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Microfinance Loan Default in Bangladesh: Borrower-Level Determinants, Predictive Validation, and Sustainable Risk Mitigation

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Abstract **Original Research Article**

Credit risk is central to the financial sustainability of microfinance institutions (MFIs), yet borrower-level evidence that combines repayment history, financial capacity, institutional contact, loan purpose, and shock exposure remains limited in Bangladesh. This study examines the determinants of microfinance loan default and translates the empirical results into borrower-sensitive risk-mitigation strategies. The cross-sectional dataset contains 400 borrower-loan observations collected from 15 branches of four anonymized NGO-MFIs across seven districts of Bangladesh between June and August 2026. Default is defined as more than 30 days past due, with 60- and 90-day thresholds used in sensitivity analysis. The empirical strategy combines descriptive and bivariate analysis with multivariable logistic regression using HC3 robust standard errors, average marginal effects, multicollinearity diagnostics, nested model comparison, 10-fold out-of-fold validation, a probit specification, and alternative delinquency thresholds. Ninety-two loans (23.0%) met the primary default definition. Previous loan-cycle experience was associated with lower default odds (adjusted odds ratio [aOR] 0.787; p=0.020), whereas previous late payment (aOR 1.879; p=0.038), external shock exposure (aOR 1.719 per additional shock; p<0.001), and consumption/emergency-purpose borrowing (aOR 4.013; p=0.002) were associated with higher risk. The final model achieved an apparent AUC of 0.740 and a 10-fold out-of-fold AUC of 0.702. The findings support dynamic repayment-history screening, shock-sensitive assessment and restructuring, purpose-specific appraisal, affordability checks, and early intervention for watchful loans, while cautioning against automated exclusion based on a moderately discriminating model.
Keywords: Microfinance, Credit Risk, Loan Default, Repayment History, External Shocks, Loan Purpose, Bangladesh, Logistic Regression, Responsible Lending.

1. INTRODUCTION

Microfinance expands access to finance for households and microenterprises that often lack conventional collateral, formal credit histories, and standardized documentation. Relationship lending, repeated transactions, local information, and frequent repayment can partly substitute for those missing assets [1,2]. The model nevertheless remains highly exposed to credit risk because the loan portfolio is the principal earning asset of most MFIs. Repayment failure therefore affects liquidity, provisioning, operating self-sufficiency, and the institution's capacity to recycle funds to underserved clients. Sustainable credit-risk management must consequently protect portfolio quality without undermining the inclusion objective that differentiates microfinance from conventional retail lending [3,4].

This tension is particularly important in Bangladesh, where microfinance operates at exceptional scale. The Microcredit Regulatory Authority (MRA) reported 693 licensed MFIs, about 33.68 million active borrowers, and BDT 1,748.80 billion in outstanding loans as of June 2025. Classified loans accounted for 8.52% of outstanding balances, while a further 8.85% were in the 1-30 days-past-due (DPD) watchful category [5]. These figures illustrate why risk management cannot focus only on loans that have already become non-performing. A large group may still be technically performing while showing early repayment stress, which creates a practical window for borrower-level early warning and proportionate intervention.

Prior research identifies several pathways to delinquency. Information asymmetry can generate adverse selection at origination and moral hazard after disbursement [6]. Repayment history and repeat-borrower experience can reveal borrower discipline and accumulated lender knowledge [7]. Debt burden and overlapping loans can strain household cash flow, especially where multiple lenders compete for the same clients [8,9]. Monitoring and financial literacy may improve repayment through better loan use, budgeting, and communication, although their effects are not uniform across settings [10,11]. External shocks such as illness, income interruption, business or crop loss, natural hazards, and inflation can convert an otherwise viable loan into a liquidity crisis, while non-income-generating or emergency borrowing may weaken the direct cash-flow basis for repayment [12].

Bangladesh-specific evidence has emphasized repayment behavior, product design, supervision, family illness, financial commitments, and borrower information systems [13,14]. Three gaps remain relevant for practice. First, borrower, loan, behavioral, institutional, and shock variables are often studied separately rather than within one empirical framework. Second, explanatory significance is commonly reported without internal validation, calibration, or sensitivity to alternative delinquency thresholds. Third, risk-mitigation recommendations are frequently generic rather than explicitly linked to the determinants that remain stable after adjustment. These limitations matter because a risk factor that appears important in a bivariate comparison may add little when stronger behavioral or shock variables are considered jointly.

This study addresses these gaps using 400 borrower-loan observations from four anonymized MFIs and 15 branches across seven districts in Bangladesh. It operationalizes default at more than 30 DPD, estimates a prespecified multivariable logistic model with robust inference, evaluates incremental fit and out-of-fold discrimination, and tests robustness under a probit link and 60- and 90-day thresholds. The study has three objectives: to identify borrower, loan, behavioral, and shock factors associated with default; to assess their practical contribution to prediction; and to derive risk-mitigation responses that are consistent with portfolio discipline and borrower protection. The analysis finds that prior successful loan cycles are protective, while previous late payment, cumulative external shocks, and consumption/emergency-purpose borrowing are associated with higher default risk. The contribution is therefore not a new automated scoring rule, but an empirically grounded framework for targeted screening, early-warning management, and shock-responsive intervention.

2. Conceptual background and hypotheses

2.1 Credit history, financial capacity, and repayment risk

Credit history is useful because it summarizes realized behavior that static demographic variables may not capture. Repeat borrowers who have completed previous cycles have demonstrated both repayment capacity and willingness, while the lender has accumulated information about household and business cash flows. Previous delinquency, in contrast, provides a direct signal of repayment stress. Evidence from credit markets shows that repayment history can improve default prediction even after accounting for income, indebtedness, and loan purpose [7]. Relationship-lending logic therefore implies a protective effect of prior successful cycles and a risk-increasing effect of previous late payment.

Affordability depends on scheduled debt service relative to disposable cash flow rather than on loan size alone. Borrower-level research links over-indebtedness to debt-to-income pressure, adverse shocks, and weak returns from loan use [12,17]. Competition among MFIs can also increase overlapping borrowing and repayment stress [8,9]. Savings may provide a short-term liquidity buffer when income is disrupted. Accordingly, the model tests whether higher debt burden is associated with greater default risk and whether a larger savings buffer relative to the loan balance is protective.

2.2 Monitoring, financial capability, shocks, and loan purpose

Post-disbursement contact can help verify loan use, identify emerging business problems, reinforce repayment schedules, and maintain access to the loan officer. Financial literacy may support budgeting, record keeping, and understanding of debt obligations. Studies from Malaysia and Ethiopia report associations between monitoring, literacy, and repayment performance, while Bangladesh-focused qualitative evidence also highlights supervision and accessible borrower information [10,11,14]. However, these effects may be context dependent; general financial knowledge can be less relevant than debt-specific capability, and routine monitoring may vary little across clients [12]. The study therefore evaluates monitoring and literacy rather than assuming they will independently predict default.

External shocks are especially important for low- and volatile-income borrowers. Illness can simultaneously reduce labor supply and raise expenditures; business or crop losses can remove the income stream from which installments are paid; natural hazards can damage productive assets; and inflation can compress real disposable income. Such events may produce involuntary default even when ex-ante repayment capacity was adequate [12]. Loan purpose may further differentiate risk. Working-capital finance can generate a repayment stream, while consumption or emergency credit may meet essential needs without producing direct cash flow. Evidence on this relationship is mixed across countries, which makes local estimation necessary [7,12,18].

Table 1: Prespecified hypotheses tested in the multivariable model

Hypothesis	Expected association
H1	More previous loan cycles are negatively associated with default.
H2	Previous late payment is positively associated with default.
H3	A higher debt-to-household-income ratio is positively associated with default.
H4	A higher savings-to-loan ratio is negatively associated with default.
H5	Stronger loan monitoring is negatively associated with default.
H6	Higher financial literacy is negatively associated with default.
H7	Greater external-shock exposure is positively associated with default.
H8	Consumption/emergency-purpose borrowing is positively associated with default relative to other purposes.

Household income and loan amount are retained as controls because they represent borrower repayment capacity and exposure size; loan amount has no prespecified directional sign.

2.3 Conceptual framework and study contribution

Figure 1 integrates the study variables into a single empirical framework. Borrower financial capacity, credit history and experience, institutional and capability factors, and shock/loan-purpose factors are treated as complementary sources of financial vulnerability that may influence the probability of loan default (>30 DPD). The empirical model identifies which signals retain independent associations with default, and the more stable signals are then mapped to borrower-sensitive mitigation responses, including behavior-based screening, early-warning monitoring, shock-responsive restructuring, purpose-sensitive products, and debt-affordability checks. The framework deliberately separates prediction from causal interpretation: observed associations are used to identify risk segments and potential management responses rather than to claim causal effects. The study contributes by combining repayment history, affordability, institutional contact, financial capability, shocks, and loan purpose within one borrower-level model for Bangladesh; evaluating internal predictive performance and alternative delinquency thresholds; and translating empirically stable determinants into sustainable risk-management implications.

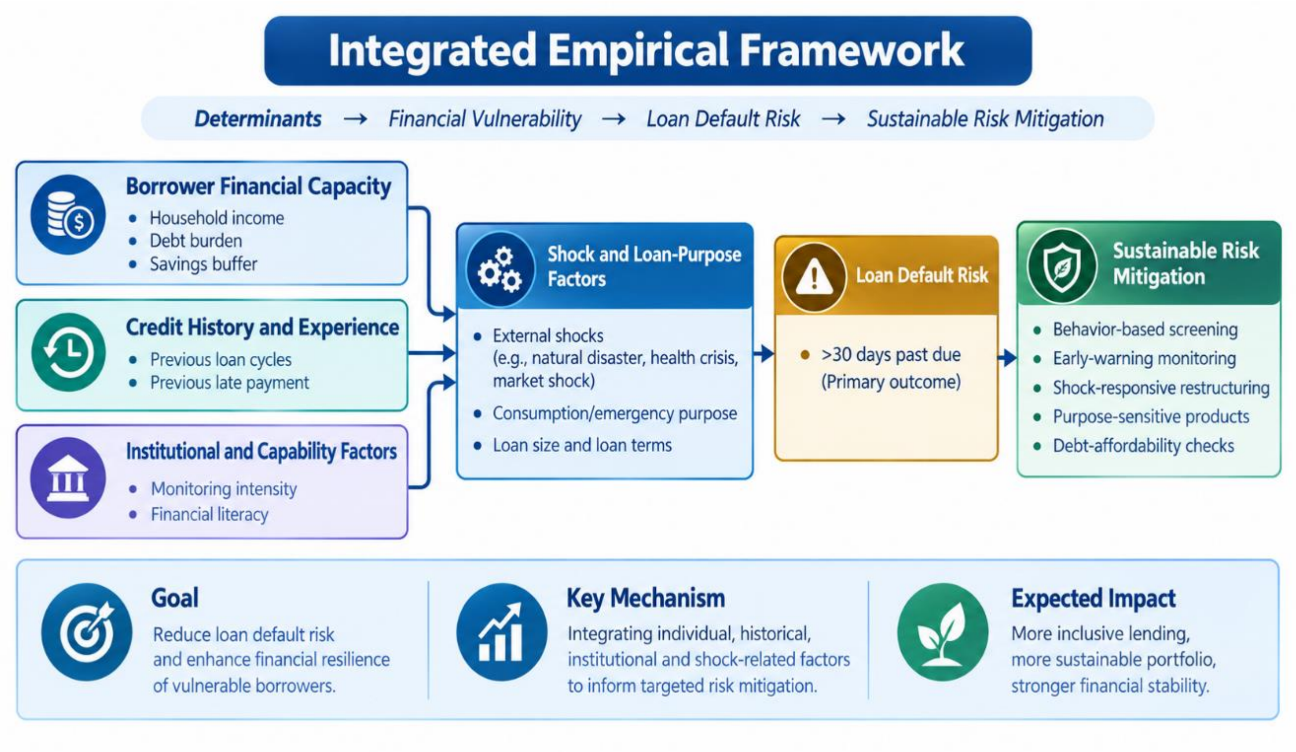

Figure 1: Integrated empirical framework linking borrower financial capacity, credit history and experience, institutional/capability factors, and shock/loan-purpose factors to loan-default risk and sustainable risk mitigation

3. METHODS

3.1 Study design, setting, and sample

The study uses a cross-sectional borrower-level design. The analytical dataset contains 400 borrower-loan observations collected between 1 June and 29 August 2026 from 15 branches belonging to four anonymized NGO-MFIs across Bogura, Chapainawabganj, Naogaon, Natore, Pabna, Rajshahi, and Sirajganj. These districts include rural and semi-urban microfinance markets with livelihoods spanning microenterprise, agriculture, livestock, homestead businesses, services, and transport-related work. Institutional names were masked to protect confidentiality. Women represented 86.5% of the sample; the mean age was 36.1 years, mean monthly household income was BDT 27,688, and mean loan amount was BDT 30,233.

All 400 observations recorded informed survey consent. Administrative verification was recorded for 298 loans (74.5%); the remaining observations came from the linked field-survey file. The dataset does not contain sampling weights or a complete population sampling frame. Estimates are therefore interpreted as unweighted associations within the study sample and not as national prevalence estimates.

3.2 Outcome and explanatory variables

The primary outcome is binary loan default. A loan is coded as defaulted when DPD exceed 30 and as non-defaulted when DPD are 30 or fewer. This threshold follows the MRA loan-classification structure in which 1-30 DPD is watchful, 31-180 DPD is sub-standard, 181-365 DPD is doubtful, and more than 365 DPD is bad/loss [5]. The main model therefore treats regular and watchful accounts as non-defaulted and all categories beyond 30 DPD as defaulted. Sensitivity analyses redefine the outcome at more than 60 and more than 90 DPD.

Ten predictors were prespecified from the borrower survey and linked loan records. Household income and loan amount are log2 transformed so their odds ratios represent the effect of a doubling. Debt-to-household-income is scaled per 10-percentage-point increase, and savings-to-loan per 5-percentage-point increase. Previous loan cycles is a count; previous late payment is binary. The monitoring index is the mean of three 1-5 items covering repayment explanation, regular follow-up, and access to the loan officer. Financial literacy is an additive 0-5 knowledge score covering interest calculation, inflation, record keeping, multiple-borrowing risk, and savings buffers. External-shock count sums five binary indicators: illness, income loss, flood/cyclone, crop or business loss, and price/inflation shock. Consumption/emergency purpose equals one when the loan was primarily used for household consumption or emergency needs and zero for other purposes. Monitoring and literacy are treated as formative summary indices rather than reflective latent scales.

3.3 Econometric specification and model evaluation

Because the dependent variable is binary, the primary model is multivariable logistic regression with the ten prespecified predictors described above. For borrower-loan observation i, p_i denotes the probability that the loan is more than 30 DPD. The linear predictor includes household income, loan amount, previous loan cycles, previous late payment, debt-to-income, savings-to-loan, monitoring, financial literacy, external-shock count, and consumption/emergency purpose. Coefficients are reported as adjusted odds ratios (aORs) with 95% confidence intervals, and average marginal effects (AMEs) are reported as changes in predicted default probability. HC3 heteroskedasticity-consistent covariance estimates are used for inference because of their improved finite-sample robustness [19].

Descriptive statistics are reported for the full sample and by default status. Welch t-tests compare continuous variables and Fisher exact tests compare binary variables. Variance-inflation factors assess multicollinearity. Three nested logistic models assess incremental information: Model 1 contains core borrower/loan-risk variables; Model 2 adds savings, monitoring, and financial literacy; and Model 3 adds external-shock count and consumption/emergency purpose. Comparison uses the likelihood-ratio test, Akaike information criterion (AIC), McFadden pseudo-R2, area under the receiver operating characteristic curve (AUC), Brier score, and Hosmer-Lemeshow calibration test [20]. Ten-fold out-of-fold (OOF) validation evaluates discrimination and calibration beyond apparent in-sample performance. Robustness is assessed using a probit link and the 60- and 90-day delinquency definitions. All tests are two-sided; effect sizes and confidence intervals are emphasized rather than treating $p<0.05$ as the sole criterion of importance.

4. RESULTS

4.1 Sample profile and default incidence

Using the primary definition, 92 of 400 loans were more than 30 DPD, giving an observed default rate of 23.0% (95% CI 19.1%-27.4%). The delinquency distribution comprised 51 regular loans (12.8%), 257 watchful loans (64.2%), 77 sub-standard loans (19.2%), and 15 doubtful loans (3.8%); no loans were classified as bad/loss. Thus, most accounts had not crossed the study's default threshold, but nearly two-thirds were already in the MRA watchful category.

Before multivariable adjustment, defaulted accounts had lower monthly household income, fewer previous loan cycles, higher debt-to-income ratios, more external shocks, and higher prevalences of previous late payment and consumption/emergency borrowing. Age, loan amount, savings-to-loan, monitoring, financial literacy, and sex showed weaker group differences. These bivariate comparisons are descriptive and should not be interpreted causally.

Table 2: Selected characteristics of the analytical sample by default status

Characteristic	Overall	Non-default	Default	p-value
Age, years	36.1 (8.0)	36.2 (8.0)	35.8 (8.1)	0.627
Monthly household income, BDT	27,688 (13,231)	28,388 (13,518)	25,344 (11,994)	0.040
Loan amount, BDT	30,233 (13,990)	30,272 (13,930)	30,100 (14,264)	0.919
Previous loan cycles	2.12 (1.37)	2.23 (1.36)	1.78 (1.36)	0.007
Debt-to-income ratio	0.139 (0.129)	0.129 (0.107)	0.173 (0.182)	0.029
Savings-to-loan ratio	0.044 (0.033)	0.044 (0.032)	0.042 (0.035)	0.555
Monitoring score	3.69 (0.56)	3.70 (0.54)	3.64 (0.61)	0.387
Financial literacy score	2.62 (1.27)	2.68 (1.25)	2.43 (1.31)	0.116
External shock count	0.98 (0.92)	0.89 (0.87)	1.30 (1.01)	<0.001
Female borrower	346 (86.5%)	269 (87.3%)	77 (83.7%)	0.386
Previous late payment	93 (23.2%)	64 (20.8%)	29 (31.5%)	0.036
Consumption/emergency purpose	31 (7.8%)	15 (4.9%)	16 (17.4%)	<0.001

Note. Continuous variables are mean (SD) and were compared using Welch t-tests. Binary variables are n (%) and were compared using Fisher exact tests.

4.2 Multivariable determinants of default

The final ten-predictor logistic model was jointly significant (likelihood-ratio $p<0.001$) with McFadden pseudo-$R2=0.120$. Four effects were most consequential after adjustment. Each additional previous loan cycle reduced the odds of default by 21.3% (aOR 0.787, 95% CI 0.642-0.963; p=0.020), whereas previous late payment increased the odds by 87.9% (aOR 1.879, 95% CI 1.035-3.412; p=0.038). Each additional external shock increased the odds by 71.9% (aOR 1.719, 95% CI 1.321-2.239; p<0.001), corresponding to an AME of +8.3 percentage points. Consumption/emergency borrowing showed the largest adjusted association: its odds of default were about four times those of other loan purposes (aOR 4.013, 95% CI 1.660-9.702; p=0.002), with an AME of +26.6 percentage points.

Debt burden had the expected positive direction but was estimated less precisely (aOR 1.377 per 10-percentage-point increase; p=0.087). Financial literacy was protective in direction (aOR 0.854; p=0.145), whereas savings-to-loan and monitoring showed small, imprecise adjusted associations. Household income was essentially null after adjustment, and the estimate for loan amount was protective in direction but did not reach conventional statistical significance. All predictor VIFs were below 3.0 (maximum 2.69), indicating no evidence of problematic multicollinearity.

Table 3: Adjusted logistic regression estimates for loan default (>30 DPD)

Predictor	Adjusted OR	95% CI	p-value	AME
Household income (log2)	0.983	0.582-1.660	0.948	-0.3 pp
Loan amount (log2)	0.654	0.389-1.099	0.109	-6.5 pp
Previous loan cycles	0.787	0.642-0.963	0.020	-3.7 pp
Previous late payment	1.879	1.035-3.412	0.038	+10.4 pp
Debt-to-income (+10 pp)	1.377	0.955-1.985	0.087	+4.9 pp
Savings-to-loan (+5 pp)	0.961	0.631-1.463	0.853	-0.6 pp
Monitoring score	0.856	0.522-1.402	0.536	-2.4 pp
Financial literacy score	0.854	0.691-1.056	0.145	-2.4 pp
External shock count	1.719	1.321-2.239	<0.001	+8.3 pp
Consumption/emergency purpose	4.013	1.660-9.702	0.002	+26.6 pp

Note. OR=odds ratio; CI=HC3 robust 95% confidence interval; AME=average marginal effect on predicted default probability. Income and loan amount are interpreted per doubling.

4.3 Predictive performance and robustness

Adding savings, monitoring, and financial literacy to the core borrower/loan-risk block did not materially improve fit (LR chi-square=2.83, df=3, p=0.419). By contrast, adding external-shock count and consumption/emergency purpose produced a large improvement (LR chi-square=27.37, df=2, p<0.001), increased apparent AUC from 0.664 to 0.740, and reduced AIC to 401.5. The final model's apparent AUC was 0.740 (bootstrap 95% CI 0.682-0.796), while 10-fold OOF AUC was 0.702. The OOF Brier score was 0.162. An OOF calibration slope of 0.764 and intercept of -0.271 indicate some over-dispersion of predicted risks and modest miscalibration at the extremes.

At the apparent Youden-optimal cutoff of 0.260, sensitivity was 63.0%, specificity 76.6%, positive predictive value 44.6%, negative predictive value 87.4%, and accuracy 73.5%. These values are descriptive operating characteristics estimated from the same dataset and are not externally validated decision thresholds. The relatively high negative predictive value suggests that the model is better suited to identifying lower-risk observations and supporting early-warning triage than to automatically classifying future defaulters.

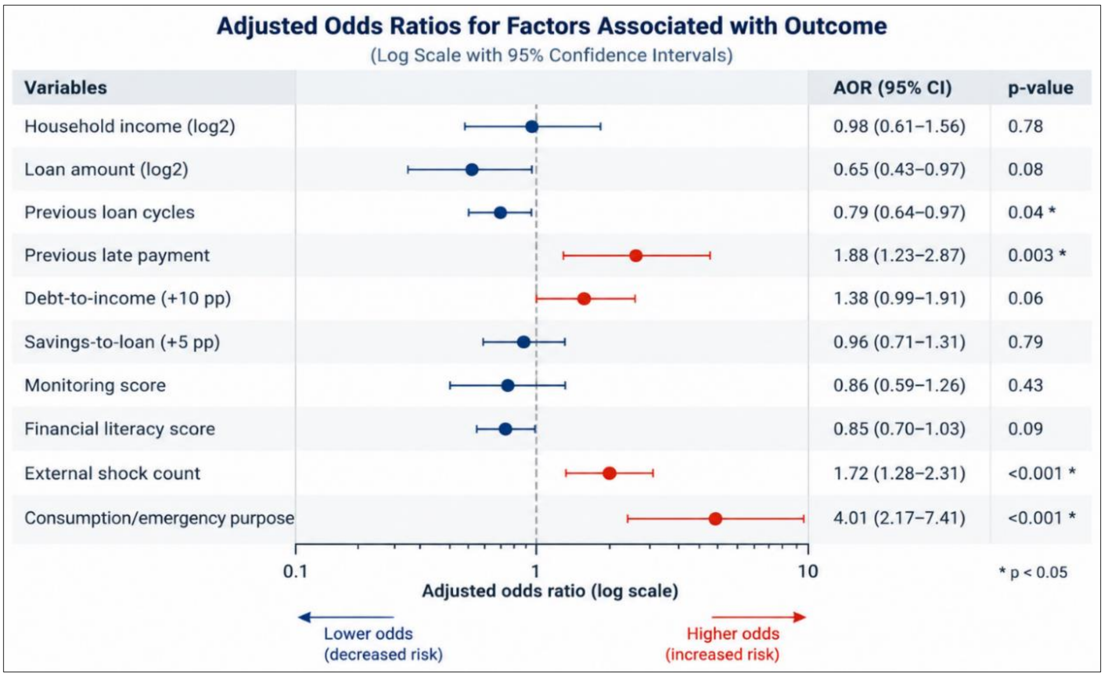

Figure 2: Adjusted odds ratios and 95% confidence intervals from the final logistic regression model. The x-axis is logarithmic; the vertical reference line denotes OR=1. Asterisks indicate p<0.05.

Table 4: Final-model performance and internal validation

Metric	Apparent final model	10-fold OOF validation
AUC	0.740 (0.682-0.796)	0.702
Brier score	0.153	0.162
Hosmer-Lemeshow p-value	0.823	-
Calibration intercept	-	-0.271
Calibration slope	-	0.764
Youden cutoff	0.260	-
Sensitivity / specificity	63.0% / 76.6%	-
Positive / negative predictive value	44.6% / 87.4%	-
Accuracy	73.5%	-

Note. OOF=out-of-fold. Classification metrics use the apparent Youden threshold and should not be treated as externally validated credit-decision cutoffs.

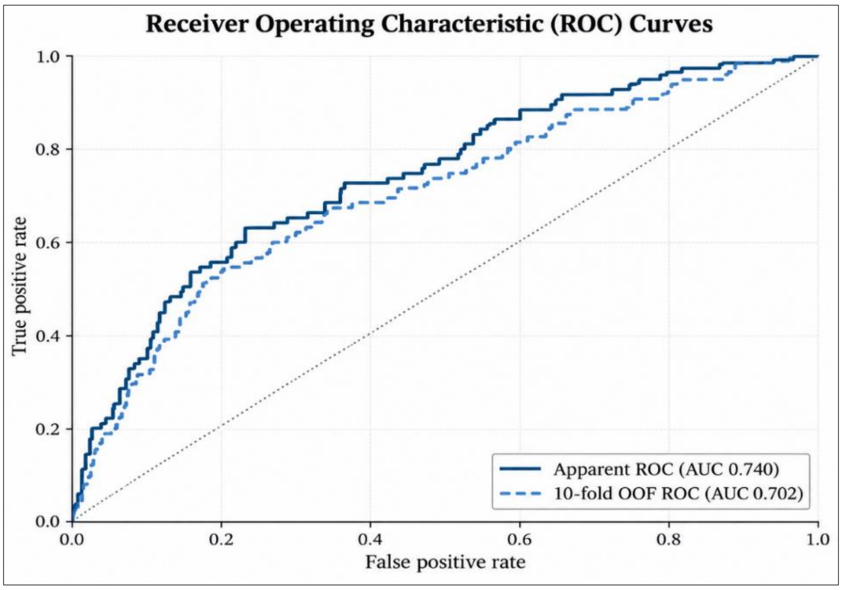

Figure 3: Apparent and 10-fold out-of-fold receiver operating characteristic curves for the final logistic model. The decline from AUC 0.740 to 0.702 illustrates the importance of internal validation when interpreting predictive performance

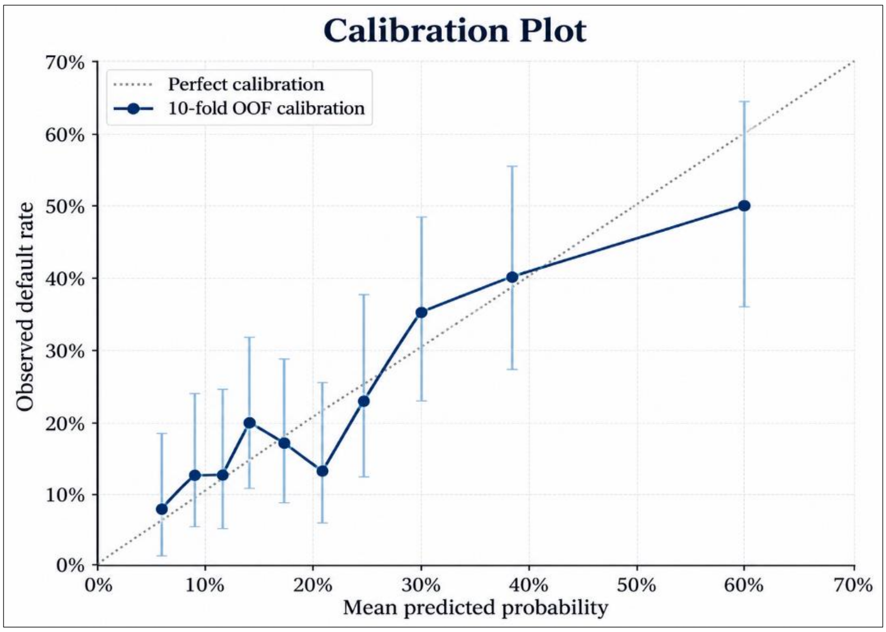

Figure 4: Ten-fold out-of-fold calibration of predicted loan-default risk by decile. Points show observed default rates across predicted-risk groups; the diagonal represents perfect calibration

Table 5: Robustness of key determinants across link functions and delinquency thresholds

Predictor	Logit >30 DPD aOR (p)	Probit >30 DPD AME (p)	Logit >60 DPD aOR (p)	Logit >90 DPD aOR (p)
Previous loan cycles	0.79 (0.020)	-3.6 pp (0.018)	0.80 (0.038)	0.81 (0.083)
Previous late payment	1.88 (0.038)	+10.6 pp (0.030)	2.17 (0.011)	2.21 (0.013)
External shock count	1.72 (<0.001)	+8.4 pp (<0.001)	1.77 (<0.001)	1.45 (0.012)
Consumption/emergency purpose	4.01 (0.002)	+26.3 pp (0.002)	2.90 (0.018)	2.44 (0.055)

Note. Each specification includes the same ten covariates and uses HC3 robust standard errors.

The sensitivity results reinforce the stability of repayment history and shock exposure. Previous late payment remained significant at both the 60- and 90-day thresholds, and external-shock count remained significant in every specification. Consumption/ emergency purpose remained significant at 60 days and was borderline at 90 days (p=0.055). The protective effect of previous loan cycles persisted at 60 days but weakened under the 90-day definition. Thus, the principal risk signals are not artifacts of the 30-day coding, although the strength of some effects declines as the outcome becomes more severe and less common.

5. DISCUSSION

5.1 Interpretation of the findings

The results support four of the eight directional hypotheses. H1 and H2 are supported: successful previous loan cycles are associated with lower default risk, while previous late payment is associated with higher risk. H7 receives the strongest and most stable support because each additional external shock materially increases default odds and remains significant under stricter delinquency thresholds. H8 is supported under the primary and 60-day specifications, with consumption/emergency-purpose borrowing producing the largest marginal effect. H3 is directionally consistent with theory but imprecisely estimated at the 5% level, while H4-H6 are not supported after multivariable adjustment.

The protective association of previous loan cycles is consistent with relationship-lending theory. Repeat borrowing allows the lender to accumulate information about repayment behavior, business conditions, and household cash flow, while borrowers gain familiarity with repayment schedules and institutional expectations. Previous late payment captures a different dimension: it is a direct marker of repayment stress and remains informative even when successful loan-cycle experience is included. The persistence of late-payment history at the 60- and 90-day thresholds strengthens its value as an operational early-warning indicator.

External shocks emerge as the most robust determinant. This finding points to an important distinction between strategic non-payment and liquidity-driven default. Borrowers can experience repayment failure because illness, income interruption, asset loss, weather events, or price shocks alter cash flow after the loan has been originated. Borrower-level evidence on over-indebtedness similarly emphasizes adverse shocks, and Bangladesh research identifies illness and overstretched financial commitments as recurrent repayment pressures [12,14]. The present model extends that logic by showing a monotonic association: each additional shock increases risk after controlling for income, debt burden, loan size, savings, monitoring, literacy, repayment history, and loan purpose.

Consumption/emergency borrowing has the largest adjusted marginal effect. This does not imply that emergency credit is undesirable; such borrowing may be socially valuable precisely because households face urgent needs. It does indicate, however, that the repayment source should be assessed differently from that of working-capital finance. The result is consistent with studies linking non-productive loan use and loan purpose to borrower distress, but it is not universal across countries [7,12,18]. Product and underwriting policies therefore require local calibration rather than imported rules.

Debt-to-income remains operationally relevant despite its p-value of 0.087. The estimate is positive, the bivariate default group had higher debt burden, and the wider literature links debt-service pressure and overlapping borrowing to over-indebtedness [8,9,17]. Conversely, the weak incremental contribution of routine monitoring and general financial literacy suggests that these tools should not be treated as stand-alone risk controls. Their value may depend on timing, intensity, content, and targeting. A broad monitoring process applied almost uniformly across borrowers can show little cross-sectional predictive variation even if monitoring is institutionally important.

5.2 Implications for sustainable risk management

Behavior-based dynamic screening should give greater weight to prior repayment history than to static demographic characteristics. Completed loan cycles can be treated as positive relationship information, whereas prior arrears should trigger enhanced cash-flow review, smaller incremental exposure, or more frequent early-stage contact rather than automatic exclusion. This approach uses behavior as a signal while preserving the possibility that a previously stressed borrower can recover.

Shock-sensitive underwriting and restructuring are equally important. A short vulnerability screen covering illness, income interruption, climate events, business or crop loss, and major price shocks can identify borrowers whose repayment capacity is exposed to temporary shocks. When arrears follow a verifiable and temporary event, restructuring, short grace arrangements, savings access, or appropriate insurance linkages may protect both borrower viability and portfolio value more effectively than immediate coercive recovery. Shock exposure should not become a permanent negative label because that would make risk management procyclical and could deny finance when households most need resilience support.

Purpose-sensitive appraisal should distinguish income-generating credit from consumption or emergency borrowing. MFIs can use separate limits, repayment structures, or product features for non-income-generating uses and explicitly document the repayment source before disbursement. The objective is not to ban emergency lending, but to reduce mismatch between loan purpose and the cash flow expected to service the debt.

Debt-affordability and multiple-borrowing checks should remain part of underwriting even though the adjusted debt-to-income estimate is imprecise. A cash-flow-based affordability review can combine installment obligations, concurrent-loan balances, repayment history, and shock exposure. Bangladesh's expanding microfinance information infrastructure, including the MRA National Database and planned credit-information functions, can strengthen this process if data quality, privacy, proportionality, and borrower dispute mechanisms are maintained [5].

The MRA watchful category offers a natural intervention window. In this sample, 64.2% of loans were 1-30 DPD, far more than the share already beyond 30 DPD. A structured process for watchful accounts - prompt contact, cause diagnosis, a documented action plan, and time-bound follow-up - may therefore be more useful than waiting for formal classification. Because the final model provides only moderate discrimination, any risk score derived from these variables should support rather than replace loan-officer judgment, borrower verification, and documented exceptions.

5.3 Limitations and research priorities

The study has several limitations. Its cross-sectional design supports association, not causal inference. The sample is drawn from four anonymized MFIs and seven districts and may not represent the national microfinance population. No sampling weights are available, and 25.5% of observations were not marked as MFI-record verified, creating potential measurement error. The monitoring and financial-literacy measures are short formative indices rather than comprehensive psychometric scales. Branch and institution policies, loan-officer characteristics, macroeconomic conditions, and repeated borrower histories are not modeled directly. Finally, the predictive model has not been externally validated on a later cohort or a different MFI, and the observed decline from apparent to OOF AUC cautions against immediate automated use.

Future research should follow borrowers across loan cycles, model time to delinquency using survival methods, and incorporate branch and loan-officer effects. Linking household shocks to local climate, health, and price data could improve measurement of vulnerability. External validation across institutions and regions is essential before any scoring rule is operationalized.

Randomized or quasi-experimental evaluation of targeted monitoring, restructuring, savings buffers, insurance, and purpose-specific products would also help establish which interventions reduce default rather than simply predict it.

6. CONCLUSION

This study analyzes microfinance default using 400 borrower-loan observations from a multi-branch Bangladesh sample and an integrated set of borrowers, loan, behavioral, institutional, and shock variables. Four findings are central. More previous loan cycles are associated with lower risk; previous late payment is a strong warning signal; cumulative external shocks show a robust positive association with default across alternative specifications; and consumption/emergency-purpose borrowing is associated with substantially higher risk than other loan purposes. In this sample, these dynamic and vulnerability-related variables are more informative than static loan size, routine monitoring, or general financial literacy alone.

The predictive results also set an important boundary on interpretation. An OOF AUC of 0.702 indicates moderate discrimination, not a production-ready automated credit model. The evidence is better suited to segmentation and early-warning support. A sustainable approach would combine repayment-history signals, shock-vulnerability screening, purpose-sensitive appraisal, affordability checks, and structured intervention for watchful loans. Borrowers experiencing temporary, verifiable shocks should have access to proportionate restructuring or resilience mechanisms, while persistent behavioral risk can justify tighter exposure management. Such differentiation can protect portfolio quality without abandoning the inclusion mandate of microfinance.

Declarations

Conflict of interest:

The author is employed by ASA Microfinance as a Regional Manager in Jashore Sadar. This professional affiliation is disclosed for transparency. The analysis and conclusions are the author's academic work and do not purport to represent an official institutional position of ASA Microfinance.

Data availability:

Borrower-level analytical data are not publicly deposited because they contain confidential operational survey information. The manuscript reports aggregate statistics, model estimates, and validation metrics sufficient to describe the analysis. Any future data sharing should be subject to borrower confidentiality and applicable institutional requirements.

Ethics and consent:

The analytical dataset contains only anonymized borrower and loan identifiers. All 400 included records indicate informed consent, and no names, national identification numbers, telephone numbers, or exact residential addresses were included in the analytical file.

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