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Drivers of willingness to repay Parish Revolving funds (PRF) under Uganda's Parish Development Model: a Bayesian Latent Class Logistic Regression (LCLR) approach

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ABSTRACT

This study examines the determinants of beneficiaries' willingness to repay the Parish Revolving Fund (PRF) under Uganda's Parish Development Model (PDM), using nationally representative data from the 2024 EPRC PDM Survey. The study applies a Bayesian Latent Class Logistic Regression (LCLR) model to account for observed and unobserved heterogeneity in repayment behaviour. Results show significant variation in repayment willingness by gender, education, region and wealth. Financial literacy, awareness of repayment terms, larger PRF amounts and shorter disbursement periods increase repayment willingness, while long delays and low household wealth reduce it. The Bayesian model identifies three borrower classes: institutionally aware borrowers (35%), economically empowered borrowers (45%) and financially constrained borrowers (20%), each with distinct traits. The model's predictive accuracy is strong, with an area under the curve (AUC) of 0.828 and overall accuracy of 87%. Policy simulations indicate that combining better financial literacy with faster disbursement yields the highest repayment gains. The principal methodological contribution is the application of the Bayesian LCLR framework, which simultaneously estimates class-specific repayment parameters and latent class memberships with full uncertainty quantification, advancing beyond conventional homogeneous logistic models used in prior microfinance research. The study recommends the need to leverage on rural social capital for repayment enforcement, the need for borrower segmentation, focused financial training and efficient fund management to strengthen PRF repayment.

IMPACT STATEMENT

This study informs how Uganda's Parish Development Model can improve loan recovery by shifting from uniform to targeted interventions based on borrower types. It shows that faster disbursement and financial literacy training lead to higher repayment, offering clear actions for policymakers. By improving repayment performance, the findings support stronger sustainability of the Parish Revolving Fund, better use of public resources, and increased access to credit for rural households.

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1. Introduction

Access to affordable credit is central to poverty reduction and inclusive economic growth in developing economies (Armendáriz & Morduch, 2010; Karlan & Zinman, 2011). However, sustaining microfinance initiatives depends on borrowers' willingness and ability to repay loans, which remain persistent challenges in community-based credit schemes (Banerjee et al., 2015; D'Espallier et al., 2011). High default rates reduce the revolving capacity of such funds, weakening their role in local development (Hermes & Lensink, 2011; Morduch, 1999).

Uganda's Parish Development Model (PDM) was launched in 2022 as a decentralised strategy to transition 3.5 million subsistence households into the monetised economy and promote financial inclusion

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at the parish level, the lowest administrative planning unit in the country. The PDM is structured around seven pillars: (i) Production, Processing and Marketing; (ii) Infrastructure and Economic Services; (iii) Financial Inclusion; (iv) Social Services; (v) Mindset Change and Community Mobilisation; (vi) Parish-Based Management Information System; and (vii) Governance and Administration (Government of Uganda, 2022). Under the third pillar (Financial Inclusion), the Parish Revolving Fund (PRF) provides low-interest loans to parish-level Savings and Credit Cooperative Organisations (SACCOs), targeting subsistence households for transition into the money economy. Despite the initiative's promise, concerns persist over repayment delays, weak financial literacy and limited administrative capacity (ACODE, 2024; EPRC, 2024). Understanding the behavioural and institutional drivers of repayment willingness is therefore vital for improving fund sustainability.

Existing studies on loan repayment behaviour in developing countries primarily rely on conventional logistic or probit models (Ssekiziyivu et al., 2018; Kiros, 2022), which assume borrower homogeneity and overlook behavioural diversity. This study addresses this gap by applying a Bayesian Latent Class Logistic Regression (LCLR) framework that simultaneously estimates class-specific repayment parameters and latent class memberships, providing full posterior distributions for uncertainty quantification (Depaoli, 2013; Gelman et al., 2014). The principal contribution of this study is methodological: the Bayesian LCLR moves beyond conventional homogeneous models to reveal structural heterogeneity in repayment behaviour, offering richer and more policy-relevant insights for community-driven financial programmes.

By focusing on the PDM, this study contributes to the growing literature on community finance and behavioural heterogeneity in microcredit (Lusardi & Mitchell, 2014; Meki & Quinn, 2024; Ölkers et al., 2025). The findings provide empirical evidence to inform targeted policy interventions that strengthen borrower capacity, improve administrative efficiency and enhance the sustainability of Uganda's revolving fund system.

The study pursues three specific objectives: (1) to examine demographic, institutional and behavioural factors associated with beneficiaries' willingness to repay the PRF under the PDM; (2) to identify unobserved borrower segments with distinct repayment behaviour using Bayesian LCLR; and (3) to evaluate how alternative policy interventions, including improvements in financial literacy and administrative efficiency, affect repayment willingness across borrower segments through simulation analysis. The study tests four hypotheses: (H_1) higher financial literacy and awareness of PRF loan conditions increase willingness to repay; (H_2) longer PRF fund disbursement lead times reduce willingness to repay; (H_3) beneficiaries exhibit behavioural heterogeneity characterised by latent borrower segments with distinct repayment determinants; and (H_4) joint improvements in financial literacy and administrative efficiency generate larger repayment gains than single-policy interventions across borrower segments.

2. Literature review

2.1. Theoretical framework

This study draws on three complementary theoretical foundations. First, the Expected Utility Theory (EUT) by Von Neumann and Morgenstern (2007) assumes that rational borrowers make repayment decisions by comparing the expected utility of repaying *versus* defaulting, given their income, information, and institutional environment. In the context of the PRF, a borrower weighs the utility of continued access to revolving credit against the short-term gain of defaulting, net of any penalties such as loss of future credit or community sanctions. The subjective nature of the probability assessments connects EUT to Savage (1954) Subjective Expected Utility Theory (SEUT), which recognises that borrowers form personal probability estimates about uncertain outcomes based on their own information and experience. EUT directly motivates the inclusion of income, wealth status, loan amount and penalty-related variables as predictors of repayment willingness.

Second, Social Capital Theory, as articulated by Putnam (2000) and Coleman (1988), posits that networks of trust, norms of reciprocity and community sanctions facilitate cooperative behaviour and reduce transaction costs. In microfinance, social capital operates through peer monitoring, group accountability and reputational incentives that encourage loan repayment (Dalla Pellegrina et al., 2021;

Wydick, 1999). Rural communities typically exhibit stronger social cohesion than urban areas, which may explain why rural borrowers demonstrate higher repayment willingness. Social capital theory links directly to the variables of residence, SACCO membership and community-level engagement.

Third, Information Asymmetry Theory, rooted in Stiglitz and Weiss (1981), explains how unequal information between lenders and borrowers leads to adverse selection and moral hazard. Financial literacy programmes reduce information asymmetry by equipping borrowers with knowledge needed to make informed repayment decisions (Hastings et al., 2013; Lusardi & Mitchell, 2014). This theory motivates the inclusion of financial literacy, awareness of payment periods and awareness of interest rates as key predictors.

Together, these theories provide a comprehensive framework. EUT explains the rational calculus and motivates income and loan variables. Social Capital Theory accounts for community-level mechanisms differentiating rural and urban patterns. Information Asymmetry Theory explains the role of financial literacy. The Bayesian LCLR operationalises these insights by allowing repayment drivers to vary across latent classes, capturing heterogeneous ways in which economic rationality, social embeddedness and informational capacity shape repayment behaviour.

2.2. Demographic and institutional drivers of loan repayment

Studies on microfinance repayment behaviour have long emphasised borrower characteristics and institutional design as key determinants. Early research using logistic and probit models found that borrower demographics, such as age, education and gender influence repayment behaviour, though often modestly (Kimuyu & Omiti, 2000; Lusardi & Mitchell, 2014). In Uganda, Ssekiziyivu et al. (2018) observed that borrower characteristics explained limited variation in repayment performance among rural MFI clients, while loan conditions such as size and term length had a stronger impact. Similar results were found in Ethiopia by Kiros (2022), who reported that timely loan disbursement improved repayment, but loan size and grace period had weak effects.

Institutional factors also play a central role. Dalla Pellegrina et al. (2021) showed that the frequency of group meetings strengthened repayment through social accountability effects, while Wright et al. (2012) and Karlan et al. (2014) found that borrower training and clear communication of loan conditions reduced default risk. However, most of these studies assume a homogeneous borrower population, overlooking differences in behavioural response to institutional structures.

2.3. Emerging evidence on repayment heterogeneity in Africa

Recent African studies have moved towards identifying unobserved heterogeneity in borrower behaviour. Koffi et al. (2024) used frailty models to examine delinquency transitions in Ghanaian microfinance institutions and found distinct unobserved borrower types with varying default risks. Similarly, Ölkers et al. (2025) applied clustering techniques to farmer loan data in Mali and identified latent repayment groups shaped by liquidity cycles and financial literacy. Meki and Quinn (2024) highlighted that average-effect models mask significant behavioural diversity among microfinance clients.

Further recent evidence reinforces these findings. Dalla Pellegrina et al. (2021) showed that social accountability mechanisms in group lending significantly improved repayment rates in African microfinance institutions, while Wydick (1999) demonstrated that social cohesion can be harnessed to address market failures in credit delivery. In East Africa, Munyegera and Matsumoto (2016) showed that mobile money adoption among Ugandan households improved financial management and reduced transaction costs, with implications for loan repayment capacity.

Within Uganda, research on the PDM and its PRF is still limited. Institutional assessments highlight loan disbursement delays, weak fund monitoring and inconsistent repayment outcomes (ACODE, 2024). Yet, there is little empirical evidence explaining why repayment varies among beneficiaries or how socio-economic and behavioural differences shape repayment willingness under the PDM.

Recent evaluations of the PDM have begun to document implementation challenges. EPRC (2025) assessed the PDM's financial inclusion pillar and identified disbursement delays and weak SACCO governance as key constraints. The World Bank (2024) assessed the PDM as an ambitious approach to

poverty reduction but noted that implementation gaps, particularly in fund disbursement and SACCO capacity, limit its effectiveness in reaching the poorest households.

2.4. Methodological limitations in existing studies

Most prior studies employ standard logistic or probit regression frameworks that assume parameter homogeneity across borrowers (Awunyo-Vitor, 2012; Bhatt & Tang, 2002). While effective for identifying average effects, these models cannot detect latent behavioural subgroups or quantify uncertainty in class membership. Even where latent class or clustering methods have been introduced, they typically rely on frequentist estimation (Greene, 2018; McLachlan & Peel, 2000).

2.5. Contribution of this study

This study extends the literature by applying a Bayesian LCLR framework to model willingness to repay the PRF. Beyond methodological innovation, the study makes three substantive contributions. First, it identifies three distinct borrower segments – institutionally aware, economically empowered and financially constrained – each characterised by unique socioeconomic profiles. Second, it demonstrates that repayment drivers operate differently across these segments. Third, it provides the first Bayesian latent class analysis of a government-administered revolving fund in Sub-Saharan Africa, offering a replicable framework for evaluating similar community finance programmes. The Bayesian LCLR thus moves beyond predictive accuracy to reveal structural heterogeneity in repayment behaviour, offering richer insights for policy design under Uganda's PDM.

3. Materials and methods

3.1. Study area

The study was conducted in Uganda using nationally representative household survey data collected under the PDM assessment. The focus is on households across all regions that were either beneficiaries or non-beneficiaries of PDM support, with specific attention to their willingness to repay the PRF.

3.2. Data source

The study used nationally representative data from the 2024 Economic Policy Research Centre (EPRC) PDM Survey (Table 1). The dataset covers households across all regions of Uganda and includes detailed information on demographics, financial access, administrative experiences and repayment attitudes. The analysis focused on 1366 PRF beneficiaries, applying sampling weights to maintain national representativeness.

The survey also collected data on non-loan households to enable comparison of socioeconomic characteristics between beneficiaries and non-beneficiaries and to contextualise the beneficiary sample within the wider parish population. While the regression analysis focuses exclusively on PRF beneficiaries, the inclusion of non-beneficiary data supports descriptive comparisons and contextualises the beneficiary sample.

3.3. Data analysis

3.3.1. Empirical framework

The analysis proceeds in stages. First, descriptive statistics summarise the characteristics of PRF beneficiaries. Second, cross-tabulations compare willingness to repay across key demographic and institutional groups. Third, multicollinearity among predictors is assessed using Variance Inflation Factors (VIFs). Finally, the study applies a Bayesian LCLR model to capture both observed and unobserved heterogeneity in repayment behaviour.

Table 1. Variable definitions and measurement.

Variable name	Definition	Measurement	Variable code
Willingness to payback PRF	PRF recipients' willingness to pay back	Dummy: 1 = Yes, 0 = Otherwise	Y
Age	Respondent age	Continuous variable	X_1
Household size	Number of household members	Count variable	X_2
Residence	Location of residence	Dummy: 1 = Urban, 0 = Rural	X_3
Gender	Gender of respondent	Dummy: 1 = Male, 0 = Female	X_4
Years of schooling	Years of formal education	Count variable	X_5
Member to other SACCOs	Member of other SACCOs	Dummy: 1 = Yes, 0 = Otherwise	X_6
Access to Credit	Access to credit from other sources	Dummy: 1 = Yes, 0 = Otherwise	X_7
Access to Market	Access to market for products	Dummy: 1 = Yes, 0 = Otherwise	X_8
Amount of PRF received	Amount of PRF received in UGX	Continuous variable	X_9
Financial Literacy training	Received financial literacy training	Dummy: 1 = Yes, 0 = Otherwise	X_{10}
Aware of the payment period	Aware of PRF payment period	Dummy: 1 = Yes, 0 = Otherwise	X_{11}
Aware of the interest rate	Aware of PRF interest rate	Dummy: 1 = Yes, 0 = Otherwise	X_{12}
Lead time (turnaround time)	Time to receive funds (months)	Count variable	X_{13}
Wealth status	Wealth status	Dummy: 1 = Relatively Poor, 0 = Better off	X_{14}
Switched enterprise	Changed enterprise after receiving PRF	Dummy: 1 = Yes, 0 = Otherwise	X_{15}

Source: Authors' construction.

3.3.2. Theoretical motivation: Expected Utility Theory

The study is anchored on the theoretical foundation of the EUT by Von Neumann and Morgenstern (2007). The theory assumes that rational borrowers make repayment decisions by comparing the expected utility of repaying *versus* defaulting, given their income, information and institutional environment. Borrowers choose the option that maximises their expected utility.

Let borrower i derive utility $U(C)$ from consumption C, where the utility function satisfies $U'(C) > 0$ and $U''(C) < 0$, implying diminishing marginal utility of consumption. Borrower i faces two choices. Repayment of the PRF loan leads to consumption after repayment defined as $C_{\text{repay}} = Y_i - R_i$ (Equation (1)), where Y_i denotes borrower income and R_i represents the repayment obligation. In contrast, default results in consumption $C_{\text{default}} = Y_i$ (Equation (2)), but the borrower incurs a penalty cost D_i, reflecting loss of future credit access or community sanctions, yielding net utility $U(Y_i) - D_i$ (Equation (3)). The borrower compares expected utilities across the two options. Expected utility from repayment is given by $EU(\text{Repay}) = p_i \cdot U(Y_i - R_i)$ (Equation (4)), while expected utility from default is expressed as $EU(\text{Default}) = (1 - p_i) \cdot [U(Y_i) - D_i]$ (Equation (5)), where p_i denotes the subjective probability that repayment yields continued access to the PRF or related institutional benefits.

Several important qualifications should be noted regarding the EUT framework. First, the model captures a single-period decision and does not explicitly incorporate dynamic motives, such as strategic repayment to secure future loans or precautionary saving behaviour. In practice, borrowers may repay partly to maintain access to subsequent PRF rounds, a motive consistent with repeated-game incentives in microfinance (Ghatak, 1999). Second, while the EUT framework does not itself model borrower heterogeneity, the empirical claim that borrowers are heterogeneous is addressed through the latent class structure of the LCLR model. The EUT provides the theoretical motivation for why individual borrowers compare repayment and default utilities, while the latent class extension allows the parameters governing this comparison to differ systematically across unobserved borrower groups. In this way, heterogeneity is modelled empirically rather than theoretically. Third, the EUT framework assumes rational utility-maximising agents (homo oeconomicus), yet the empirical hypotheses acknowledge that borrowers exhibit bounded rationality: their decisions are shaped by imperfect information, cognitive limitations and social influences. This apparent tension is resolved by the latent class structure, which captures systematic departures from full rationality. Different borrower classes respond to the same institutional and economic signals in systematically different ways precisely because they differ in information processing, financial capability and social embeddedness. The EUT thus serves as a benchmark from which the latent classes represent empirically identified deviations. Fourth, the use of subjective probabilities p_i connects to Savage (1954). Subjective EUT, recognising that borrowers form personal probability estimates based on their own information and experience rather than objective frequencies, which is particularly relevant in the PDM context where perceptions of institutional reliability are inherently subjective.

Assuming a logistic distribution of the error term, repayment willingness follows a logistic regression specification. The probability that borrower i is willing to repay is expressed as

$$P(Y_i = 1|X_i) = \frac{\exp(X_i'\beta)}{1 + \exp(X_i'\beta)} \tag{6}$$

where $Y_i = 1$ indicates that borrower i is willing to repay, X_i denotes the vector of borrower and institutional characteristics influencing repayment behaviour and β represents the corresponding vector of parameters to be estimated.

3.4. Model specification

The Bayesian LCLR assumes that the borrower population comprises K unobserved classes, each with distinct behavioural patterns. The model is specified through three key equations:

Equation (1) (Class-Specific Logistic Model): Conditional on class k, willingness to repay follows:

$$P(Y_i = 1|X_i, C_i = k) = \frac{\exp(X_i'\beta_k)}{1 + \exp(X_i'\beta_k)} \tag{7}$$

where β_k are class-specific regression parameters.

Equation (2) (Latent Class Mixture): The unconditional probability of repayment, summing over all K classes, is:

$$P(Y_i = 1|X_i) = \sum_k \pi_k \cdot P(Y_i = 1|X_i, C_i = k) \tag{8}$$

where π_k is the probability of belonging to class k.

Equation (3) (Bayesian Posterior): Posterior inference combines likelihood and priors:

$$P(\beta, \pi|Y, X) \propto L(Y|X, \beta, \pi) \cdot P(\beta) \cdot P(\pi) \tag{9}$$

where weakly informative Normal priors $N(0, 2.5^2)$ are assigned to regression coefficients and a symmetric Dirichlet $(1, 1, ..., 1)$ prior to class probabilities.

3.5. Model estimation and evaluation

Estimation was implemented in R using four independent Markov chains, each with 4000 iterations, of which 2000 were retained after warm-up. The No-U-Turn Sampler (NUTS) was used for posterior sampling (Hoffman & Gelman, 2014). Convergence was evaluated using R-hat statistics, effective sample size (n_eff) and MCSE/SD ratios. Model selection was guided by WAIC and LOOIC, where lower values indicate superior predictive performance. Posterior predictive checks validated goodness-of-fit.

4. Results

4.1. Descriptive analysis

Table 2 presents descriptive statistics. About 86.7% of PRF beneficiaries expressed willingness to repay. The average respondent was 45 years old. Education averaged eight years. Households averaged six members, and 51% lived in rural areas. Around 57% had received financial literacy training, while 39% were members of other SACCOs. The average loan amount was UGX 1.08 million (approximately USD 287 at the November 2024 exchange rate of UGX 3760 per USD). To contextualise the economic significance, the Uganda National Household Survey 2023/24 reports average monthly household income of approximately UGX 400,000 (USD 106) in rural areas, meaning the average PRF loan represents roughly 2.7 months of rural household income), with 63% reporting market access and 29% credit access.

A notable proportion of 13.3% of borrowers reported unwillingness to repay. Cross-tabulation analysis suggests several explanations: many experienced extended disbursement delays (average lead time of 10.1 months compared to 6.8 months for willing borrowers), others reported that funds were too small to generate meaningful returns, and a subset lacked financial literacy training, qualitative data says respondents unwilling to pay back treat PRF is a gift/political appreciation from government, as PRF enforcement mechanisms were still being established. This absence of sanctions may have encouraged

Table 2. Descriptive statistics for all variables.

Variable	*N*	*n*	Mean (*N*)	Mean (*n*)	Median (*N*)	Median (*n*)	Min (*N*)	Min (*n*)	Max (*N*)	Max (*n*)
Willingness to payback PRF	1,431,586	1,366	0.8675	0.8675	1	1	0	0	1	1
Age	1,431,586	1,366	45.34007	45.34007	44	44	10	10	90	90
Gender (male)	1,433,158	1,366	0.5	0.4802	0	0	0	0	1	1
Years of schooling	1,237,765	1,366	7.97	7.8265	7	7	1	1	16	16
Member to other saccos	1,431,694	1,366	0.39	0.4041	0	0	0	0	1	1
Access to Credit	1,433,158	1,366	0.29	0.2877	0	0	0	0	1	1
Access to Market	1,426,963	1,366	0.63	0.6061	1	1	0	0	1	1
Amount of PRF received	1,433,158	1,366	1,084,670	1,084,670	1,000,000	1,000,000	280,000	280,000	3,744,000	3,744,000
Financial Literacy training	1,024,920	1,366	0.57	0.3594	1	0	0	0	1	1
Aware of the payment period	1,432,610	1,366	0.79	0.754	1	1	0	0	1	1
Aware of the interest rate	1,410,367	1,366	0.71	0.6406	1	1	0	0	1	1
Lead time (turnaround time)	1,038,467	1,366	8.47	8.0117	6	7	0	0	32	32
Wealth status	1,433,158	1,366	0.36	0.4092	0	0	0	0	1	1
Household size	1,433,158	1,366	6.0	5.8675	6	6	1	1	17	17
Residence (Rural)	1,433,158	1,366	0.51	0.4473	1	0	0	0	1	1
Switched enterprise	1,420,428	1,366	0.39	0.3001	0	0	0	0	1	1

Source: Authors' construction using EPRC-PDM Household survey (2024).

Table 3. Cross-tabulations of willingness to repay by gender, residence, wealth status and access to financial literacy, credit and market.

Variable	Category	Not willing	Willing	Total	% Willing
Gender	Female	98	612	710	86.2
	Male	83	573	656	87.35
Residence	Rural	89	666	755	88.21
	Urban	92	519	611	84.94
Wealth status	Better off	95	712	807	88.23
	Poor	86	473	559	84.62
Financial literacy	No	135	740	875	84.57
	Yes	46	445	491	90.63
Access to credit	No	128	845	973	86.84
	Yes	53	340	393	86.51
Access to market	No	63	475	538	88.29
	Yes	118	710	828	85.75

Source: Authors' construction using EPRC-PDM Household survey (2024).

candid responses, though stated unwillingness may partly reflect frustration with programme delivery rather than a beneficiary intention to default.

Table 3 summarises how repayment willingness varies across key socioeconomic groups. Gender differences are minimal, with nearly equal repayment willingness among men (87.3%) and women (86.2%). Rural respondents show higher willingness (88.2%) than urban ones (84.9%). Financial literacy stands out as the most influential factor, with 90.6% of financially trained respondents willing to repay *versus* 84.6% of those without training.

Although rural borrowers show a higher overall willingness to repay (88.2%), this masks variability across latent segments. Rural borrowers in Class 2 (economically empowered) exhibit the highest willingness (93.1%), while rural borrowers in Class 3 (financially constrained) show substantially lower rates (76.4%). For Class 2, urban residency has a negative coefficient (−0.38), suggesting that the benefits of economic empowerment in repayment discipline are amplified in rural contexts where social capital and community accountability are stronger.

To assess multicollinearity, VIF were computed from auxiliary OLS regressions (Table 4a). All VIF values are below 2.0, well below the conventional threshold of 5.0 (Hair et al., 2019), confirming that multicollinearity does not pose a concern. The pairwise correlation matrix (Table 4b) is also presented for completeness.

4.2. Model estimation summary and convergence diagnostics

Figure 1 displays trace plots for selected parameters, showing well-mixed Markov Chain Monte Carlo chains with consistent horizontal overlap and no visible drifts, confirming stable convergence. This indicates efficient exploration of the posterior distributions and stable convergence. The consistency across chains confirms that posterior means accurately reflect underlying parameter values and that the results

Table 4a. Variance inflation factors (VIF) for continuous predictors.

Variable	VIF
Age	1.18
Years of schooling	1.17
Lead time	1.02
Household size	1.01
PRF amount received	1.05

Source: Authors' construction using EPRC-PDM Household survey (2024).

Table 4b. Correlation matrix (continuous variables).

Variable	Age	Education	Lead time	Household size
Age	1	−0.38	0.05	0.02
Education	−0.38	1	−0.1	0.08
Lead time	0.05	−0.1	1	−0.03
Household size	0.02	0.08	−0.03	1

Source: Authors' construction using EPRC-PDM Household survey (Nov 2024).

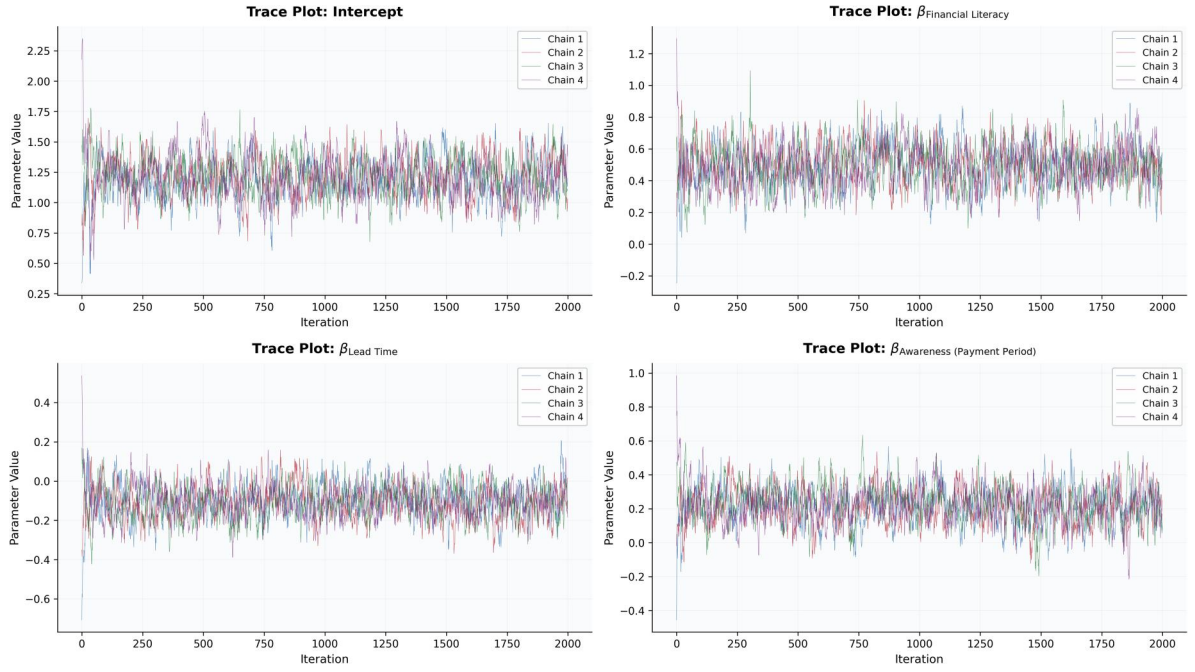

Figure 1. Trace plots for selected parameters (showing stable chain mixing). Source: Authors' construction using EPRC-PDM Household survey (2024).

are reproducible, reliable and free from sampling path dependence, meeting key conditions for credible Bayesian inference.

Table 5 presents convergence diagnostics for all model parameters, including R-hat, effective sample size (n_eff) and the MCSE/SD ratio. R-hat values between 0.99 and 1.01 show that all Markov chains converged to a common posterior distribution. Effective sample sizes above 2000 indicate sufficient independent draws, while MCSE/SD ratios below 0.01 confirm low simulation error and high numerical stability. Together, these results show that the Bayesian estimation converged efficiently and produced reliable posterior estimates free from sampling issues.

4.3. Model comparison and class selection

Table 6 summarises the model comparison statistics used to select the optimal number of latent classes in the Bayesian LCLR. Using the WAIC, LOOIC and log-likelihood criteria, the three-class model achieved the best performance, with the lowest WAIC (1165.2) and LOOIC (1167.5) and a log-likelihood of −575.6. These results show that the three-class structure offers the best trade-off between fit and simplicity.

Table 5. Convergence statistics (R-hat, n_eff, MCSE/SD ratio).

	Parameter	R-hat	n_eff	MCSE/SD ratio
Intercept	Intercept	0.9993	3083	0.0080
beta_1	β_Gender (Male)	0.9910	3078	0.0030
beta_2	β_Age	1.0090	2763	0.0036
beta_3	β_Household Size	1.0029	2031	0.0085
beta_4	β_Residence (Urban)	1.0097	2062	0.0098
beta_5	β_Years of Schooling	0.9979	3188	0.0048
beta_6	β_Member of Other SACCO	1.0004	3154	0.0024
beta_7	β_Access to Credit	1.0061	3552	0.0061
beta_8	β_Access to Market	1.0029	2676	0.0034
beta_9	β_PRF Received	0.9917	2466	0.0075
beta_10	β_Financial Literacy	1.0076	2747	0.0013
beta_11	β_Aware of Payment Period	0.9913	2520	0.0097
beta_12	β_Aware of Interest Rate	0.9957	2227	0.0051
beta_13	β_Lead Time	1.0067	2737	0.0047
beta_14	β_Wealth Status (Poor)	0.9978	2238	0.0085
beta_15	β_Switched enterprise	0.9079	2236	0.0004

Source: Authors' construction using EPRC-PDM Household survey (2024).

Table 6. Model comparison statistics.

K classes	WAIC	LOOIC	Loglikelihood
1	1250.5	1252.1	−620.2
2	1180.3	1182	−585.1
3	1165.2	1167.5	−575.6
4	1170.8	1173.2	−578.4
5	1175.4	1177.9	−580.7

Source: Authors' construction using EPRC-PDM Household survey (2024).

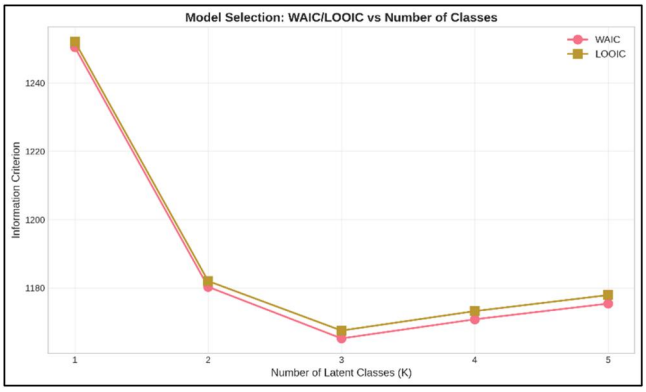

Figure 2. Plot of WAIC/LOOIC against number of classes. Source: Authors' construction using EPRC-PDM Household survey (Nov 2024).

Models with fewer classes failed to capture behavioural diversity, while those with more classes added complexity without substantial improvement.

Figure 2 presents the model selection curve. The decline from one to three classes indicates improved fit. Beyond three classes, the curve flattens, supporting the three-class model as optimal.

4.4. Posterior parameter estimates

Table 7 reports the posterior means and 95% credible intervals for predictors across the three borrower classes. These classes emerged endogenously from the data rather than being pre-defined. The posterior model was estimated using 4000 MCMC iterations with weakly informative priors, and convergence diagnostics (R-hat between 0.99 and 1.01; n_eff $>$ 2000) confirmed stable estimation.

In the Bayesian inference, statistical relevance is evaluated using posterior credible intervals rather than frequentist p values. A predictor demonstrates statistical relevance when its 95% credible interval excludes zero, indicating a high posterior probability of a non-zero effect. Results in Table 7 reveal clear class-specific determinants of repayment willingness. In Class 1, financial literacy (0.49, CI [0.12, 0.86]) and awareness of the payment period (0.22, CI [0.01, 0.43]) increase repayment willingness, while

Table 7. Posterior means and 95% credible intervals for each predictor by class.

Predictor	Class	Post. Mean	CI lower	CI upper
Gender: male	1	−0.48	−1.12	0.16
Gender: male	2	−0.16	−0.58	0.27
Gender: male	3	−1.05	−2.14	0.05
Age	1	0.44	−0.08	0.95
Age	**2**	**0.21**	**0.03**	**0.39**
Age	3	−0.52	−1.18	0.14
Household size	1	0.52	−0.14	1.19
Household size	2	0.94	−0.03	1.92
Household size	3	0.76	−0.22	1.74
Years of schooling	1	0.44	−0.08	0.95
Years of schooling	**2**	**0.21**	**0.04**	**0.38**
Years of schooling	3	−0.52	−1.07	0.03
Member to Other SACCO	1	−0.55	−1.24	0.13
Member to Other SACCO	2	0.51	−0.09	1.12
Member to Other SACCO	3	0.11	−0.52	0.74
Access to credit	1	−0.81	−1.63	0.01
Access to credit	2	−0.09	−0.62	0.45
Access to credit	3	0.23	−0.41	0.87
Access to market	1	0.2	−0.38	0.78
Access to market	2	−0.11	−0.61	0.38
Access to market	3	0.43	−0.18	1.04
PRF received	1	−0.27	−0.89	0.34
PRF received	2	−0.35	−0.82	0.13
PRF received	3	−0.48	−1.06	0.1
Financial literacy	**1**	**0.49**	**0.12**	**0.86**
Financial literacy	2	−0.34	−0.74	0.07
Financial literacy	**3**	**−0.48**	**−0.91**	**−0.05**
Aware of payment period	**1**	**0.22**	**0.01**	**0.43**
Aware of payment period	2	0.07	−0.24	0.38
Aware of payment period	3	−0.12	−0.56	0.33
Aware of interest rate	1	−0.04	−0.52	0.43
Aware of interest rate	**2**	**−0.59**	**−1.18**	**−0.01**
Aware of interest rate	3	0.33	−0.14	0.8
Lead time	1	−0.02	−0.08	0.05
Lead time	2	−0.004	−0.05	0.04
Lead time	**3**	**−0.25**	**−0.49**	**−0.02**
Wealth status: poor	1	−0.59	−1.22	0.05
Wealth status: poor	2	0.06	−0.38	0.49
Wealth status: poor	**3**	**−0.34**	**−0.67**	**−0.01**
Residence: urban	1	0.6	−0.05	1.24
Residence: urban	**2**	**−0.38**	**−0.74**	**−0.01**
Residence: urban	3	−0.2	−0.72	0.32
Switched enterprise	**1**	**−1.03**	**−1.78**	**−0.28**
Switched enterprise	2	0.48	−0.06	1.02
Switched enterprise	**3**	**1.13**	**0.31**	**1.94**

Source: Authors' construction using EPRC-PDM Household survey (2024).
Note: Bold entries indicate credible intervals that exclude zero (statistically meaningful at 95% level).

switching enterprise (−1.03, CI [−1.78, −0.28]) reduces willingness, suggesting instability among borrowers who change economic activities. In Class 2, age (0.21, CI [0.03, 0.39]) and education (0.21, CI [0.04, 0.38]) positively influence repayment willingness, whereas awareness of the interest rate (−0.59, CI [−1.18, −0.01]) and urban residence (−0.38, CI [−0.74, −0.01]) show negative associations, indicating potential dissatisfaction or alternative credit access among urban borrowers. In Class 3, financial literacy (−0.48, CI [−0.91, −0.05]), lead time (−0.25, CI [−0.49, −0.02]) and wealth status (−0.34, CI [−0.67, −0.01]) reduce repayment willingness, while switching enterprise (1.13, CI [0.31, 1.94]) increases willingness, pointing to adaptive entrepreneurial behaviour within this segment. Predictors with intervals overlapping zero exhibit substantial posterior uncertainty within their respective classes, although coefficient signs still provide directional insight into behavioural tendencies across borrower segments.

The classification of borrower groups was derived from these coefficient patterns. In Class 1, positive coefficients for financial literacy, awareness and market access, combined with negative effects of lead time and enterprise switching, indicate institutionally aware borrowers. In Class 2, positive effects of age, education and wealth show economically empowered borrowers. For Class 3, negative coefficients for financial literacy, wealth and awareness reflect financially constrained borrowers.

Figure 3 presents the caterpillar plot of coefficient estimates with 95% credible intervals, showing clear class-specific variation. Key variables, such as financial literacy, awareness and lead time display

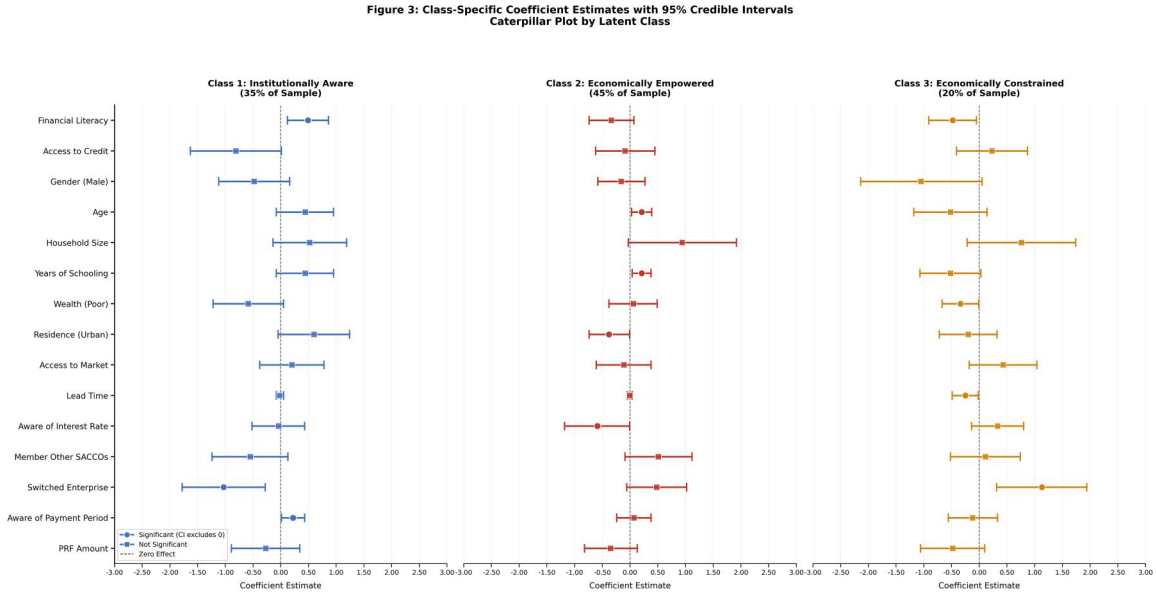

Figure 3. Class-specific coefficient estimates with 95% credible intervals. Source: Authors' construction using EPRC-PDM Household survey (2024).

distinct effects across classes, with several non-overlapping intervals. Positive coefficients for awareness variables and negative ones for lead time indicate consistent behavioural responses to programme design. The wider intervals observed for Class 3 reflect higher uncertainty among poorer or less-informed borrowers, typical of heterogeneous groups with weaker institutional engagement.

4.5. Class probabilities and assignments

Table 8a summarises the estimated posterior class probabilities: 35% belong to Class 1 (institutionally aware), 45% to Class 2 (economically empowered) and 20% to Class 3 (financially constrained). The dominance of Class 2 indicates that nearly half of the beneficiaries have stronger repayment capacity and engagement, while the smaller share of Class 3 highlights persistent financial and structural barriers. This class distribution reflects the socioeconomic diversity within the PDM, with most beneficiaries economically active but a notable fraction still facing constraints to repayment performance.

Table 8b presents the sociodemographic profiles of the three latent classes. Class 1 (institutionally aware) has a median age of 42 years, 52% female, average education of 8.5 years and 58% rural. Class 2 (economically empowered) has a median age of 48, 46% female, 9.2 years education and 54% rural. Class 3 (financially constrained) has a median age of 40, 55% female, 6.1 years education and 47% rural. The economically empowered class is older and better educated, while the financially constrained class has the lowest education and highest female proportion.

Table 9 summarises classification accuracy. Results show 450 of 478 in Class 1, 580 of 615 in Class 2 and 253 of 273 in Class 3 correctly classified. Misclassifications are minimal and mostly occur between adjacent classes. This high accuracy confirms that the model reliably distinguishes behavioural types, capturing genuine differences in repayment motivation. The robustness of the latent structure makes it suitable for policy segmentation and targeted intervention planning.

4.6. Posterior predictive checks and model fit

Table 10 summarises the Bayesian LCLR model's fit and predictive accuracy indicators. The results show strong performance, with an area under the curve (AUC) of 0.828, indicating high discriminatory power in distinguishing willing from unwilling PRF borrowers. The Brier Score of 0.0914 reflects low prediction error and strong calibration between predicted and observed outcomes. The Entropy value of 0.85 confirms clear separation among the three latent classes, and an overall accuracy rate of 0.87 shows the

Table 8a. Estimated posterior class probabilities and assigned proportions.

Class	Posterior probability	Assigned proportions
1	0.35	478
2	0.45	615
3	0.2	273

Source: Authors' construction using EPRC-PDM Household survey (2024).

Table 8b. Sociodemographic profiles of latent borrower classes.

Characteristic	Class 1: Institutionally aware	Class 2: Economically empowered	Class 3: Financially constrained
Median age (years)	42	48	40
Female (%)	52	46	55
Average education (years)	8.5	9.2	6.1
Rural residence (%)	58	54	47
Financial literacy (%)	62	58	38
Average lead time (months)	7.2	6.8	10.1
Average PRF amount (UGX)	1,050,000	1,180,000	920,000
Willingness to repay (%)	87.4	91.2	76.6

Source: Authors' construction using EPRC-PDM Household survey (2024).

Table 9. Posterior classification matrix.

True class	Assigned: Class 1	Assigned: Class 2	Assigned: Class 3
Class 1	450	20	8
Class 2	15	580	20
Class 3	5	15	253

Source: Authors' construction using EPRC-PDM Household survey (2024).

Table 10. Model fit and predictive accuracy indicators.

Metric	Value
AUC	0.828
Brier score	0.0914
Entropy	0.85
Accuracy	0.87

Source: Authors' construction using EPRC-PDM Household survey (2024).

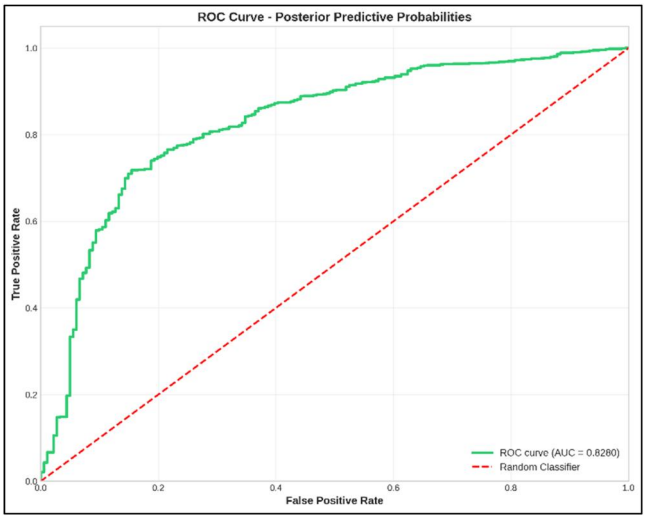

Figure 4. ROC curve based on posterior predictive probabilities. *Source:* Authors' construction using EPRC-PDM Household survey (2024).

model correctly classified nearly nine out of ten respondents. Collectively, these indicators demonstrate that the Bayesian model fits the data well and reliably predicts repayment behaviour under the PDM.

Figure 4 presents the Receiver Operating Characteristic (ROC) curve based on posterior predictive probabilities. The curve rises sharply towards the upper-left corner, showing high sensitivity and low false-positive rates. With an AUC of 0.828, the model demonstrates strong classification accuracy, far exceeding random prediction. This indicates that the model effectively distinguishes borrowers likely to

Table 11. Simulation of repayment probabilities under policy scenarios.

Scenario	Class 1	Class 2	Class 3
Baseline	0.82	0.9	0.75
Reduce lead time	0.85	0.92	0.78
Increase financial literacy	0.84	0.91	0.77
Both interventions	0.88	0.94	0.80

Source: Authors' construction using EPRC-PDM Household survey (2024).

repay from those at risk of default, making it a useful diagnostic tool for guiding targeted repayment and risk management interventions under the PDM.

4.7. Policy simulation results

Table 11 summarises simulated repayment probabilities across policy scenarios to show how administrative efficiency and borrower training influence repayment behaviour in the three borrower classes. Under the baseline, predicted repayment probabilities are 0.82 for Class 1 (institutionally aware), 0.90 for Class 2 (economically empowered) and 0.75 for Class 3 (financially constrained). These results confirm that economically empowered borrowers are most willing to repay, while financially constrained ones lag due to liquidity and structural barriers. When lead time is shortened, repayment probabilities rise to 0.85, 0.92 and 0.78, respectively, demonstrating that faster fund disbursement improves repayment motivation. The largest gain occurs in Class 1, showing that institutionally aware borrowers are especially sensitive to administrative efficiency and that timely fund release builds trust and accountability within parish SACCOs.

Figure 5 compares repayment probabilities under four scenarios: baseline, reduced lead time, increased financial literacy and combined interventions, with the largest gains when both policies are applied together. The results highlight the complementarity between administrative efficiency and financial literacy: quicker disbursement builds trust and motivation, while financial education strengthens borrowers' ability to manage repayments, jointly promoting a more inclusive and sustainable credit system.

5. Discussion of findings

5.1. Demographic determinants and repayment behaviour

The positive relationship between age and repayment willingness across all latent classes supports Lusardi and Mitchell (2014) view that older borrowers possess greater financial maturity. Similar findings by Wongnaa and Awunyo-Vitor (2013) show that older farmers in Ghana repay more reliably, though Banerjee et al. (2015) note that age-related constraints can weaken repayment ability. Gender patterns present a balanced outcome, with nearly identical willingness (87.3 and 86.2%), differing from earlier conclusions by Armendáriz and Morduch (2010) that women outperform men. This parity likely reflects the PDM's community-level SACCO structures that foster shared accountability.

5.2. Financial literacy, awareness and institutional knowledge

Financial literacy and awareness of loan conditions are major determinants. The positive effects among Class 1 support Hastings et al. (2013) argument that financial education improves understanding of credit terms. Awareness of payment schedules proved significant, aligning with Karlan and Zinman (2011) view that informed borrowers experience fewer repayment shocks. The differing effects across classes highlight behavioural heterogeneity, consistent with Behrman et al. (2012).

5.3. Administrative efficiency and institutional performance

The consistent negative relationship between lead time and repayment willingness highlights the institutional role of administrative efficiency. Longer delays reduce borrower confidence across all classes, aligning with Stiglitz and Weiss (1981) theory. Class 3 faces the longest average lead time (10.1 months)

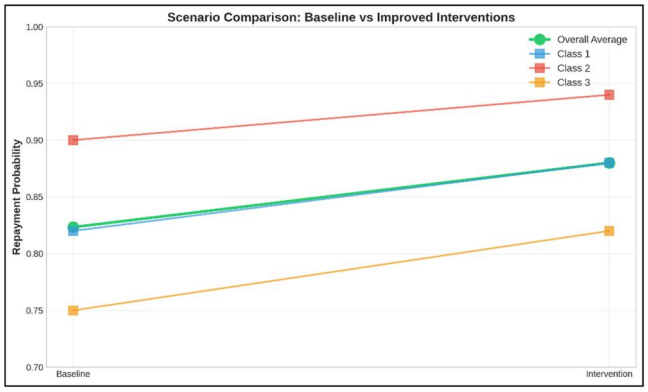

Figure 5. Scenario comparison plot – baseline *vs*. improved intervention conditions. *Source:* Authors' construction using EPRC-PDM Household survey (Nov 2024).

and lowest repayment willingness, illustrating how administrative inefficiencies compound financial vulnerability.

5.4. Market access, economic empowerment and repayment capacity

The positive association between market access and repayment willingness, particularly in Class 2, provides empirical support for Barrett's (2008) proposition that farmers linked to active markets possess stronger cash flows. This is further substantiated by Fafchamps and Hill (2005), who documented that market integration improves creditworthiness in Sub-Saharan Africa.

5.5. Rural-Urban differences, social capital and repayment discipline

A notable finding is that rural borrowers show greater willingness to repay (88.2%) than urban borrowers (84.9%), particularly among the economically empowered segment. The negative urbanisation coefficient among Class 2 (−0.38) suggests that economic empowerment without strong community ties may be less effective. This is consistent with Social Capital Theory (Coleman, 1988; Putnam, 2000), which posits that dense social networks and community sanctions in rural areas create informal enforcement mechanisms. Rural parish SACCOs operate within tightly knit communities where defaulting carries reputational costs (Dalla Pellegrina et al., 2021; Wydick, 1999). The stronger repayment performance of economically empowered rural borrowers reflects the synergy between individual economic capacity and community-level accountability. Conversely, the weaker rural advantage among Class 3 indicates that social capital alone cannot compensate for severe economic deprivation. These findings suggest that the parish-based PDM approach is structurally sound for leveraging rural social capital, but requires class-specific adjustments.

5.6. Latent Class heterogeneity and behavioural segmentation

The identification of three borrower classes marks a methodological step forward. The study reveals clear behavioural heterogeneity: institutionally aware (35%), economically empowered (45%) and financially constrained (20%). The strong performance of Class 2 supports Lusardi and Mitchell (2014) view that higher education and financial capability improve financial discipline. The weaker performance of Class 3 reflects enduring barriers noted by Morduch (1999) and Mayoux (2002).

5.7. Policy implications and programmatic interventions

The policy simulations show that combining reduced lead times with enhanced financial literacy yields the highest repayment probabilities: 88% for Class 1, 94% for Class 2 and 80% for Class 3. This

complementarity supports Armendáriz and Morduch (2010) argument that sustainable credit delivery depends on jointly strengthening institutional systems and client capacity.

5.8. *Willingness* versus *actual repayment: the intention-behaviour gap*

An important caveat concerns the distinction between willingness to repay (intended behaviour) and actual repayment. Research documents the 'intention-behaviour gap' – the systematic discrepancy between intentions and actions (Sheeran, 2002; Sniehotta et al., 2005). Meta-analytic evidence suggests intentions explain only 20–30% of variance in subsequent behaviour. In the PRF context, borrowers who express willingness may nonetheless default due to income shocks, competing expenditures or weak enforcement. The estimated repayment probabilities should therefore be interpreted as upper-bound estimates. Policy interventions should address structural barriers that prevent good intentions from translating into timely repayment – including automatic reminders, flexible schedules and stronger SACCO-level monitoring.

6. Conclusion and recommendations

6.1. Conclusion

This study analysed the determinants of beneficiaries' willingness to repay the PRF under Uganda's PDM using a Bayesian LCLR framework. Financial literacy, awareness of loan terms, fund size and administrative efficiency were the strongest predictors. Long disbursement delays and low wealth reduced willingness. The three borrower segments – institutionally aware, economically empowered and financially constrained – demonstrate significant behavioural heterogeneity. The model yielded an AUC of 0.828 and 87% accuracy.

A key finding is that economic empowerment achieves the highest repayment returns in rural communities where social capital strengthens financial commitment. The negative urbanisation coefficient among economically empowered borrowers confirms that community-level trust amplifies repayment benefits. The parish-based PDM approach is structurally sound for leveraging rural social capital, but requires class-specific adjustments: institutionally aware borrowers benefit from improved administrative efficiency; economically empowered borrowers respond to market linkages; and financially constrained borrowers require comprehensive livelihood interventions. The evidence underscores that willingness to repay represents intended rather than actual behaviour, and policy design should account for the intention-behaviour gap by incorporating structural supports.

6.2. Recommendations

6.2.1. Strengthen financial literacy and borrower education

The Ministry of Finance, Planning and Economic Development, together with the PDM Secretariat, should institutionalise regular financial literacy training within parish SACCO operations, tailored to different borrower segments.

6.2.2. Reduce administrative lead time in fund disbursement

The government should streamline fund approval and release processes through digital workflow systems and performance benchmarks for SACCO managers.

6.2.3. Segment and target borrowers based on behavioural classes

Policymakers should design differentiated interventions for each class – financial empowerment for economically active borrowers, training for institutionally aware borrowers and comprehensive livelihood support for financially constrained ones.

6.2.4. Integrate market access and enterprise support into the PDM framework

Linking PRF beneficiaries to structured value chains, cooperatives and local procurement opportunities would improve loan recovery.

6.2.5. Leverage rural social capital for repayment enforcement

Given that economic empowerment yields the highest repayment returns in rural communities, the PDM should strengthen community-based monitoring and peer accountability within parish SACCOs. In urban areas, alternative enforcement strategies such as digital repayment tracking should be explored.

6.3. Limitations and areas of further research

The key dependent variable is based on self-reported responses and may be influenced by social desirability bias. The analysis could not incorporate contextual institutional factors such as SACCO management efficiency or enforcement mechanisms.

Most importantly, the study measures intended rather than actual repayment behaviour. The intention-behaviour gap literature suggests that stated willingness may overestimate actual repayment rates (Sheeran, 2002). The probabilities reported should be interpreted as upper-bound estimates. Future research should use longitudinal or administrative data to examine the correspondence between intentions and actual repayment.

Future studies could extend the Bayesian framework to include spatial or hierarchical effects. Comparative analyses of similar government credit programmes, such as Emyooga and Operation Wealth Creation, would further enhance understanding of local financing models in Uganda.

Author contributions

CRediT: **Solomon Stephen Nuwagaba**: Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing; **Swaibu Mbowa**: Supervision.

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Data availability statement

The data supporting this study are available on formal request from the Economic Policy Research Centre (EPRC). Interested researchers may contact the corresponding author.

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