



SAVEIN

Credit Risk Model

Predicting Early
Delinquency for
Healthcare Lending



PROBLEM STATEMENT

Build a credit risk model to predict early delinquency, enabling automated approvals while protecting portfolio quality through risk-based decisioning.

Healthcare Lending

SaveIN provides instant financing at point-of-care, requiring rapid credit decisions while maintaining portfolio quality.

The Challenge

Identify customers likely to go delinquent early in their loan tenure using bureau data and demographic signals.

Key Question

Which customers should be approved and at what risk stance? Build a practical underwriting strategy.

Target Selection & Justification

TARGET	DEFINITION	BAD RATE	STATUS
MOB2_Bad	30+ DPD by Month 2 (Very Early)	4.72%	Too Early
MOB3_Bad	30+ DPD by Month 3 (Early Risk)	9.64%	SELECTED
MOB6_Bad	60+ DPD by Month 6	4.45%	Too Late

Why MOB3_Bad?

01 Early warning system for healthcare lending

02 Enables proactive intervention before severe delinquency

03 9.64% bad rate provides sufficient signal for modeling

Transition Analysis

30.5% of MOB3_Bad customers → MOB6_Bad
Validates MOB3 as a strong early predictor of severe delinquency.

Dataset Summary

10,000

Total Customers

32,774

Tradelines

40

Features Engineered

20%

NTC Customers

Feature Engineering

- ✓ Bureau-Income Interaction (top predictor)
- ✓ Credit Utilization Ratio
- ✓ Debt-to-Income, Loan-to-Income
- ✓ DPD History Statistics (mean, recent 3M)
- ✓ Tradeline Aggregations
- ✓ NTC Flag & Device Score Interaction

NTC Customer Risk

Non-NTC Bad Rate

6.49%

NTC Bad Rate

22.25%



3.4x Higher Risk

NTC customers require special handling strategy

Model Comparison & Selection

MODEL	TRAIN AUC	TEST AUC	OVERFIT GAP	STATUS
Logistic Regression	0.723	0.713	0.01 ✓	SELECTED
Random Forest	0.881	0.674	0.21	Overfitting
XGBoost	0.936	0.660	0.28	Overfitting
LightGBM	0.927	0.661	0.27	Overfitting

0.713

Test AUC

0.426

Gini Coefficient

0.362

KS Statistic

68%

Recall @ 0.5

Why Logistic Regression?

Best generalization (lowest train-test gap), interpretable coefficients for regulatory compliance, and stable performance across customer segments.

Model validation

Risk Decile Statistics:

	Total	Goods	Bads	Bad_Rate_%	Pct_Population
risk_decile					
1	200	196	4	2.0	10.0
2	200	188	12	6.0	10.0
3	200	191	9	4.5	10.0
4	200	193	7	3.5	10.0
5	200	184	16	8.0	10.0
6	200	187	13	6.5	10.0
7	200	187	13	6.5	10.0
8	200	169	31	15.5	10.0
9	200	166	34	17.0	10.0
10	200	146	54	27.0	10.0



REVISED NTC STRATEGY RECOMMENDATION

! KEY FINDING: Model performance is weak on NTC segment (AUC 0.58)
This requires a differentiated approach for NTC vs Non-NTC customers

NON-NTC CUSTOMERS (78.5% of portfolio):

- Use ML model score with threshold 0.5
 - Expected approval: ~80%
 - Expected bad rate: ~5%
- Model AUC: 0.62 (acceptable for automation)

NTC CUSTOMERS (21.5% of portfolio):

! Model is weak (AUC 0.58) - use alternative approach:

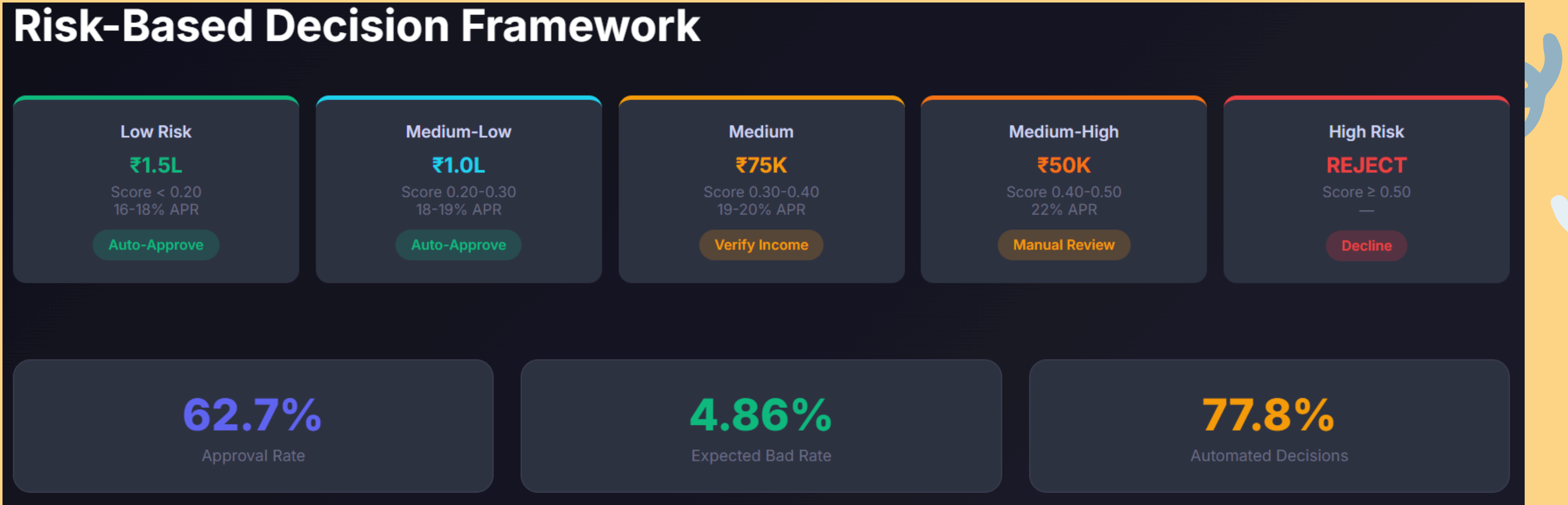
RECOMMENDED: RULES-BASED SCORECARD

- Key signals (since bureau data unavailable):
 - Income stability: \geq ₹25,000/month
 - Employment: Salaried preferred
 - Device score: \geq 0.6
 - Residence: Owned/Family preferred
 - Loan-to-Income: <6x

- Conservative limits: 30-50% of standard
 - Initial limit cap: ₹25,000-50,000
- Graduation path: Increase limits after 3 on-time payments
- Target approval: 30-40% of NTC



UNDERWRITING STRATEGY



1. WHICH CUSTOMERS SHOULD BE APPROVED?

✓ AUTO-APPROVE: 799 customers (40.0%)

- Risk score < 0.30 (non-NTC) or < 0.40 (strong profile)
- Low to medium-low risk profile
- Expected bad rate: 3-5%
- Standard credit limits

⚠ MANUAL REVIEW: 468 customers (23.4%)

- Risk score $0.40-0.50$ OR NTC with risk $0.30-0.40$
- Requires verification before approval
- Expected bad rate: 6-8%
- Reduced credit limits

✓ CONDITIONAL APPROVE: 0 customers (0.0%)

- NTC customers with acceptable risk
- Reduced limits + enhanced monitoring
- Expected bad rate: 5-7%

REJECT: 733 customers (36.6%)

- Risk score ≥ 0.50
- High risk - portfolio protection
- Would have ~100.0% bad rate

OVERALL APPROVAL RATE: 40.0%

EXPECTED BAD RATE (APPROVED PORTFOLIO): 5.05%

2. AT WHAT RISK STANCE?

RISK-BASED CREDIT LIMITS:

- Low Risk (score < 0.20): Up to ₹150K (3x monthly income)
 - 16-18% interest rate
 - Premium tier, minimal restrictions
- Medium-Low Risk ($0.20-0.30$): Up to ₹100K (2.5x income)
 - 18-19% interest rate
 - Standard tier
- Medium Risk ($0.30-0.40$): Up to ₹75K (2x income)
 - 19-20% interest rate
 - Requires income verification
- Medium-High Risk ($0.40-0.50$): Up to ₹50K (1.5x income)
 - 22% interest rate
 - Manual review required
- High Risk (≥ 0.50): REJECT
 - Too risky for portfolio

NTC ADJUSTMENTS:

- 40-60% limit reduction vs standard customers
- Enhanced monitoring for first 6 months
- Graduation pathway: limits increase after 3 on-time payments
- Manual review for NTC in $0.30-0.50$ range

3. MODEL PERFORMANCE

- ✓ Model: Logistic Regression (beats tree models due to generalization)
- ✓ Test AUC: 0.7131 (Gini: 0.4261)
- ✓ KS Statistic: 0.3619
- ✓ Non-NTC AUC: 0.6216 (acceptable)
- ✓ NTC AUC: 0.5752 (weak - requires rules-based approach)

THRESHOLD SELECTION:

- ✓ Chosen Threshold: 0.50
- ✓ Rationale: Balances growth (approval rate) with portfolio quality
- ✓ Alternative 0.75 threshold: Higher profit but 7.91% bad rate (too risky)

6. CRITICAL INSIGHTS

NTC CHALLENGE: Model AUC 0.58 for NTC customers

→ Solution: Rules-based scorecard using income, device score, employment

THRESHOLD OPTIMIZATION: 0.50 selected over 0.75

- Better portfolio quality (4.9% vs 7.9% bad rate)
- More sustainable long-term approach

FEATURE IMPORTANCE: Top predictors

- Bureau-income interaction (engineered feature)
- Income level
- NTC status (3.69x higher risk)