Task 2: Predicting Delinquency with AI – Modeling Plan

1. Model Logic (Generated with GenAI)

Model objective: Predict the probability that a customer will become delinquent (Delinquent_Account = 1) using customer profile, affordability, and repayment behaviour variables.

Recommended modeling approach:
A) Baseline (high interpretability): Logistic Regression with regularization (L1/L2)
B) Primary (strong accuracy): Gradient Boosting Trees (LightGBM/XGBoost)

Pipeline / workflow (GenAI-generated structure, adapted to Geldium dataset):
1) Data ingestion
- Read customer-level dataset (Customer_ID as key).
2) Pre-processing
- Standardize Employment_Status categories (e.g., employed/unemployed/retired).
- Treat missing values:
Income (~8%) → impute median by Employment_Status/Location + add missing flag
Loan_Balance (~6%) → impute median by Loan_Tenure/Loan_Amount buckets
- Cap/flag Credit_Utilization > 1.0 (treat as outlier / data issue).
3) Feature engineering (most predictive)
- Affordability: Debt_to_Income_Ratio, EMI_to_Income (if EMI present), Loan_Balance/Income
- Behaviour: Missed_Payments, and Month_1–Month_6 → derive:
late_count, missed_count, max_delay_streak, recent_late_flag
- Credit profile: Credit_Score, Credit_Utilization
- Segments: Employment_Status, Location, Credit_Card_Type
4) Split strategy
- Train/Validation/Test split (70/15/15) with stratification on Delinquent_Account (≈16%).
5) Model training
- Fit Logistic Regression baseline.
- Fit Gradient Boosting model with class weights / scale_pos_weight to address imbalance.
6) Thresholding for collections use-case
- Choose probability threshold to maximize Recall for delinquency while keeping Precision acceptable.
- Output: risk score (0–1) + risk band (Low/Medium/High).
7) Explainability
- Logistic: coefficients
- Boosting: SHAP values for local + global drivers (audit-friendly).

2. Justification for Model Choice

I recommend a two-model strategy: Logistic Regression as the baseline and Gradient Boosting Trees (LightGBM/XGBoost) as the primary production model. Logistic regression is transparent, easy to deploy, and provides interpretable coefficients that align well with financial risk governance requirements. However, Geldium's delinquency outcome is influenced by non-linear interactions (e.g., high credit utilization combined with high DTI and repeated recent misses), which tree-based boosting handles significantly better, typically improving recall for at-risk customers. Gradient boosting also supports probability outputs, scalable training, and strong performance on tabular credit datasets while remaining explainable via SHAP. This combination balances business needs—accuracy for proactive interventions, interpretability for leadership and compliance, and operational simplicity for deployment and monitoring.

3. Evaluation Strategy

Performance metrics (accuracy alone is insufficient due to class imbalance ~16% delinquent):
1) Discrimination metrics
- AUC-ROC: ability to rank delinquent vs non-delinquent customers.
- AUC-PR: more informative for minority delinquent class.
2) Classification metrics at chosen threshold
- Recall (Delinquent class): % of true delinquents correctly flagged (collections priority).
- Precision: avoid overwhelming agents with false positives.
- F1 score: balances precision/recall.
- Confusion matrix: translate to business impact (missed delinquents vs unnecessary calls).
3) Calibration
- Brier score / reliability curve: ensure predicted probabilities match observed delinquency rates.
4) Fairness & bias checks
- Compare Recall/False Positive Rate across segments: Employment_Status, Location, Age bands, Credit_Card_Type.
- Disparate impact analysis: ensure no segment is systematically over-flagged without justification.
- If bias detected: reweighing, threshold by segment (carefully), or remove proxy variables.
5) Monitoring after deployment
- Data drift: monitor Income distribution, utilization, missingness changes.
- Performance drift: rolling AUC/Recall, stability index, and periodic recalibration.
Ethical considerations: Predictions should trigger supportive interventions (reminders, restructuring offers) rather than punitive actions; maintain customer privacy and avoid using sensitive attributes beyond legitimate risk purpose.