Predictive Model Plan

1. Model Logic (Generated with GenAI)

Model Objective:

The model aims to predict whether a customer will become delinquent (1) or not (0) based on financial behavior and account attributes. It will support Geldium's risk management by identifying high-risk customers in advance.

Model Type:

- Primary model: **Logistic Regression**
- Backup model (optional): **Random Forest Classifier**

Step-by-Step Predictive Pipeline Logic:

1. **Data Collection**
   Load the customer-level dataset with features like income, credit score, missed payments, and delinquency status.
2. **Feature Selection**
   Choose important features that are relevant to risk:
   - Credit_Utilization
   - Missed_Payments
   - Debt_to_Income_Ratio
   - Account_Tenure
   - Credit_Score
3. **Data Cleaning and Preprocessing**
   - Handle missing values: median imputation for Income, Loan_Balance, and Credit_Score
   - Normalize numerical features
   - One-hot encode categorical variables such as Employment_Status and Credit_Card_Type

4. **Model Training**
    - Use **Logistic Regression** to train on the features and learn the relationship with Delinquent_Account
    - Optionally train a **Random Forest** to compare performance
5. **Prediction**
    - Model outputs a probability (e.g., 0.75) indicating the likelihood of delinquency
    - Apply a threshold (e.g., 0.5) to convert probability into binary classification (0 or 1)
6. **Model Evaluation**
    - Use metrics such as Accuracy, Precision, Recall, AUC, and F1 Score
    - Run fairness checks across groups (e.g., employment type)

Pseudo-Code :

```
# Step 1: Load and clean the data
data = load_data("delinquency_dataset.csv")
data = impute_missing(data)
data = encode_categorical(data)
# Step 2: Split and train
X_train, X_test, y_train, y_test = train_test_split(data.features, data.labels)
model = LogisticRegression()
model.fit(X_train, y_train)
# Step 3: Predict
y_pred = model.predict(X_test)
# Step 4: Evaluate
evaluate_model(y_test, y_pred)
```

2. Justification for Model Choice

We selected Logistic Regression as the primary model for predicting customer delinquency due to its unique balance of performance, interpretability, and industry alignment.

- **Accuracy**
  - Logistic regression is well-suited for binary classification tasks like predicting Delinquent_Account.
  - It performs well on medium-sized datasets and can achieve competitive accuracy when the relationship between features and the target is linear or monotonic.
- **Transparency**
  - Logistic regression offers clear, explainable outputs, showing the direction and weight of each feature's impact on the prediction.
  - This is critical for Geldium's internal teams and stakeholders, especially when explaining decisions to auditors or regulators.
- **Ease of Use**
  - It is easy to implement and requires relatively low computational power.
  - The model is fast to train and integrates well into most existing data pipelines.
- **Relevance for Financial Prediction**
  - Logistic regression is widely adopted in the financial industry due to its interpretability and regulatory friendliness.
  - It aligns with common credit risk models used in banks and lending institutions.
- **Suitability for Geldium's Business Needs**

- Geldium requires a transparent, auditable, and fair model to assess customer credit risk.
- The logistic model supports probability-based risk scoring, which can help in tiering customers and prioritizing interventions.
- If needed, we can further test advanced models like Random Forests for performance improvement, while keeping Logistic Regression as the explainable baseline.

3. Evaluation Strategy

To ensure the model is both effective and fair, we will evaluate it using a combination of performance metrics, bias detection strategies, and ethical considerations.

- **Evaluation Metrics**

  We will use the following metrics to assess model performance:

  - **Accuracy**: Measures overall correctness. Useful when classes are balanced.
  - **Precision**: The proportion of customers predicted as delinquent who actually are delinquent — important to reduce false positives.
  - **Recall**: The proportion of actual delinquents correctly identified — crucial for identifying risky customers.
  - **F1 Score**: Harmonic mean of precision and recall, especially valuable for imbalanced datasets.
  - **AUC (Area Under the ROC Curve)**: Evaluates the model's ability to distinguish between delinquent and non-delinquent customers.

- **Interpretation of Metrics**

  - A high **recall** indicates the model is catching most of the risky cases.
  - High **precision** shows it's not falsely labeling good customers as risky.
  - **F1 score** helps ensure a good balance between precision and recall.

- A high **AUC** (closer to 1) means the model reliably separates risk vs. no-risk customers.

➢ **Bias Detection & Mitigation**

- Evaluate model performance across **different demographic or employment groups** to ensure no group is disproportionately flagged.
- Use tools like **confusion matrix disaggregation** and **demographic parity tests** to spot inconsistencies.
- If bias is detected, apply mitigation strategies such as:
  - Adjusting classification thresholds
  - Reweighting the training data
  - Removing or auditing sensitive features

➢ **Ethical Considerations**

- Predictions should be used to **support and assist** at-risk customers, not penalize them.
- The model must not reinforce existing financial inequalities or unfairly disadvantage certain customer groups.
- Transparency in model decision-making is critical to maintain trust and comply with financial regulations.