**Predictive Model Plan**

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

To forecast customer delinquency, I would propose using a Logistic Regression model. This choice balances interpretability with predictive power, which is critical in financial services. The model would process customer data through a structured pipeline, transforming raw inputs into a probability of delinquency.

Key input features:

Credit\_Score: A fundamental indicator of a customer's creditworthiness.

Missed\_Payments: Directly reflects past payment behavior and is a strong indicator of future risk.

Credit\_Utilization: Represents the proportion of available credit being used, indicating financial strain.

Debt\_to\_Income\_Ratio: Measures a customer's ability to manage monthly payments.

Employment\_Status: Provides insight into a customer's financial stability and income source.

The general workflow would involve:

Data Ingestion: Loading the pre-processed dataset.

Feature Preprocessing: This includes handling any remaining missing values (e.g., using median imputation for Income and Credit\_Score), encoding categorical variables (like Employment\_Status, Credit\_Card\_Type, Location, and Month\_X statuses) into numerical formats (e.g., one-hot encoding or ordinal encoding), and scaling numerical features to ensure they contribute equally to the model.

Feature Selection: Refining the set of input features based on their correlation with delinquency and importance, focusing on the top 5 identified.

Model Training: Splitting the data into training and testing sets, then training the Logistic Regression model on the training data.

Prediction: Using the trained model to predict the probability of delinquency for new or unseen customer data.

Output: Generating a delinquency risk score or a binary prediction (delinquent/non-delinquent) for each customer.

**2. Justification for Model Choice**

The selection of Logistic Regression for predicting delinquency is well-suited to Geldium's needs due to its interpretability, robustness, and ease of deployment within a financial services context. In an industry heavily regulated and requiring transparency, a Logistic Regression model allows for straightforward interpretation of how each input feature contributes to the final delinquency probability. For example, the model can clearly show that a decrease in Credit\_Score or an increase in Missed\_Payments directly increases the likelihood of delinquency, which is crucial for explaining decisions to customers and satisfying regulatory compliance. While more complex models like Random Forests or Gradient Boosting Machines might offer slightly higher predictive accuracy, they often come at the cost of reduced interpretability, making it challenging to explain why a particular customer was flagged as high-risk. Logistic Regression provides a clear balance, offering solid performance for binary classification problems while ensuring the necessary transparency for Geldium's decision-makers and intervention strategies.

**3. Evaluation Strategy**

Evaluating the model's performance will be multifaceted, focusing on both predictive accuracy and fairness, which are paramount in financial risk assessment.

Key Metrics and Interpretation:

Accuracy: While a common metric, it can be misleading in imbalanced datasets (where delinquent accounts are much rarer than non-delinquent ones).

Precision: Of all customers predicted as delinquent, how many actually became delinquent? High precision means fewer false positives (incorrectly flagging healthy accounts).

Recall (Sensitivity): Of all truly delinquent customers, how many did the model correctly identify? High recall means fewer false negatives (missing actual delinquent accounts).

F1-score: The harmonic mean of precision and recall, providing a balanced measure, especially useful when both false positives and false negatives are costly.

AUC-ROC (Area Under the Receiver Operating Characteristic Curve): Measures the model's ability to distinguish between delinquent and non-delinquent classes across all possible classification thresholds. A higher AUC indicates a better performing model, especially valuable for imbalanced classes.

Plans to detect or reduce bias in your model: To ensure the model avoids biased or unfair treatment, especially across different customer segments, we would implement the following:

Disparate Impact (80% Rule): This checks if the selection rate for a protected group is less than 80% of the selection rate for the majority group. For example, if the model flags a disproportionately higher percentage of customers from certain age groups or locations as high-risk, this rule would flag potential bias.

Equal Opportunity Difference: This measures if the false negative rate (missed delinquencies) is similar across different demographic groups. Significant differences could indicate bias where the model performs worse for certain groups.

Demographic Parity: Checks if the proportion of positive predictions (e.g., predicted delinquent) is roughly the same across different groups, regardless of the true outcomes.

Ethical considerations in making predictions about customer financial behavior:

Transparency and Explainability: Ensuring model decisions can be understood and explained to customers and regulators is paramount.

Fairness: Actively testing for and mitigating bias to ensure the model does not unfairly disadvantage certain demographic groups.

Privacy: Protecting sensitive customer financial data throughout the modeling process.

Accountability: Establishing clear lines of responsibility for model outcomes and impacts.

If fairness metrics reveal significant disparities, it indicates bias in the model's predictions. This would necessitate further investigation into the features contributing to the bias, potentially re-evaluating feature selection, exploring different data balancing techniques, or employing bias mitigation algorithms (e.g., re-weighting, adversarial debiasing) during model training to ensure equitable outcomes across all customer groups. The goal is to achieve a model that is both accurate and fair, aligning with ethical AI principles and responsible lending practices.