

Business Summary Report: Predictive Insights for Collections Strategy

1. Summary of Predictive Insights

Based on EDA and the proposed model framework, delinquency is concentrated in a few clear segments:

- Employment: highest risk observed in the top employment categories by delinquency rate (e.g., Unemployed and Employed).
- Card type: higher delinquency observed for Business and Student cardholders relative to lower-risk card types.
- Affordability: delinquency rate rises across Debt-to-Income buckets, with the highest bucket showing the greatest risk.

Overall delinquency prevalence in the dataset is ~16%.

Top 3 Risk Factors

- High **Debt-to-Income Ratio (DTI)** – customers with higher affordability stress show higher delinquency likelihood.
- High **Credit Utilization** – heavy usage signals liquidity pressure and correlates with missed/late payment patterns.
- **Recent missed/late payment behaviour (Month_1–Month_6, Missed_Payments)** – repeated late/missed streaks are the strongest early-warning signal.

2. Recommendation Framework (SMART)

Restated insight:

Customers with high credit utilization and high DTI are more likely to become delinquent, especially when they show recent late/missed payment behaviour.

Proposed SMART recommendation:

Specific: Launch an “Early Intervention Program” that targets customers in the top risk band (e.g., predicted risk score ≥ 0.60) AND credit utilization > 0.70 .

Measurable: Reduce delinquency rate in the targeted cohort by 10% and increase on-time payment rate by 15%.

Actionable: Trigger automated reminders + a call campaign within 7 days of identifying risk; offer flexible repayment options (micro-rescheduling / partial-payment plans).

Relevant: Directly supports collections efficiency and prevents accounts from rolling into higher DPD buckets.

Time-bound: Pilot for 8 weeks, review weekly, and scale across regions after results.

Justification:

This intervention is feasible with existing collections workflows and focuses resources on customers most likely to slip into delinquency, reducing cost of late-stage collections while improving customer outcomes.

3. Ethical and Responsible AI Considerations

Fairness risks and mitigations:

1) Segment bias risk (Employment_Status / Location): The model may over-flag certain employment groups or locations if historical patterns reflect socio-economic bias.

Mitigation: Evaluate recall/false positive rates across segments; apply reweighting or threshold tuning; avoid using variables that act as unfair proxies.

2) Data quality / missingness bias: Missing income or inconsistent employment labels can create systematic errors for specific groups.

Mitigation: Use missing-indicators, segment-wise imputation, and continuous monitoring of missingness drift.

Explainability to stakeholders:

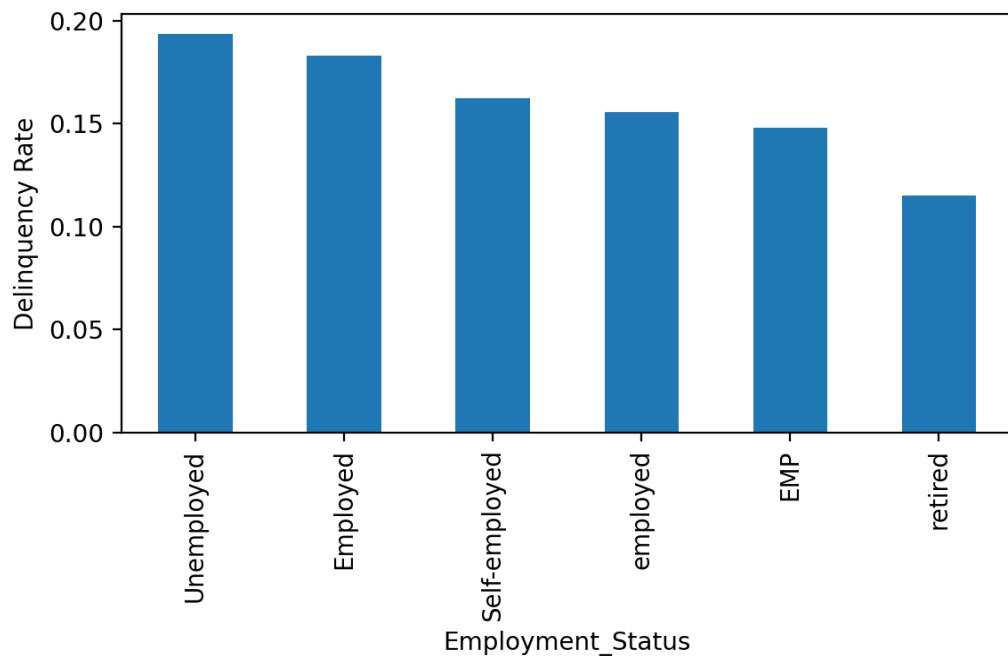
Use simple “Top drivers” explanations (e.g., high utilization + repeated late payments + high DTI) for each flagged customer. Provide SHAP-based summaries at both portfolio and individual level, and maintain an audit trail for decisions.

Responsible AI approach:

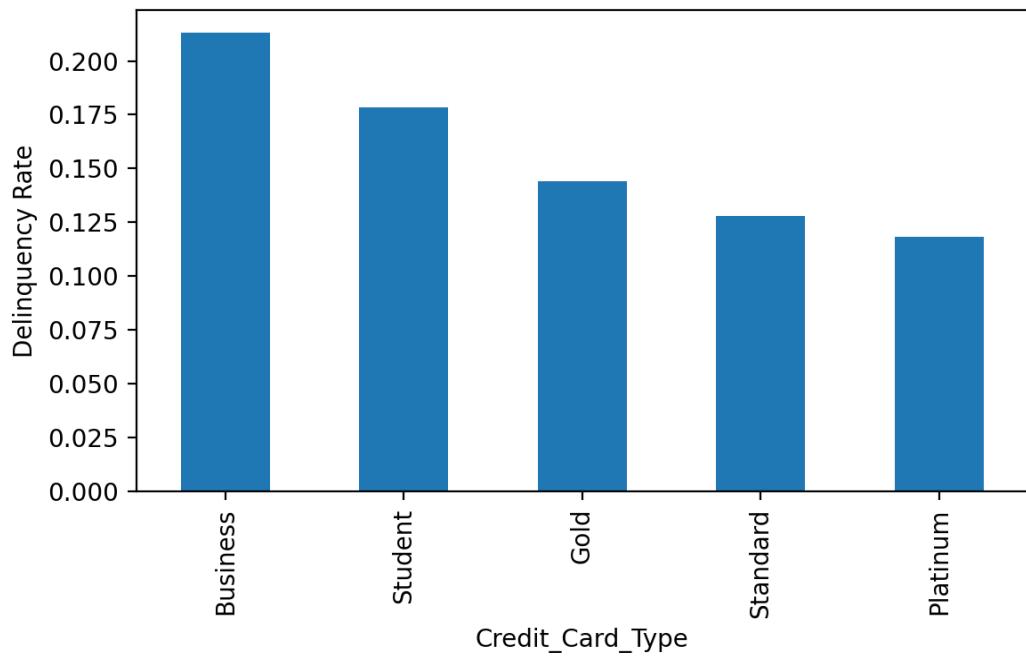
Predictions should trigger supportive interventions (reminders, restructuring options) rather than punitive actions. Ensure privacy by using customer IDs internally, role-based access, and monitoring model drift and fairness over time.

Appendix: Supporting Charts

Delinquency Rate by Employment Status



Delinquency Rate by Credit Card Type



Delinquency Rate by DTI Bucket

