**Predictive Model Plan**

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

Model Type: Two options considered

* Simple: Logistic Regression
* Complex (Selected): XGBoost Model

Goal:  
The model is designed to predict the likelihood that a customer will become delinquent on their credit obligations based on various financial and behavioural features.

XGBoost Predictive Model Logic (Step-by-Step):

1. **Data Ingestion**:  
   Load customer financial and demographic data including payment history, credit utilization, income, and account details.
2. **Feature Selection**:  
   Select top predictive features such as:
   * Credit Utilization Rate
   * Past Missed Payments
   * Debt-to-Income Ratio
   * Credit History Length
   * Number of Recent Credit Inquiries
3. **Preprocessing**:
   * Handle missing data via imputation (e.g., median for income, mode for categorical values).
   * Encode categorical features using one-hot encoding.
   * Normalize or scale numerical features where necessary.
4. **Model Training**:
   * Use XGBoost classifier to train on labeled data (delinquent vs. non-delinquent customers).
   * Apply hyperparameter tuning via cross-validation for optimal performance.
5. **Prediction**:
   * Generate a risk score (probability of delinquency) for each customer.
   * Classify customers as high or low risk based on a defined threshold.
6. **Output**:
   * Output predictions with probability scores.
   * Provide explainability using SHAP values for transparency.

2. **Justification for Model Choice**

* **High Accuracy**:  
  XGBoost provides strong predictive performance, which is important for correctly identifying high-risk (delinquent) customers.

**Handles Complex Data Well**:  
It can capture non-linear relationships between features like credit utilization and income, which logistic regression might miss.

**Works Well with Missing Data**:  
XGBoost can handle missing values directly, reducing the need for complex data cleaning.

**Balances Performance and Interpretability**:  
While not as simple as logistic regression, XGBoost still allows us to understand which features matter most (using feature importance or SHAP values).

**Good for Financial Use Cases**:  
Widely used in banks and fintech due to its strong results with credit risk and fraud detection problems.

**Supports Regulatory Needs**:  
Offers transparency tools (like SHAP) to explain why a customer is flagged as high-risk—important for compliance.

**Scalable and Fast**:  
Can process large amounts of customer data quickly, making it suitable for real-time risk scoring systems.

**More Reliable than Simpler Models**:  
Outperforms basic models (like decision trees or logistic regression) especially when many variables interact in complex ways.

3 **Key Evaluation Metrics**

1. **Accuracy**
   * Measures the overall correctness of the model.
   * Limitation: Can be misleading in imbalanced datasets (e.g., many non-delinquent customers).
2. **Precision & Recall**
   * **Precision**: Of all customers predicted to be delinquent, how many actually are.
   * **Recall**: Of all actual delinquent customers, how many we correctly identified.
   * Important for minimizing **false positives (unfair flagging)** and **false negatives (missed risk)**.
3. **F1 Score**
   * Harmonic mean of precision and recall.
   * Best when classes are imbalanced and we want a balance between false positives and false negatives.
4. **AUC-ROC (Area Under the Curve - Receiver Operating Characteristic)**
   * Measures the model's ability to distinguish between delinquent and non-delinquent customers.
   * A higher AUC (closer to 1) indicates better discriminatory power.

**Fairness and Bias Checks**

1. **Disparate Impact Ratio**
   * Compares prediction outcomes across different groups (e.g., gender, age, region).
   * Helps detect if the model unfairly disadvantages a protected group.
2. **Equal Opportunity Difference**
   * Measures if all groups have equal true positive rates.
   * Ensures fairness in identifying risky customers across demographics.
3. **Calibration by Group**
   * Checks whether predicted risk scores mean the same thing across groups.
   * Prevents over- or under-estimating risk for any one segment.

**Bias Mitigation Techniques**

* **Reweighing** or **resampling** the dataset to balance underrepresented groups.
* **Feature auditing** to exclude biased or proxy variables (e.g., ZIP codes tied to income).
* **Post-processing techniques** like threshold adjustments for different groups.

**Interpretation and Monitoring**

* Use **SHAP values** or **feature importance** to explain individual predictions.
* Set up regular **model performance reviews** to retrain/update the model as customer behavior or economic conditions change.
* Trigger **re-evaluation** if:
  + AUC drops significantly (e.g., below 0.75),
  + Disparate impact exceeds a regulatory threshold,
  + F1 score drops for high-risk group segments.