**1. Model Logic (Generated with GenAI)**

The goal of this model is to **predict whether a customer is likely to become delinquent** based on their financial and behavioral attributes. I used ChatGPT (GenAI) to generate a **logistic regression model structure**, which is well-suited for binary classification problems like delinquency prediction.

**GenAI-Generated Pseudo-Code Summary:**

# Step 1: Data Preparation

Load dataset → Handle missing values (impute) → Encode categorical variables → Scale numerical features

# Step 2: Feature Selection

Select features such as: Missed\_Payments, Credit\_Utilization, Credit\_Score, Debt\_to\_Income\_Ratio, Account\_Tenure

# Step 3: Model Training

Use Logistic Regression to train on labeled data (target = Delinquent\_Account)

# Step 4: Prediction

Generate probability scores (0 to 1) → Apply threshold (e.g., 0.5) → Predict Delinquent (1) or Not (0)

# Step 5: Evaluation

Evaluate with metrics like Accuracy, Precision, Recall, F1 Score, and AUC

# Step 6: Explainability

Use coefficients or SHAP values to interpret model decisions

**What the model does:**  
It estimates the **probability of a customer defaulting on payments**, using known financial metrics and past behavior, then classifies them as either “at risk” or “not at risk” for delinquency. This helps the Collections team prioritize proactive outreach.

**2. Justification for Model Choice**

I selected **logistic regression** for three main reasons:

1. **Transparency & Explainability**: Each input variable’s influence on the prediction is visible via the model's coefficients. This is crucial for explaining results to stakeholders and for regulatory compliance.
2. **Ease of Implementation**: Logistic regression is computationally efficient and easily deployable in production systems.
3. **Relevance to Financial Prediction**: Since the goal is to predict a **binary outcome** (delinquent vs. non-delinquent), logistic regression is an ideal, industry-standard choice. It’s also interpretable, which aligns with Geldium’s need for clear and fair decision-making.
4. **Business Suitability**: Geldium operates in a regulated space, so model interpretability and ethical fairness are vital. Logistic regression provides a risk score that can be used to **prioritize customer intervention** transparently.

**3. Evaluation Strategy**

To ensure the model performs reliably and ethically, I would evaluate it using the following approach:

1. **Performance Metrics**

* **Accuracy**: Overall correctness of predictions.
* **Precision**: How many predicted “at-risk” customers were actually delinquent.
* **Recall**: How many of the real delinquent customers were successfully identified.
* **F1 Score**: Balance between precision and recall.
* **AUC-ROC**: Measures how well the model separates delinquent vs. non-delinquent customers.

1. **Interpretation & Improvement**

* A confusion matrix will help spot whether false negatives (missed risky customers) are too high.
* If recall is low, I’ll tune the classification threshold or apply oversampling (e.g., SMOTE) to handle class imbalance.

1. **Bias Detection and Mitigation**

* **Demographic Parity Check**: Assess whether certain groups (e.g., by Employment\_Status or Location) are unfairly labeled high risk.
* **Proxy Variable Analysis**: Identify if features like Location might indirectly encode sensitive attributes.
* **SHAP values**: Used to ensure feature impact is fair and explainable.

1. **Ethical Considerations**

* Avoid over-reliance on automated predictions in decision-making.
* Ensure human review before acting on any “at-risk” prediction.
* Regular audits of the model for **fairness and accuracy over time**.