**Predictive Model Plan**

# 1. Model Logic (Generated with GenAI)

**Model Type:** Logistic Regression (with a Decision Tree as a more complex alternative)

**Purpose:** To predict whether a customer will become delinquent based on their financial and behavioral data.

**Key Input Features:**

* **Income:** Higher income may reduce risk of delinquency.
* **Credit Utilization:** Higher utilization indicates more credit risk.
* **Number of Missed Payments:** Direct indicator of delinquency risk.
* **Customer Tenure:** Longer tenure may suggest stability and lower risk.
* **Past Delinquency Trends:** Historical delinquency behavior improves prediction.

**General Workflow:**

1. **Data Ingestion:** Load the dataset with customer features and delinquency labels.
2. **Preprocessing:** Handle missing data (imputation), scale numerical features if needed, encode categorical variables.
3. **Feature Selection:** Use domain knowledge and exploratory data analysis to select the top features listed above.
4. **Model Training:** Train a logistic regression model on the training set, predicting the probability of delinquency.
5. **Prediction:** Use the model to calculate risk scores (probabilities) for each customer.
6. **Thresholding:** Convert probabilities into binary predictions (delinquent or not) using a set threshold (e.g., 0.5).
7. **Evaluation:** Measure model performance using accuracy, precision, recall, F1 score, and AUC-ROC.
8. **Refinement:** Tune hyperparameters or adjust thresholds to optimize performance.

# 2. Justification for Model Choice

**Selected Model:** Logistic Regression

**Justification:**

Logistic regression is a widely accepted and interpretable model for binary classification tasks such as predicting credit delinquency (i.e., whether a customer will default or not). It is particularly suitable for financial use cases because it provides **transparent, probabilistic outputs**, which are important in **high-stakes, regulated industries like finance**. This interpretability allows Geldium to **understand the influence of individual features** (like income, missed payments, or credit utilization) on the final prediction — which supports **regulatory compliance** and **explainability to customers and stakeholders**.

Additionally, logistic regression is computationally efficient and **easy to deploy** across large customer datasets. It handles **imbalanced data relatively well** when combined with techniques like class weighting or SMOTE. While more complex models (like random forests or neural networks) might offer slightly higher accuracy, they come at the cost of interpretability and require more resources to monitor and validate.

For these reasons, logistic regression strikes a **balanced trade-off between performance, simplicity, and business trust**, making it an excellent starting point for Geldium’s delinquency risk prediction needs.

# 3. Evaluation Strategy

To assess the performance and fairness of the delinquency prediction model, we will use a **comprehensive evaluation strategy** that includes **accuracy**, **precision**, **recall**, **F1 score**, **AUC-ROC**, and **fairness checks**.

**Key Evaluation Metrics:**

1. **Accuracy**
   * Measures the overall correctness of the model's predictions.
   * Can be misleading if data is imbalanced.
2. **Precision**
   * Percentage of predicted delinquents that are actually delinquent.
   * Useful when **false positives** (flagging non-risky customers) are costly.
3. **Recall (Sensitivity)**
   * Percentage of actual delinquents that were correctly identified.
   * Critical to **catch as many risky customers** as possible.
4. **F1 Score**
   * Harmonic mean of precision and recall.
   * Best used when there is a need to balance false positives and false negatives.
5. **AUC-ROC (Area Under the Receiver Operating Characteristic Curve)**
   * Evaluates the model's ability to distinguish between delinquent and non-delinquent customers across all thresholds.
   * Higher AUC = better discriminatory power.

**Fairness & Bias Detection:**

* **Check for disparate impact** across sensitive features (e.g., age, gender, income level).
* Perform **demographic parity analysis** to ensure equitable outcomes across groups.
* Use **SHAP values** to explain feature influence and check if certain groups are unfairly penalized.

**Bias Mitigation Techniques:**

* **Re-sampling strategies** (like SMOTE or undersampling).
* **Fairness-aware modeling** (penalizing unfair predictions in training).
* **Feature audits**: removing or modifying biased features.
* **Threshold tuning** per group to ensure fair treatment.

**Ethical Considerations:**

* Avoid over-reliance on **historical bias** in the data (e.g., previously underserved demographics).
* Ensure the model does not lead to **unjust denial of credit access**.
* Regularly **re-evaluate model performance** to address shifting trends or economic conditions.