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The Role of Digital Loans in Improving or Undermining Financial Well-Being in Kenya

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Abstract

This study examines the relationship between digital loan use and household financial well-being in Kenya using nationally representative data from the 2021 FinAccess Household Survey covering 22,025 households across 47 counties. Household-level sampling weights are applied throughout the analysis. Digital loan use is classified as current use, past use, or never use, while financial recovery is measured as whether a household reports having overcome its financial problems. Logistic regression models are estimated to assess this relationship before and after controlling for socioeconomic characteristics and credit history. Descriptively, digital loan users report higher financial recovery than non-users. However, this association becomes statistically insignificant after adjustment for educational attainment, employment type, income, and credit history, suggesting that the observed difference is substantially associated with borrowers' socioeconomic circumstances. Education, formal employment, and income are positively associated with financial recovery, whereas negative Credit Reference Bureau listing is associated with lower recovery. Interaction analysis further indicates that the relationship between digital loan use and financial recovery varies across income groups, with the apparent benefits of digital credit attenuated among middle-income households. Overall, the findings suggest that expanding digital credit access alone may be insufficient to improve household financial resilience. Strengthening education, employment stability, income security, and credit rehabilitation may be more important for sustainable financial recovery. The study contributes nationally representative evidence on digital credit, financial inclusion, and household financial well-being in Kenya and offers implications for responsible digital lending regulation.

Keywords

Digital Loans, Financial Well-Being, Financial Recovery, Logistic Regression, Credit Risk, Financial Inclusion, Kenya, FinAccess

1. Introduction

Kenya has emerged as a pioneer in digital financial innovation, driven by mobile money platforms such as M-Pesa and the rapid growth of mobile-based lending. Digital loans, short-term credit that is distributed and repaid through mobile devices, have expanded credit access for households historically excluded from formal banking. Reports from the Central Bank of Kenya and the Financial Sector Deepening (FSD) Kenya document that more than half of Kenyan adults have taken digital loans. However, more than a quarter have defaulted, and many are unaware of the full cost of borrowing and the consequences of a negative listing on the Credit Reference Bureau (CRB) FSD Kenya (2021).

This study investigates whether digital loans improve or undermine household financial well-being in Kenya. Building on the framework of Polloni-Silva, Da Costa, Moralles and Sacomano Neto (2021), which examined financial access, poverty, and inequality in Latin America, we adapt their approach to Kenya's digital credit landscape. Unlike Polloni-Silva et al. (2021), which used consumption-based welfare measures, we focus on household-level financial recovery status and loan default behaviour, modelled using logistic regression on nationally representative 2021 FinAccess data. The findings contribute context-specific evidence to the fintech and financial inclusion literature while informing regulatory policy in rapidly digitalizing emerging markets.

2. Data and Methods

2.1. Data Sources and Survey Design

The analysis uses Secondary data from the 2021 FinAccess Household Survey, conducted jointly by the Central Bank of Kenya (CBK), the Kenya National Bureau of Statistics (KNBS) and Financial Sector Deepening (FSD) Kenya, covering 22,025 households in all 47 counties Central Bank of Kenya (2021). The survey instrument collects information from one adult respondent per household, who answers on behalf of the household. Financial outcome variables reflect the household's financial situation as reported by the responding adult. Household-level sampling weights (*hh weights*) provided in the dataset are applied throughout all descriptive and regression analyses to account for differential household selection probabilities. Strata and cluster identifiers were not incorporated into the variance estimation; accordingly, standard errors may be modestly underestimated relative to design-based estimates, which is an acknowledged limitation.

The digital loan access variable is derived from the FinAccess module on digital financial services, capturing use of any mobile-based loan product, including mobile banking credit (e.g., M-Shwari, KCB M-Pesa) and mobile application loans (e.g., Tala, Branch, Fuliza) within a 12-month recall period preceding the survey.

Eligible respondents were adults aged 18 and above residing in Kenya with access to a mobile phone. Households were classified into three mutually exclusive categories: *Currently use* ($N = 367$), *Used to use* ($N = 387$), and *Never used* ($N = 21{,}271$). Together, current and former users constitute 754 identified digital loan households, representing 3.42% of the full sample.

The default risk analysis (Section 3.3) uses a broader analytical sample of 11,550 households with complete risk indicator data. Critically, this sample is not restricted to the 754 digital-loan households. The variable *defaultloan* is therefore interpreted as default on any loan product throughout; all headings and interpretations reflect this distinction explicitly.

2.2. Data Processing

All cleaning and analysis were conducted in Python. The following processing decisions are documented for reproducibility: 1) categorical variables were recoded into dummy variables, with string categories standardized to remove whitespace (affecting the "technical training" educational category); 2) monthly income was winsorized at the 1st and 99th percentiles to reduce outlier influence; 3) income brackets for the interaction model were defined as Low Income (≤KES 5000), Middle Income (KES 5001 - 20,000), and High Income (>KES 20,000), consistent with the sample quartile structure; 4) loan purpose categories were retained in original survey form for descriptive analysis; and 5) listwise deletion was applied in all regression models, yielding $N = 2102$ for the financial recovery model and $N = 11{,}550$ for the default risk analysis. The difference reflects distinct variable sets and item non-response patterns across survey modules.

2.3. Measurement of Key Variables

Financial Recovery (Overcome_binary). The primary outcome is *Overcome_binary*, derived from the FinAccess household survey item: "*I have been able to overcome financial problems*." Five response options were recoded as follows: *Overcome_binary* = 1 if the responding adult selected "Agree" (interpreted as the household having overcome financial problems); *Overcome_binary* = 0 for all other responses ("Disagree", "Neither agree nor disagree", "Don't know", "Refused to answer"). This conservative recoding treats uncertainty, disagreement, and non-response as a single reference category. Households with a missing value on this item were excluded via listwise deletion.

Default Status (defaultloan). Default status is a binary household-level indicator: 1 = the household reported missing at least one scheduled loan repayment on any loan product; 0 = did not default.

Credit History Variables. *Negative CRB listing*: binary (1 = household negatively listed with a Credit Reference Bureau; 0 = otherwise). *Bad credit history*: self-reported binary (1 = poor repayment history on any prior loan; 0 = otherwise). Both variables may be outcomes of prior digital loan borrowing and are therefore treated as potentially endogenous (see Section 3.4).

2.4. Econometric Strategy

The primary analytical model is logistic regression that estimates the probability of household recovery:

$$\operatorname{logit}\left(P\left(Y_i = 1\right)\right) = \beta_0 + \boldsymbol{\beta}_1^{\top} \boldsymbol{X}_{\text{loan},i} + \boldsymbol{\beta}_2^{\top} \boldsymbol{X}_{\text{demo},i} + \boldsymbol{\beta}_3^{\top} \boldsymbol{X}_{\text{credit},i}$$

where Y_i is *Overcome_binary* for household i; $\boldsymbol{X}_{\text{loan},i}$ is a vector of the characteristics of digital loans; $\boldsymbol{X}_{\text{demo},i}$ is a vector of demographic characteristics of the head of the household; and $\boldsymbol{X}_{\text{credit},i}$ is a vector of credit history variables. To address the potential endogeneity of credit history variables, which may result from prior borrowing, two models are estimated: Model 1 (Baseline) excludes bad credit history and CRB listing; Model 2 (Adjusted) adds these variables and is interpreted as an adjusted association rather than a direct loan effect. Coefficients are reported as odds ratios.

3. Results

3.1. Sample Characteristics

The 22,025 surveyed households include 59% male and 41% female respondents. The age distribution peaks in the 25 - 35 years range. Monthly income is heavily right-skewed (modal income: KES 5000), reflecting Kenya's predominantly informal economy: casual work (27.6%), family support (25.2%), and farming (21.1%) are the three largest income sources, while formal employment accounts for only 9.3%. The overwhelming majority of households (96.58%) had never used digital loans; 1.76% used to use them, and 1.67% currently use them.

3.2. Digital Loan Access and Financial Recovery

Table 1 presents the percentage cross-tabulation of digital loan access against household financial recovery. A clear gradient is evident: households that previously used digital loans report the highest recovery rate (37.24%), followed by current users (34.25%), and non-users (22.79%). The chi-square test confirms a statistically significant association ($\chi_8^2 = 108.05$, $p < 0.001$). However, this bivariate relationship does not control for confounding factors addressed in Section 3.4.

Table 1. Percentage cross-tabulation: digital loan access vs. overcoming financial problems.

Digital Loan Access	Agree (%)	Disagree (%)	Neither (%)
Currently use	34.25	56.44	9.32
Never used	22.79	71.44	5.77
Used to use	37.24	52.34	10.42

Income differs significantly across access groups: current and past digital loan users report a median income of KES 10,000 and KES 9000, respectively, compared to KES 4000 for non-users (ANOVA:F = 156.55, $p < 0.001$), confirming that higher-income households are more likely to engage with digital credit.

Financial recovery rates increase monotonically with educational attainment: from 13.51% among those with no formal education to 44.99% among university graduates (**Table 2**). Similarly, households dependent on investment income (53.3% agree) and rental income (47.0% agree) report higher recovery rates than those relying on casual work (19.8%) or family support (18.3%).

Table 2. Financial recovery by educational level (percentage).

Educational Level	Agree (%)	Disagree (%)	Neither (%)
None	13.51	83.64	2.85
Primary school	21.21	73.53	5.26
Secondary school	25.82	66.82	7.36
Technical training	35.19	56.19	8.62
University	44.99	44.89	10.12

3.3. Loan Default Risk

The default risk analysis is conducted on a broader analytical sample of 11,550 households with complete risk indicator data. The *defaultloan* variable captures default on any loan product and is not restricted to digital loans, since restricting to the 754 identified digital-loan households would yield too small a sample for stable multivariate estimation.

Monthly income is a significant predictor of default: households that defaulted have a median income of KES 4500 compared to KES 5000 for non-defaulters, and an independent samples t-test confirms a statistically significant difference in mean income ($t = -9.66$, $p < 0.001$). Box and violin plots confirm that non-defaulters have a broader upper income distribution.

Default rates decline with educational attainment: from 71.76% among households with no formal education to 40.77% among university-educated households ($\chi^2_6 = 293.73$, $p < 0.001$). Default rates also vary significantly by income sources ($\chi^2_8 = 158.10$, $p < 0.001$): farming (60.62%), NGO or government income (59.14%), and casual work (58.50%) record the highest rates, while investment income (33.33%), pension (37.68%), and formal employment (41.60%) show the lowest. These patterns are consistent with the income stability hypothesis: predictable income streams enable consistent loan servicing Stiglitz and Weiss (1981).

The correlation heatmap of default risk indicators confirms that bad credit history and negative CRB listings are the most relevant linear predictors of default ($r = 0.12$ each), and are themselves moderately correlated ($r = 0.21$), reflecting the pathway through which a bad credit history leads to a negative CRB listing. Absence of a payslip ($r = 0.00$) and guarantor ($r = 0.01$) shows a negligible association with default (**Table 3**).

Table 3. Quartiles and median of monthly income by default status (KES).

Default Status	Q1	Median	Q3
Defaulted on loans	2000	4500	8000
Did not default on loans	2000	5000	10,000

3.4. Logistic Regression Results

Two logistic regression models are estimated.

Model 1 (Baseline) excludes bad credit history and CRB listing to avoid conditioning on potentially endogenous post-borrowing outcomes.

Model 2 (Adjusted), presented in Table 4, adds these credit history variables and should be interpreted as an adjusted association rather than a direct loan effect. The difference in digital loan access coefficients between the two models indicates the extent to which credit damage mediates the relationship between digital borrowing and financial recovery.

Table 4. Logistic regression: Predictors of household financial recovery (Sorted by odds ratio).

Predictor	Coef.	Std. Err.	*p*-value	OR
Panel A: Educational Level Ref: No formal education				
Technical training (post-sec.)	1.8920	0.392	<0.001	6.633
University	1.6712	0.307	<0.001	5.319
Technical training (vocational)	1.5439	0.290	<0.001	4.683
Secondary school	1.4669	0.247	<0.001	4.336
Primary school	1.4627	0.241	<0.001	4.318
Panel B: Income Source Ref: Casual worker				
Employed	0.5860	0.168	<0.001	1.797
Self-employed	0.4168	0.144	0.004	1.517
Farming	0.3047	0.158	0.054	1.356
Panel C: Digital Loan Access Ref: Currently use				
Used to use	0.4287	0.282	0.129	1.535
Never used	−0.1635	0.212	0.440	0.849
Panel D: Other Controls				
Gender (Male)	0.2041	0.115	0.076	1.226
Monthly Income	1.9×10^{-5}	4.8×10^{-6}	<0.001	1.000
Chronic Disease	−0.2599	0.142	0.068	0.771
Age	−0.0059	0.005	0.254	0.994
Panel E: Credit History				
Bad credit history	−0.4641	0.165	0.005	0.629
Negative CRB listing	−0.6567	0.194	0.001	0.519
Intercept	−2.4565	0.420	<0.001	0.086
$N = 2102$; Pseudo $R^2 = 0.069$; LLR p-value $= 1.269 \times 10^{-24}$; Converged: Yes				

The adjusted logistic regression model (**Table 4**) was estimated on 2102 complete household observations with 24 predictors, converging in 6 iterations (Pseudo $R^2 = 0.069$, LLR p-value = 1.269×10^{-24}).

Educational attainment is the dominant predictor of financial recovery. Even primary school completers are 4.3 times more likely to report overcoming financial problems relative to those with no formal education (OR = 4.318, $p < 0.001$), rising to 5.3 times for university graduates (OR = 5.319, $p < 0.001$). Formal employment (OR = 1.797, $p < 0.001$) and self-employment (OR = 1.517, $p = 0.004$) significantly improve recovery odds. Bad credit history reduces odds by 37.1% (OR = 0.629, $p = 0.005$) and negative CRB listing by 48.1% (OR = 0.519, $p = 0.001$).

Crucially, digital loan access is not a statistically significant predictor of financial recovery in the adjusted model (Never used: OR = 0.849, $p = 0.440$; Used to use: OR = 1.535, $p = 0.129$). The marginal effect of digital loan access is approximately −0.031 for never users ($p = 0.440$) and +0.080 for past users ($p = 0.128$), with confidence intervals crossing zero in both cases. This indicates that the bivariate recovery advantage among digital loan users is attributable to their more favourable socioeconomic profiles rather than to credit access itself, consistent with Banerjee et al. (2015) and Koomson, Villano and Hadley (2020).

The interaction model (**Table 5**), estimated on N = 20,546 with household weights, reveals important heterogeneity. In isolation, current users (OR = 1.963, $p < 0.001$) and past users (OR = 2.057, $p < 0.001$) show significantly higher recovery odds. However, these benefits are significantly attenuated among middle-income households: the interaction of current use with middle income reduces recovery probability by 19.4 percentage points ($dy/dx = -0.194$, $p < 0.001$), and past use with middle income by 12.0 percentage points ($dy/dx = -0.120$, $p = 0.021$), suggesting that middle-income households face repayment pressures that offset the liquidity benefits of digital credit. No significant attenuation is observed for high-income households.

Table 5. Interaction model: Digital loan access × income bracket.

Predictor	Coef.	OR	z	p-value
Panel A: Main Effects Ref. Never used; Low Income				
Currently use	0.675	1.963	4.926	<0.001
Used to use	0.721	2.057	5.343	<0.001
Middle Income	0.942	2.565	16.468	<0.001
High Income	1.570	4.807	17.430	<0.001
Panel B: Interactions				
Currently use × Middle Income	−1.082	0.339	−3.566	<0.001
Used to use × Middle Income	−0.668	0.513	−2.304	0.021
Currently use × High Income	−0.172	0.842	−0.397	0.692
Used to use × High Income	−0.119	0.888	−0.303	0.762

Continued

Panel C: Selected Average Marginal Effects (dy/dx)				
Currently use (vs. Never used)	0.121	-	4.935	<0.001
Used to use (vs. Never used)	0.130	-	5.354	<0.001
Middle Income (vs. Low Income)	0.169	-	16.828	<0.001
Currently use × Middle Income	−0.194	-	−3.570	<0.001
Used to use × Middle Income	−0.120	-	−2.305	0.021
N = 20,546; Pseudo R^2 = 0.027; Converged: Yes				

4. Discussion

This study provides three principal findings. To begin with, digital loan access is positively associated with household financial recovery at the bivariate level, but this advantage is largely attributed to borrower characteristics, higher income, greater education, and more stable employment rather than to the loans themselves. This "selection into credit" pattern is consistent with Banerjee et al. (2015) and Koomson et al. (2020), who find that welfare effects of credit access are substantially attenuated once household-level controls are introduced. The implication is that digital credit access is a necessary but insufficient condition for financial recovery: without complementary human capital and income stability, loans may simply expose vulnerable households to overindebtedness.

Also, education and formal employment are the dominant structural determinants of financial resilience, substantially outperforming credit access in effect size and statistical significance. Policies that expand credit without addressing educational and labour market deficits are therefore unlikely to generate meaningful welfare improvements among the most vulnerable households.

Moreover, credit history variables, particularly negative CRB listing (OR = 0.519), impose a compounding disadvantage. Households that default receive CRB listings that restrict future credit access, reduce capacity to manage future shocks, and further reduce recovery prospects. This self-reinforcing exclusion dynamic, identified by Stiglitz and Weiss (1981) and documented in Kenya by Kaffenberger et al. (2018), calls for regulatory frameworks providing structured rehabilitation pathways for over-indebted households such as graduated credit limits and time-limited listings for small-value defaults.

The findings that loan purposes are dominated by consumption and emergencies (over 65% of mobile app loans) rather than productive investment further limit the welfare potential of digital credit. Consumption smoothing, while valuable in the short term, does not generate the future income flows needed to sustain repayment, consistent with Banerjee et al. (2015) and Kaffenberger et al. (2018).

5. Conclusions and Policy Recommendations

This study examined whether digital loans improve or undermine household financial well-being in Kenya using the 2021 FinAccess Household Survey (N =

22,2025) with household sampling weights. The multivariate logistic regression demonstrates that educational attainment, formal employment, and monthly income, not digital loan access, are the primary determinants of financial recovery. Digital loan access loses statistical significance once these socioeconomic controls are introduced. Negative CRB listing and bad credit history substantially reduce recovery prospects, pointing to a self-reinforcing financial exclusion cycle. The interaction model reveals that middle-income households experience significant attenuation of recovery benefits from digital loan use ($\frac{dy}{dx} = -0.194$, $p < 0.001$).

These findings yield four policy recommendations.

To begin with, regulators should strengthen affordability assessments requiring digital lenders to verify repayment capacity before disbursement, reducing over-indebtedness.

Also, digital lenders should develop loan products targeting productive purposes, business investment, agriculture, and income generation, since consumption-dominated borrowing limits long-term welfare gains.

Moreover, financial literacy programs should be expanded, prioritizing households with lower educational attainment and informal employment, who face the highest default risk.

Lastly, credit rehabilitation frameworks, including time-limited CRB listing periods and structured debt restructuring for small defaults, should be developed to break the exclusion cycle that currently prevents the most vulnerable households from recovering financially.

Limitations

The cross-sectional nature of the 2021 FinAccess data precludes causal inference. Self-reported financial recovery may reflect subjective perceptions. Strata and cluster identifiers were not incorporated into variance estimation, which may modestly underestimate standard errors.

Future research should employ longitudinal data, fully design-based estimation, and qualitative methods to examine borrower decision-making processes and the mechanisms through which digital credit affects household welfare over time.

Author Contributions

Each other has contributed equally to research, data collection and analysis.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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