Business Summary Report: Predictive Insights for Collections Strategy

1. Summary of Predictive Insights

Key Delinquency Predictors:

- **Missed Payments**, **Credit Utilization**, and **Income** were the strongest indicators of customer delinquency.
- Customers with **Credit Utilization > 80%** and **Missed Payments ≥ 2** had the highest risk.
- Even **high-income customers** showed delinquency when **credit scores were low/missing**—highlighting behavioral risk.

High-Risk Segments:

Key Insight	Customer Segment	Influencing Variables	Potential Impact
Low-to-moderate income with high utilization and missed payments	Mid-to-low-income customers with poor payment history	Credit Utilization, Missed Payments, Income	Prioritize for early intervention calls or payment restructuring offers.
Even **high-income customers** can become delinquent if their **credit score is low or missing**.	High-income customers with low credit scores	Income, Credit Score, Loan Balance	Don't assume low risk based on income alone—monitor these customers closely.

2. Recommendation Framework

Restated Insight:
High credit utilization and missed payments signal urgent risk of delinquency.
Proposed Strategy: "High-Utilization Risk Flag Program"

- **Specific:** Auto-flag customers with **Utilization > 0.8** and **Missed Payments ≥ 2** for a **pre-delinquency support program**.

- **Measurable:** Target **10% reduction** in delinquency in flagged group within **3 months**.

- **Actionable:** Use model outputs to route flagged customers to **Collections/Customer Care** for personalized outreach.

- **Relevant:** Aligns with Geldium's goal to **reduce delinquency while maintaining trust**.

- **Time-bound:** Roll out in **2 weeks**; pilot for **3 months** with monthly reviews.

Business Rationale:
Proactive support is **more cost-effective** than recovery. This strategy targets quantifiable risk behaviours (missed payments, high usage), promotes **ethical credit management**, and enhances **regulatory compliance and brand trust**.

3. Ethical and Responsible AI Considerations

Fairness & Bias:

- Income bias risk: Low-income groups flagged more frequently.
- Credit score imputation may misclassify new-to-credit users (e.g., young professionals).

Example: A responsible, low-income graduate with limited history might be falsely flagged.

Explainability:

- Logistic Regression ensures clear interpretation of risk drivers.
- Coefficients can be explained to non-technical audiences, regulators, and customers.
- For future models (e.g., Random Forest), use SHAP for transparency.

Responsible Financial Practices:

- Focus is supportive (counselling, flexible plans), not punitive.
- Encourages financial well-being for customers, aligning with fair treatment.

Additional Principles:

- Transparency: Decisions based on explainable, financial data.
- Accountability: Track metrics like delinquency reduction.
- Privacy: Only anonymized data used; no sensitive personal info modelled.

Final Reflection

To ensure fairness, Geldium should monitor model performance by demographic segments. This approach combines data-driven insights with empathetic action, maintaining both predictive accuracy and ethical standards.