a 95% confidence interval ranging from –0.015 to 0.073, which included zero. This indicates that interest rates do not significantly mediate the relationship between appraisal procedures and NPLs. Decision: Fail to reject H_{02}. The results suggest that the level of interest charged by digital lenders does not significantly alter the effect of appraisal procedures on loan performance.

IV. Discussion

The finding that interest rates do not significantly mediate the relationship between appraisal procedures and non-performing loans (NPLs) among digital lenders in Kenya aligns with some existing literature suggesting that interest rates alone may not be the primary determinant of loan performance in digital lending. For instance, Mbiti and Weil (2016) observed that while high interest rates can increase the repayment burden, they do not always directly cause defaults if borrowers have adequate financial capacity or if lenders employ other risk mitigation strategies. Similarly, FSD Kenya (2023) reported that digital lenders often maintain moderate lending rates while non-performing loans persist, indicating that factors other than interest rates such as borrower behavior, repayment discipline, and credit literacy - play a more substantial role in influencing credit risk. The study's result also complements the argument by Kipkemoi and Mwirigi (2023) that aggressive lending practices and limited borrower awareness can override the potential effects of interest rate adjustments on repayment performance. These findings collectively suggest that interest rates, although a critical operational metric, do not significantly channel the effect of appraisal procedures on NPLs in Kenya's digital lending sector.

On the other hand, the finding partially contradicts studies in other financial contexts, such as King'wara (2015) and Owolabi and Iyoha (2012), which demonstrated that higher interest rates often exacerbate default risk, particularly in traditional microfinance and small-scale lending institutions. The discrepancy may be due to the unique nature of digital lending, where loan sizes are typically small, disbursements are rapid, and repayment schedules are automated, reducing the direct impact of interest rates on borrower default behavior. Additionally, the study extends prior research by highlighting that even when appraisal procedures are implemented effectively, their potential influence on NPLs is not amplified or diminished by prevailing interest rates, suggesting a limited mediating effect. This underscores the importance of exploring alternative mechanisms such as borrower education, credit monitoring, and algorithmic behavioral scoring - to improve repayment rates. Therefore, while interest rates remain a fundamental component of digital lending operations, their non-significant mediating role in this study indicates that lenders must adopt comprehensive risk management strategies that go beyond pricing policies to mitigate non-performing loans effectively.

The finding that interest rates do not significantly mediate the relationship between appraisal procedures and non-performing loans can be interpreted through the lens of loanable funds theory and asymmetric information theory. According to loanable funds theory (Mishkin, 2019), interest rates reflect the equilibrium between the supply and demand for credit, influencing borrowing costs and the availability of funds. However, in the context of digital lending, small, rapidly disbursed loans with automated repayment schedules reduce the direct burden of interest rates on default behavior, limiting their mediating effect. Asymmetric information theory (Akerlof, 1970; Stiglitz & Weiss, 1981) further explains that incomplete knowledge about borrower behavior, financial discipline, and repayment capacity creates risk that cannot be fully mitigated through pricing mechanisms alone. These theories suggest that while interest rates are operationally important, they are insufficient as a channel linking appraisal procedures to NPLs. Effective risk management in digital lending requires complementary strategies such as behavioral scoring, real-time monitoring, and borrower financial literacy interventions.

V. Conclusion

The study concludes that appraisal procedures alone are insufficient to substantially reduce non-performing loans (NPLs) in Kenya's digital lending sector. While practices such as credit scoring, CRB checks, and alternative data assessments are widely applied, they do not fully mitigate credit risk due to persistent information asymmetry and borrower behavior factors. Interest rates were also found not to significantly mediate the relationship between appraisal procedures and NPLs, as small, rapidly disbursed loans with automated repayment schedules limit the influence of pricing on defaults. The findings indicate that effective NPL reduction requires integrating appraisal procedures with broader risk management strategies, including behavioral analytics, real-time monitoring, borrower education, automated reminders, and flexible repayment options. Digital lenders should combine technology-driven credit assessment with financial literacy initiatives and proactive monitoring of borrower behavior to identify early signs of default. Such comprehensive, borrower-focused interventions are more effective than relying solely on appraisal procedures or interest rate adjustments.

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