Task 2: Predicting Delinquency with AI – Modeling Plan (Geldium)

1. Model Logic (GenAI-assisted scaffold)

Chosen primary model: Gradient Boosted Decision Trees (e.g., LightGBM/XGBoost) with probability calibration and SHAP-based explanations. Baseline model: Logistic Regression as a transparent benchmark.

Top 5 input features (based on EDA)

1) Debt_to_Income_Ratio (affordability stress)
2) Credit_Utilization (credit stress / revolving usage)
3) Credit_Score (overall creditworthiness)
4) Missed_Payments (historical repayment behaviour)
5) Loan_Balance (exposure / outstanding balance)

Pipeline / Workflow

Ingest data → validate schema & ranges → handle missing values (income, loan balance, score) → encode categories (employment status, card type, location) → feature engineering (payment behaviour aggregates, bands) → train/validation split with stratification → train baseline logistic regression → train GBDT model with class weights → calibrate probabilities → generate explanations (SHAP) → deploy scoring as batch/API for collections prioritization.

2. Model Choice Justification (1 paragraph)

GBDT models are well-suited to delinquency prediction because they capture non-linear relationships and interactions (e.g., high utilization combined with high DTI) while performing strongly on tabular credit data. For Geldium, this approach balances accuracy and operational needs: it is fast to score, works with mixed numeric/categorical features, and supports monitoring and retraining. To maintain transparency and regulatory readiness, model outputs can be explained using SHAP feature contributions and supported by a logistic regression baseline for benchmarking. This combination enables proactive collections interventions using interpretable risk scores rather than broad segmentation.

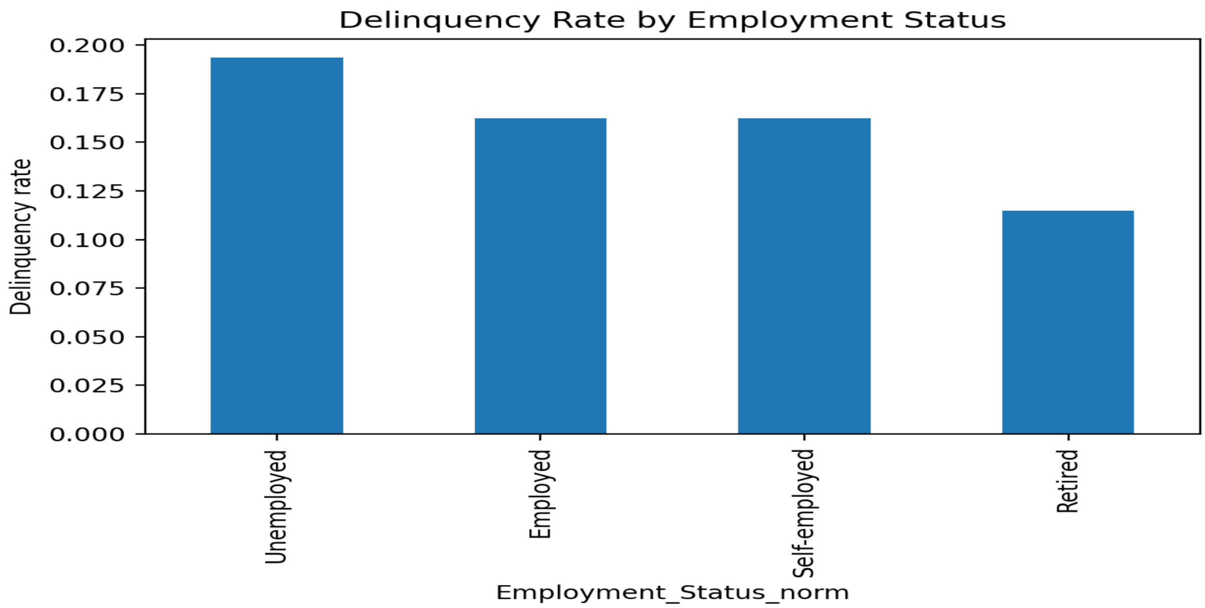
3. Evaluation Strategy

Primary metrics: ROC-AUC and PR-AUC (robust under class imbalance), F1/Recall@K for collections prioritization, and calibration (Brier score / reliability curve). Secondary: accuracy (for reference), confusion matrix. Bias/fairness checks: performance parity across key groups (employment status, location, age bands, card type) using TPR/FPR differences, equal opportunity gap, and calibration across groups. Monitoring: data drift (PSI/KS), prediction drift, stability of feature importance. Decision criteria: target Recall@Top20% with acceptable precision, stable calibration, and no major group-level performance degradation.

4. Output / Business Use

Final output is a probability of delinquency (0–1) and a risk band (Low/Medium/High) with top 3 drivers per customer. Collections uses this to prioritize outreach and tailor interventions.

Supporting EDA chart



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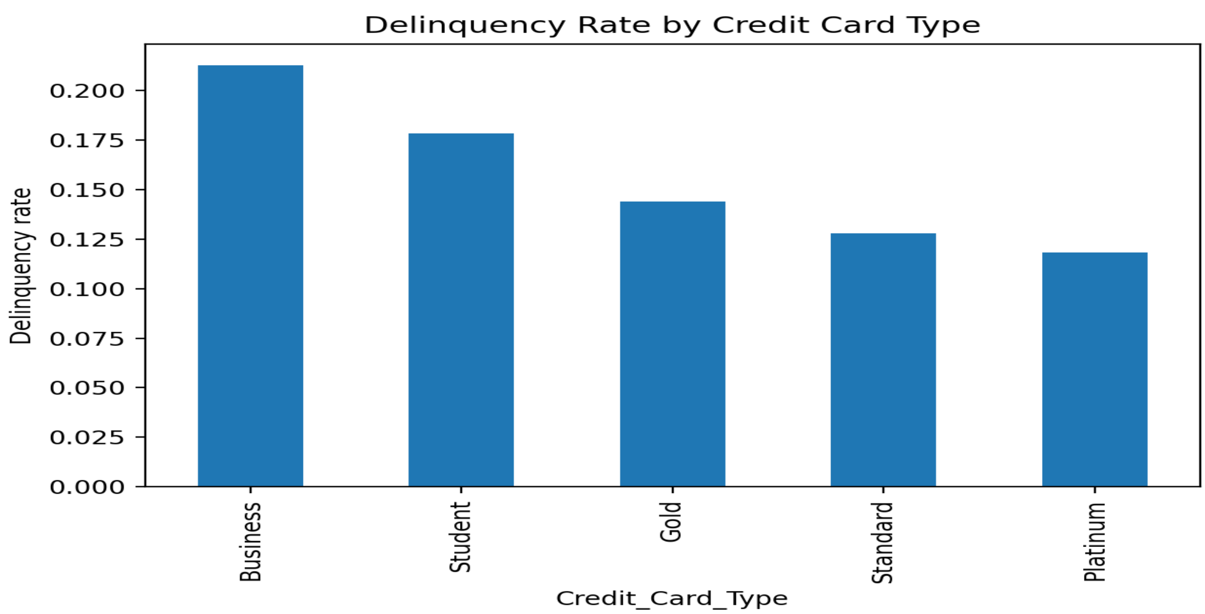

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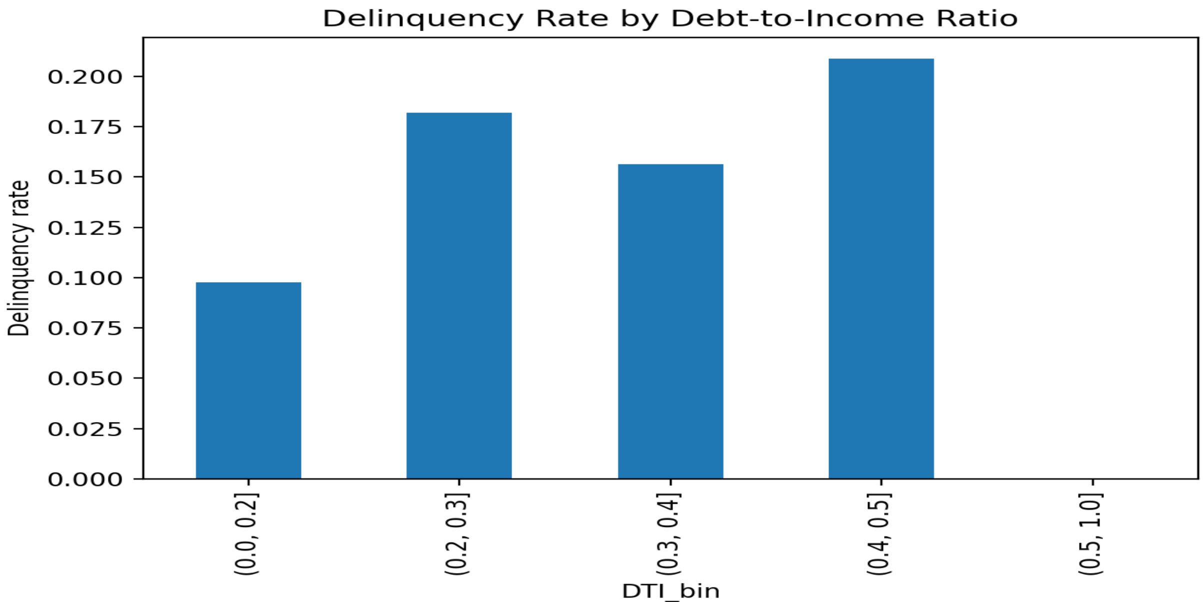

Supporting EDA chart