Step 1 – Generated Model Logic (using GenAI guidance)

Model Type Chosen:

Logistic Regression — This model is selected for its interpretability, suitability for binary classification (delinquent vs. non-delinquent) and compliance alignment in financial modeling. A secondary Decision Tree will be used for transparency comparison and validation.

Model Logic (Conceptual Pipeline):

1. **Data Ingestion:**
   Load Geldium's delinquency dataset and verify structure, ensuring the target variable is Delinquent_Account.

2. **Data Quality Checks:**
   Identify missing values (Income, Loan_Balance, Credit_Score) and handle them via median imputation (simple, robust method). Validate numerical and categorical data types.

3. **Feature Engineering:**

   ○ Derive Debt_to_Income_Ratio, Credit_Utilization, and Account_Tenure_Group (e.g., short/medium/long).

   ○ Create binary indicators for recent missed payments using month-level payment columns.

   ○ Normalize continuous features to improve model convergence.

4. **Feature Selection:**
   Top 5 features identified through EDA and correlation analysis:

   ○ Income

   ○ Account_Tenure

   ○ Credit_Score

   ○ Debt_to_Income_Ratio

   ○ Credit_Utilization

5. **Modeling Stage:**

- **Logistic Regression:** Computes probability of delinquency (output between 0 and 1).
- Formula:
  P(Delinquent) = 1 / (1 + e^-(β0 + β1*X1 + β2*X2 + ... + βn*Xn))
- where βi\beta_iβi represents feature coefficients estimated via Maximum Likelihood Estimation (MLE).

6. **Model Evaluation:**
   - Split data into training (70%) and testing (30%).
   - Evaluate using Accuracy, Precision, Recall, F1 Score, AUC-ROC, and a Confusion Matrix.
   - Use SHAP values to interpret each feature's impact on prediction.
   - Cross-validate results (5-fold CV) for robustness.
7. **Fairness & Explainability Checks:**
   - Test demographic parity and disparate impact ratios to ensure no group bias.
   - Use SHAP/feature importance plots for interpretability.
8. **Deployment Plan (Conceptual):**
   - Generate delinquency probability scores for all customers.
   - Apply business-defined thresholds (e.g., flag risk if probability ≥ 0.65).
   - Monitor monthly drift in model accuracy and bias metrics.

Step 2 – Model Justification

Logistic Regression was selected as the primary modeling approach because it offers a strong balance between predictive power and interpretability, which are critical in financial risk modeling. Unlike neural networks, logistic regression provides transparent probability scores that can be clearly explained to stakeholders and regulators — aligning with compliance and ethical AI standards in credit decisioning. It efficiently handles structured, tabular financial data and works well even with modest dataset sizes.

While Decision Trees offer clear decision paths, they can easily overfit and become unstable with small changes in data. Neural Networks, though powerful, are difficult to interpret and often unnecessary for relatively small, structured financial datasets. Logistic Regression, therefore, best serves Geldium's goals — enabling accurate, explainable, and fair credit risk predictions that can be trusted in customer-facing financial decisions.

Step 3 – Model Evaluation Strategy

To ensure reliability, fairness, and explainability of the model, the following evaluation framework will be applied:

Metric	Purpose	Interpretation / Goal
Accuracy	Measures overall correct predictions	≥ 85% preferred for balanced dataset
Precision	Fraction of predicted delinquents that are truly delinquent	High precision reduces false alarms
Recall (Sensitivity)	Fraction of true delinquents correctly predicted	High recall prevents missed risky cases
F1 Score	Harmonic mean of precision & recall	Used when both errors are costly
AUC-ROC	Ability to distinguish delinquent vs non-delinquent	Closer to 1 = better discrimination
Confusion Matrix	Visualizes classification errors	Used to identify false positives/negatives
Fairness Metrics	Demographic parity, disparate impact	Ensure no group is unfairly penalized

Bias & Fairness Plan:

- Check for selection bias and proxy bias (e.g., location or employment status inadvertently reflecting demographics).
- Use Demographic Parity Ratio (> 0.8 threshold) to assess equal treatment.
- Apply SHAP values to explain individual predictions and ensure feature influence aligns with domain logic.
- Conduct periodic fairness audits post-deployment to monitor drift in group outcomes.