| **Assumption Name** | **Assumption Description** | **Materiality of Assumption** | **Rationale for This Assumption** |
| --- | --- | --- | --- |
| **Missing Value Treatment** | Missing values in the dataset were handled through imputation (e.g., imputing with 0 for variables like MaxDelqStat or treating them as a separate category). | Medium | Quantitative methodology-driven: ensures completeness of data for model training. |
| **Outlier Treatment** | Outliers were retained in the dataset as they could represent rare but meaningful fraud-related signals. | High | Business-driven: fraud patterns often involve rare but critical data points. |
| **Feature Scaling** | Feature scaling was not applied because XGBoost does not require normalized or standardized input features. | Low | Quantitative methodology-driven: XGBoost handles unscaled features natively. |
| **Temporal Assumptions** | The training dataset reflects historical fraud patterns, and it is assumed that these patterns remain predictive of future fraud behavior. | High | Business-driven: aligns with the fundamental assumption of fraud detection models. |
| **Data Integrity Checks** | Preprocessing steps included checks for data consistency, removal of duplicate records, and ensuring all mandatory fields were present in the input data. | High | Quantitative methodology-driven: ensures data quality for reliable model outputs. |
| **Variable Selection** | Recursive Feature Elimination (RFE) was used to select features contributing most to the model’s predictive power while eliminating redundant or irrelevant variables. | High | Quantitative methodology-driven: improves model performance and interpretability. |
| **Fraud Label Definition** | The target variable was based on flagged applications for fraud (fraud and non-fraud) sourced from historical data on account performance and fraud tagging processes. | High | Business-driven: ensures alignment with business use case and objective. |

This table ensures that the assumptions made during the model development and production processes are clearly documented, along with their materiality and rationale.

Here’s a structured table for the **Data Limitations** section in the MDR based on LexisNexis Fraud Intelligence Model V1:

| **Limitation Name** | **Limitation Description** | **Impact on Business Use** | **Monitoring Description & Frequency** |
| --- | --- | --- | --- |
| **Temporal Data Gaps** | Training data was collected from specific historical periods and may not capture shifts in fraud patterns over time. | Potential decrease in predictive accuracy if fraud patterns change significantly in future periods. | Monitor the model's AUC and FDR quarterly on out-of-time (OOT) datasets to ensure consistent performance. |
| **Rare Fraud Examples** | Limited number of rare fraud cases in the dataset, which may underrepresent certain types of fraud behavior. | May reduce model sensitivity to rare but critical fraud scenarios. | Periodically review model outputs for missed rare fraud cases and augment training data with newly flagged cases. |
| **Data Labeling Accuracy** | Fraud and non-fraud labels rely on manual or semi-automated processes, introducing potential errors in target labeling. | Mislabeling could lead to incorrect scoring or model bias. | Conduct biannual label audits by comparing flagged cases with post-investigation outcomes to improve labeling accuracy. |
| **Incomplete Feature Data** | Missing or incomplete data in key variables, such as transaction history or identity attributes. | May impact model performance by reducing the effectiveness of certain predictive features. | Monitor the proportion of missing data in production datasets and implement automated imputation checks monthly. |
| **Data Drift** | Input feature distributions in production may diverge from those in the training dataset. | Could lead to reduced model performance and stability. | Use data drift detection tools to track feature distribution changes quarterly and retrain the model if significant drift is observed. |
| **Outdated Fraud Definitions** | Definitions of "fraud" and "non-fraud" evolve over time, potentially mismatching current business needs. | Could limit the model’s ability to address new fraud techniques effectively. | Conduct annual reviews of fraud definitions with subject matter experts to ensure alignment with current fraud behavior. |

This table provides a comprehensive overview of data limitations, their potential business impact, and the corresponding monitoring measures to mitigate associated risks.

MODEL Assumptions:

Here's a response table for the **Model Assumptions** section in the MDR based on the provided information:

| **Assumption Name** | **Assumption Description** | **Materiality of Assumption** | **Rationale for This Assumption** |
| --- | --- | --- | --- |
| **Data Stability** | The model assumes that historical patterns and relationships between features and the target variable will remain stable over time. Model performance depends on the consistency of data reporting and consumer behavior patterns. Significant changes in data quality or consumer behavior may impact stability. | High: Extreme shifts in consumer behavior or reporting could lead to degraded model performance. | Quantitative methodology-driven: Ensures alignment with historical trends observed in training data. |
| **Score Application** | The score ranks individuals based on the probability of the target outcome occurring, not as an exact probability estimate. Model performance depends on the live population matching the development population and the stability of feature-target correlations over time. | High: Variations between the development and live populations can reduce model effectiveness. | Business-driven: Ensures the score maintains its purpose of ranking risk appropriately. |

This table reflects the critical assumptions made during model development and the rationale for their implementation. These assumptions ensure that the model is robust and aligned with the intended application.

Table 1

Here is the response table for the **Model Limitations** section based on the listed information:

| **Limitation Name** | **Limitation Description** | **Impact on Business Use** | **Monitoring Description & Frequency** |
| --- | --- | --- | --- |
| **External Factors** | Model performance relies on external factors such as macroeconomic conditions, customers' business policies, decision-making processes, and portfolio management remaining stable over time. Any significant change in these factors could degrade model performance. | The model's predictive power may decrease if external factors diverge significantly from those present during model development. | Regular evaluation of external factors and their influence on model performance. Annual reviews of business policy changes. |
| **Target Population Alignment** | The model was developed using pre-book and post-book U.S. bankcard applicant data sourced from internal LexisNexis samples. Differences between live population characteristics and the development population may impact performance. | If the live population differs significantly, the model may fail to accurately identify fraud risk. | Periodic comparison of the live environment population to the training data. Quarterly checks are recommended. |
| **Fraud Tag Consistency** | The "confirmed fraud" post-book fraud tag used in model development corresponds to financial loss. However, suspect fraud cases not corresponding to financial loss are treated as pre-book fraud tags, leading to potential differences in live use. | Misalignment of fraud tagging between development and live use could impact model predictions and business decisions. | Regular validation of fraud tagging processes to ensure consistency. Bi-annual reviews to assess any deviations. |

This response outlines the model's limitations, their potential impact on business use, and the monitoring strategies to mitigate related risks effectively.

Table 2

Here is the table for the **Model Limitations** section in the new format:

| **Model Weakness or Limitation** | **Associated Model Risk(s)** | **Model Risk Mitigants/Remediation** |
| --- | --- | --- |
| **Dependence on External Factors** | Changes in macroeconomic conditions, customer business policies, decision-making processes, and portfolio management could negatively impact model performance. | Regular monitoring of external factors affecting the live environment. Annual reviews of macroeconomic and business policy changes. |
| **Target Population Misalignment** | Differences between the live population and the development population could result in decreased predictive accuracy and incorrect risk assessments. | Periodic analysis of the live population to ensure alignment with the development population. Quarterly reviews and adjustments as needed. |
| **Fraud Tagging Differences** | Inconsistencies in fraud tagging (e.g., confirmed fraud vs. suspect fraud) could lead to inaccuracies in model predictions and business decisions. | Routine validation of fraud tagging processes to ensure alignment with model development assumptions. Bi-annual audits of tagging practices. |
| **Data Instability Risk** | Model performance may degrade if there are significant shifts in consumer behavior or reporting practices over time, impacting input data stability. | Regular score monitoring to identify and address shifts in behavior or data quality. Monthly stability tracking and annual recalibration if necessary. |
| **Static Model Design** | Model performance is not adjusted for changes over time due to a lack of recalibration, realignment, or rescaling of score distributions. | Scheduled periodic assessments to evaluate model adequacy in changing environments. Implement recalibration processes as part of ongoing risk management. |

This table captures model weaknesses, their associated risks, and measures to mitigate or remediate those risks effectively.