Medication Error Risk Intelligence & Forecasting Analysis
Global Medical Response | January 2021 – July 2024

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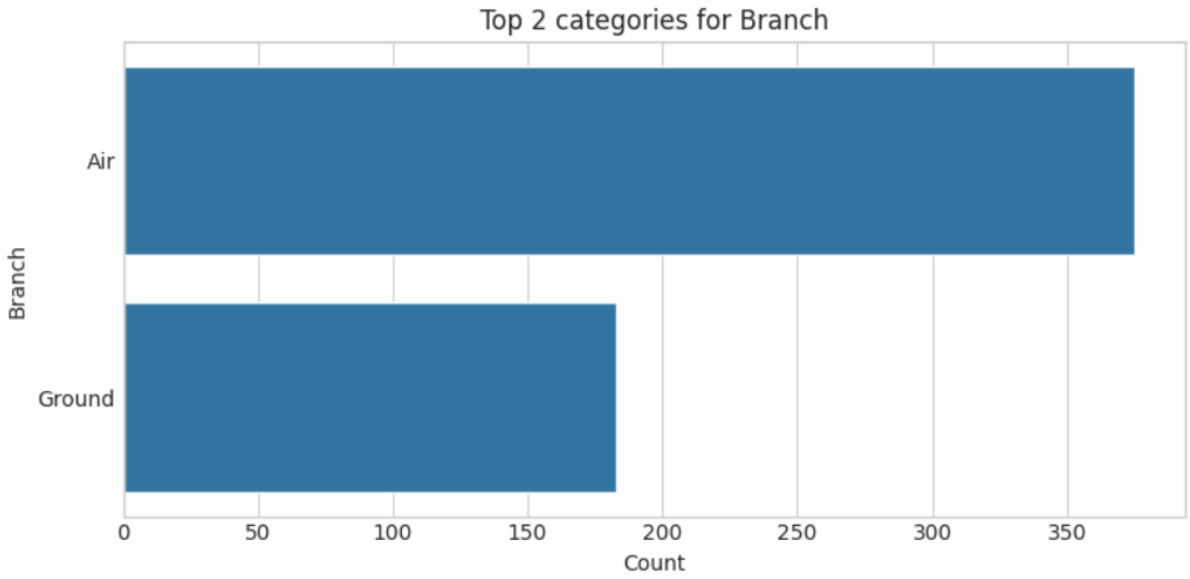
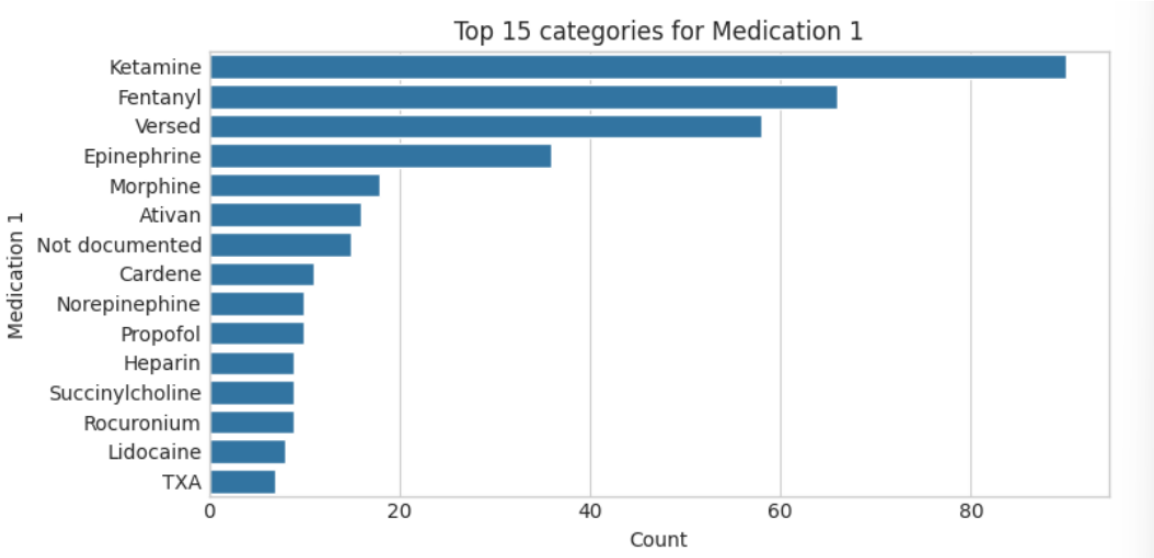
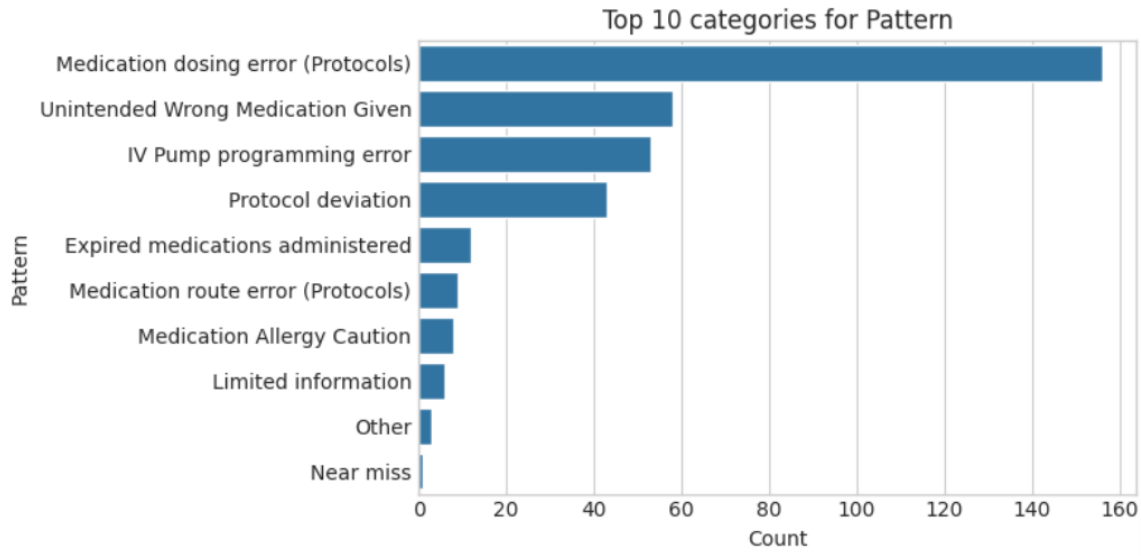
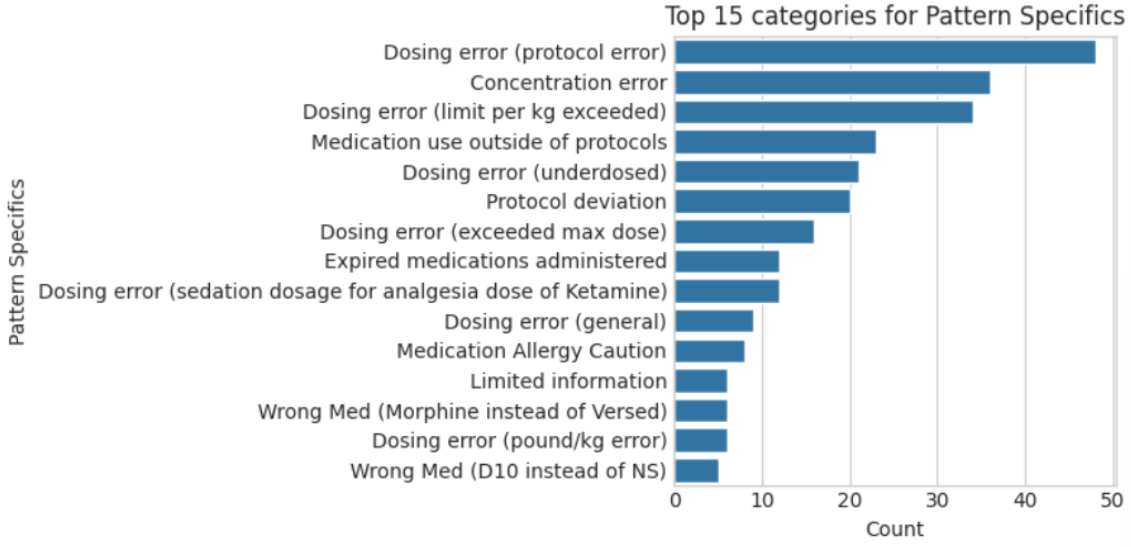
In conducting a thorough medication-error analysis, the initial phase involves meticulous data handling and exploration of the Medication dataset, which comprises two critical components: the Medication sheet, providing detailed event-level information, and the Med Error Summary sheet, summarizing certificate-level counts categorized by specific patterns. The primary objective of this data-loading step is to ensure the integrity and structure of the Excel file while confirming the presence of essential variables such as Pattern Specifics and various certificate columns. Following this, exploratory data analysis (EDA) delves into the dataset's univariate patterns, allowing for an examination of key numeric fields and categorical variables relevant to medication errors. This analysis aims to identify predominant trends within the data and focuses on the frequency of various failure modes, particularly through an in-depth look at the most commonly occurring Pattern Specifics, thereby enhancing understanding the underlying issues in medication administration.




Top 15 categories for Medication 1
Ketamine
Fentanyl
Versed
Epinephrine
Morphine
Ativan
Not documented
Cardene
Norepinephine
Propofol
Heparin
Succinylcholine
Rocuronium
Lidocaine
TXA
Medication 1
0
20
40
60
80
Count

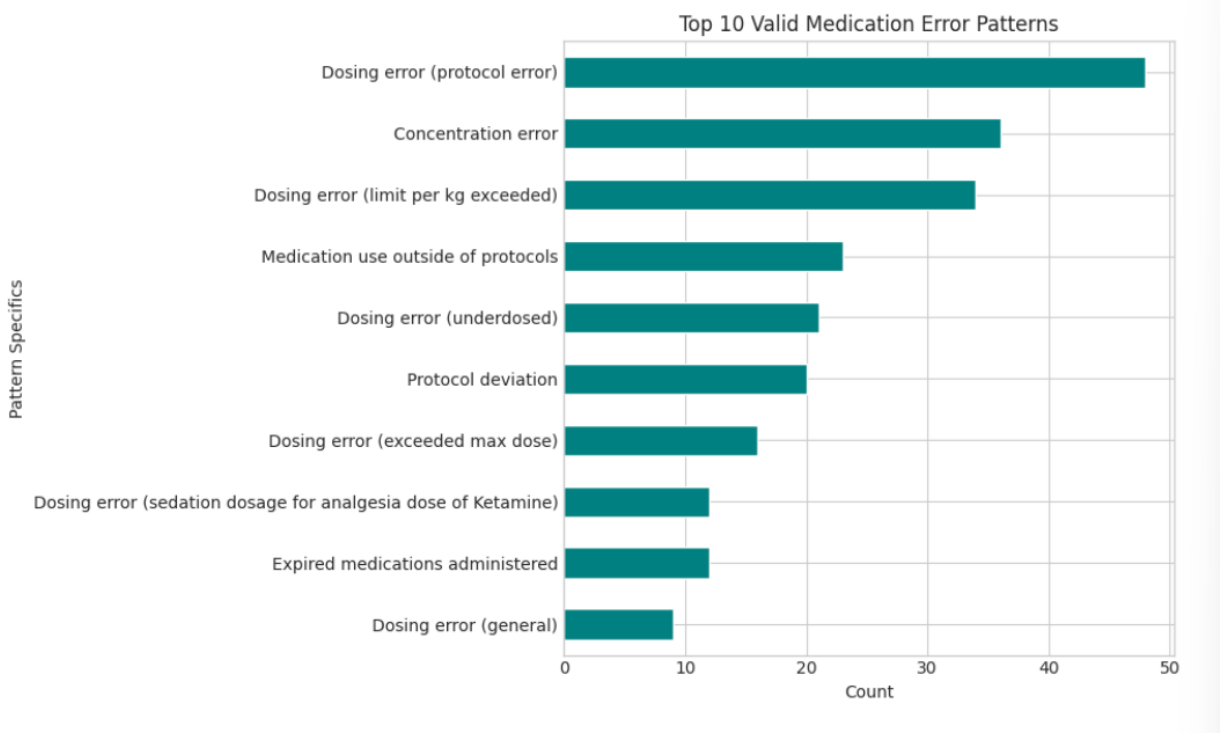

Top 10 categories for Pattern
Medication dosing error (Protocols)
Unintended Wrong Medication Given
IV Pump programming error
Protocol deviation
Expired medications administered
Medication route error (Protocols)
Medication Allergy Caution
Limited information
Other
Near miss
Pattern
0
20
40
60
80
100
120
140
160
Count


Top 15 categories for Pattern Specifics
Dosing error (protocol error)
Concentration error
Dosing error (limit per kg exceeded)
Medication use outside of protocols
Dosing error (underdosed)
Protocol deviation
Dosing error (exceeded max dose)
Expired medications administered
Dosing error (sedation dosage for analgesia dose of Ketamine)
Dosing error (general)
Medication Allergy Caution
Limited information
Wrong Med (Morphine instead of Versed)
Dosing error (pound/kg error)
Wrong Med (D10 instead of NS)
Pattern Specifics
0
10
20
30
40
50
Count

In the Data Overview phase, the focus is on the Medication dataset with particular attention to the Pattern Specifics column, which serves as the primary variable for identifying error types. The first objective is to assess the overall dimensions of the dataset by determining the total number of medication-related records and the number of columns present. This step is crucial as it provides insight into the dataset's structure, allowing for a comprehensive understanding of the available information for future analyses. Next, the completeness and content of the Pattern Specifics column will be examined to ascertain how many records contain valid and specific pattern data, while excluding entries marked as missing or labeled "Not documented." Additionally, the Top 10 most frequently occurring error patterns will be identified, helping to highlight common issues within the dataset. To further contextualize the error descriptions, a handful of example rows will be reviewed, offering a clearer perspective on the nature of the errors recorded.

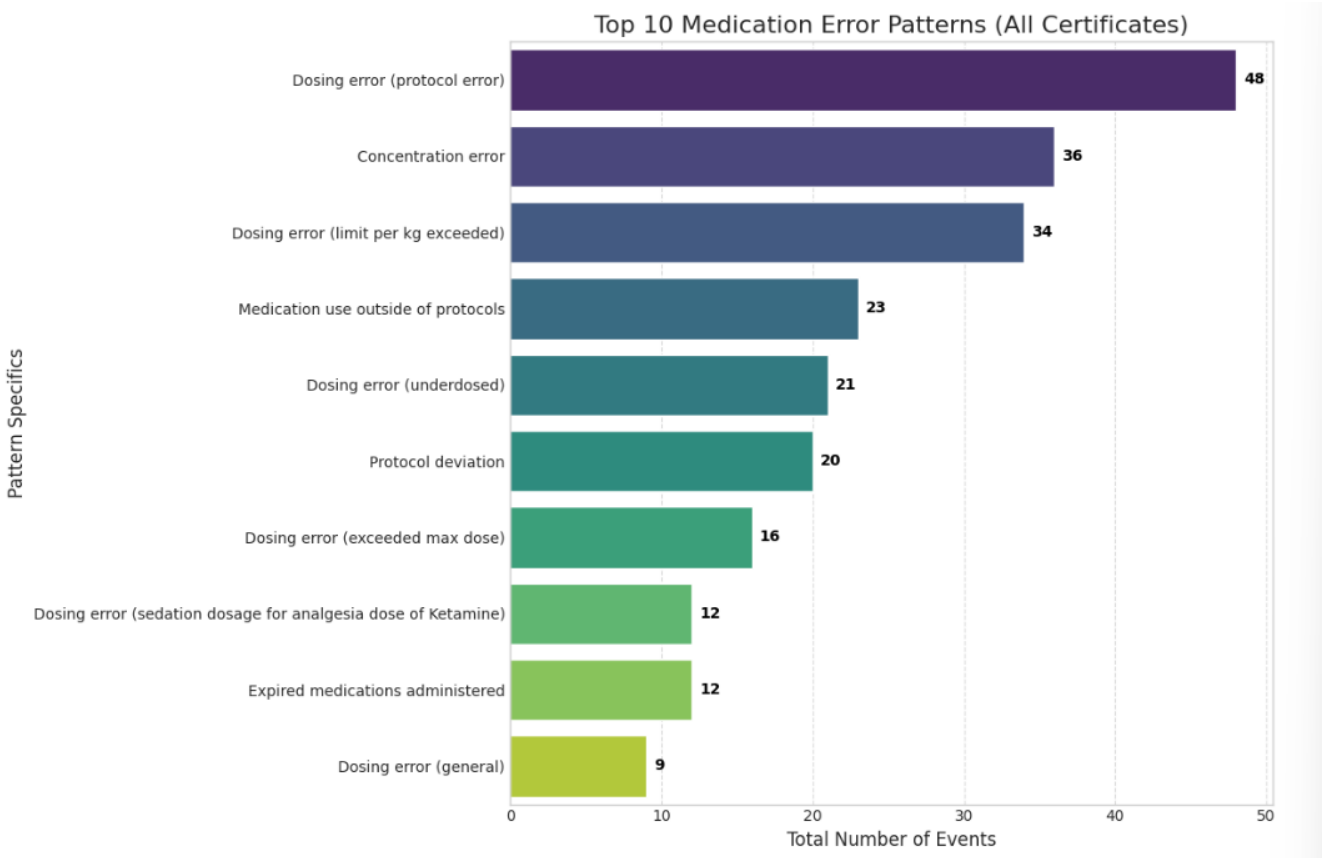
```
--- Dataset Dimensions ---
Total Records: 558
Total Columns: 18

--- Column Names ---
['Report ID', 'Month', 'Day', 'Year', 'Source', 'Branch', 'Primary Risk', 'Risk Event', 'Medicat
ion 1', 'Medication 2', 'Event', 'Medication Cross Check', 'Precursor/Stressor', 'Outcome', 'Pat
tern', 'Pattern Specifics', 'Unnamed: 16', 'Unnamed: 17']

--- 'Pattern Specifics' Completeness ---
Valid Pattern Records: 349
Missing/Unspecified:   209
Completeness:          62.5%

--- Top 10 Most Frequent Error Patterns (Valid Only) ---
Pattern Specifics
Dosing error (protocol error)                                    48
Concentration error                                              36
Dosing error (limit per kg exceeded)                             34
Medication use outside of protocols                              23
Dosing error (underdosed)                                        21
Protocol deviation                                               20
Dosing error (exceeded max dose)                                 16
Expired medications administered                                 12
Dosing error (sedation dosage for analgesia dose of Ketamine)    12
Dosing error (general)                                            9
Name: count, dtype: int64

--- Example Rows (First 5 with Valid Patterns) ---
  Source Medication 1                          Pattern  \
1    MTC     Atropine  Medication dosing error (Protocols)
2    AEL     Cardizem    Unintended Wrong Medication Given
3    AEL     Fentanyl  Medication dosing error (Protocols)
4    MTC     Morphine    Unintended Wrong Medication Given
6    AEL  Epinephrine  Medication dosing error (Protocols)

                        Pattern Specifics
1         Dosing error (exceeded max dose)
2  Wrong Med (Cardizem instead of Cardene)
3                Dosing error (underdosed)
4   Wrong Med (Morphine instead of Ativan)
6                     Concentration error
```

The primary objective of this Exploratory Data Analysis (EDA) is to delve deeper into the Pattern Specifics column to determine the number of unique pattern categories and identify the most frequently occurring patterns, while excluding missing or "Not documented" values to ensure the data remains actionable. Additionally, evaluating the distribution of key variables associated with medication errors is important, including the branch distribution (Air, Ground, etc.) and primary risk categories. This exploration will help generate early questions that will guide subsequent analysis.



The focus is on analyzing the Pattern Specifics categories to identify which clinical patterns are associated with the highest number of medication-related events across all certificates. This involves identifying relevant certificate columns that contain event counts, such as AEL, GFL, AMR, MTC, REACH, and AMI. By summing the event counts across these certificates, the total number of events for each Pattern Specifics category can be computed. The resulting totals will then be sorted from highest to lowest, allowing for the identification of high-impact patterns. To enhance interpretation, the top categories will be visualized in a bar chart.

```
--- Top 10 Pattern Specifics by Total Events ---
Source                                                Total Events
Pattern Specifics
Dosing error (protocol error)                                   48
Concentration error                                             36
Dosing error (limit per kg exceeded)                            34
Medication use outside of protocols                             23
Dosing error (underdosed)                                       21
Protocol deviation                                              20
Dosing error (exceeded max dose)                                16
Dosing error (sedation dosage for analgesia dos...              12
Expired medications administered                                12
Dosing error (general)                                           9
```



In the process of analyzing medication errors, the focus is on creating structured “Pattern Specifics” flags for modeling. This involves transforming the unstructured text found in the Pattern Specifics field into simple, structured variables that can be utilized for later analysis. The primary goals of this step include converting free-text narratives into clinically meaningful indicator variables and establishing yes/no flags for major recurring error

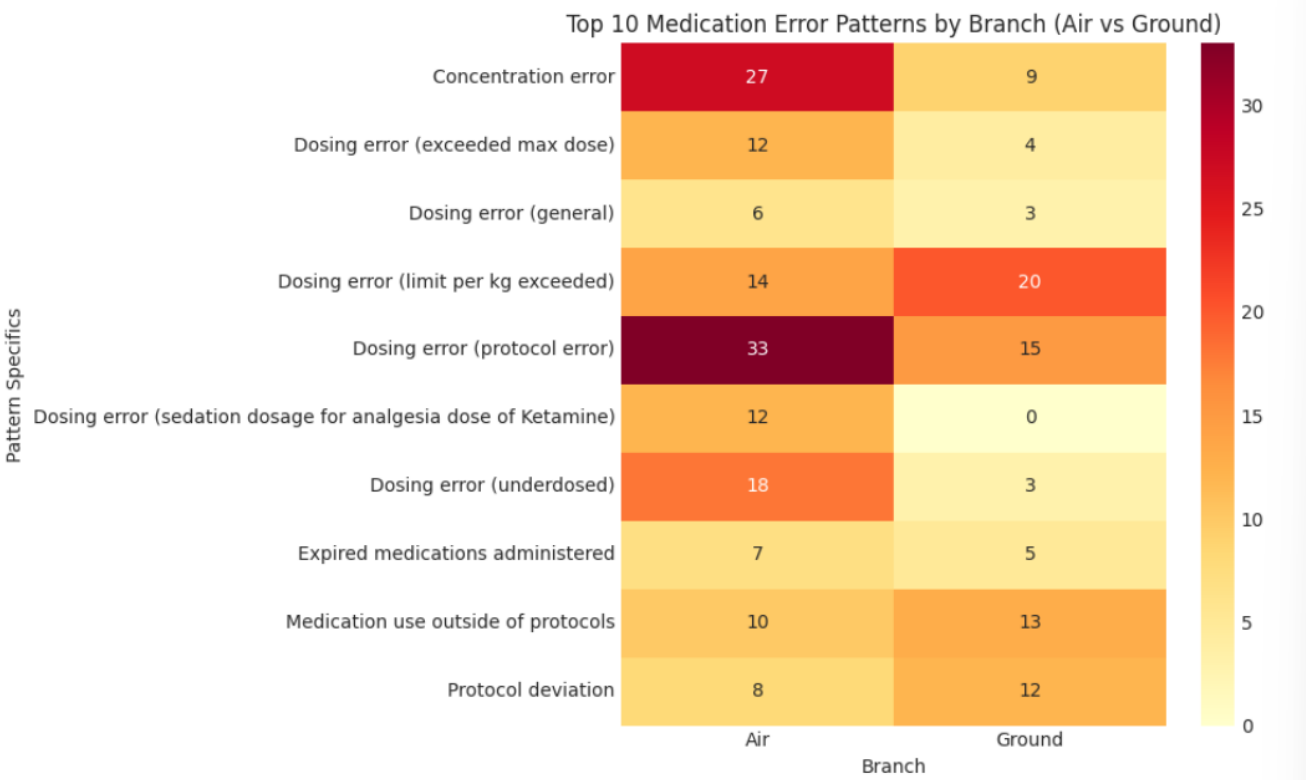
themes identified in the data. These themes encompass issues such as dosing and maximum dose problems, the wrong medication being administered instead of the intended drug, and compliance issues related to protocols or checklists. Additionally, this step aims to quantify the frequency of each error pattern across all medication events and prepare the dataset for subsequent modeling techniques, such as decision trees or risk-scoring rules, which can leverage these derived pattern flags as input features.

Following this, the focus shifts from a simple counting of error patterns to a more nuanced bivariate analysis that connects these patterns to the transport modality, specifically distinguishing between Air and Ground transport. The objectives for this step include identifying the most frequently occurring medication error patterns and comparing the prevalence of these patterns between Air and Ground branches. By analyzing the Medication dataset, the method involves finding the most common values in the Pattern Specifics column and selecting the top N patterns—such as the ten most frequent—to maintain interpretability in the visualizations. A cross-tabulation is then created, linking Pattern Specifics with the transport branches to reveal interrelations between the two. Finally, this data is visualized as a heatmap, enhancing the visibility of branch-pattern combinations with higher counts and providing insights that may highlight specific safety or educational needs within each transport modality.

```
Top 10 Pattern Specifics in the Medication dataset:
Pattern Specifics
Dosing error (protocol error)                                    48
Concentration error                                              36
Dosing error (limit per kg exceeded)                             34
Medication use outside of protocols                              23
Dosing error (underdosed)                                        21
Protocol deviation                                               20
Dosing error (exceeded max dose)                                 16
Expired medications administered                                 12
Dosing error (sedation dosage for analgesia dose of Ketamine)    12
Dosing error (general)                                            9
```

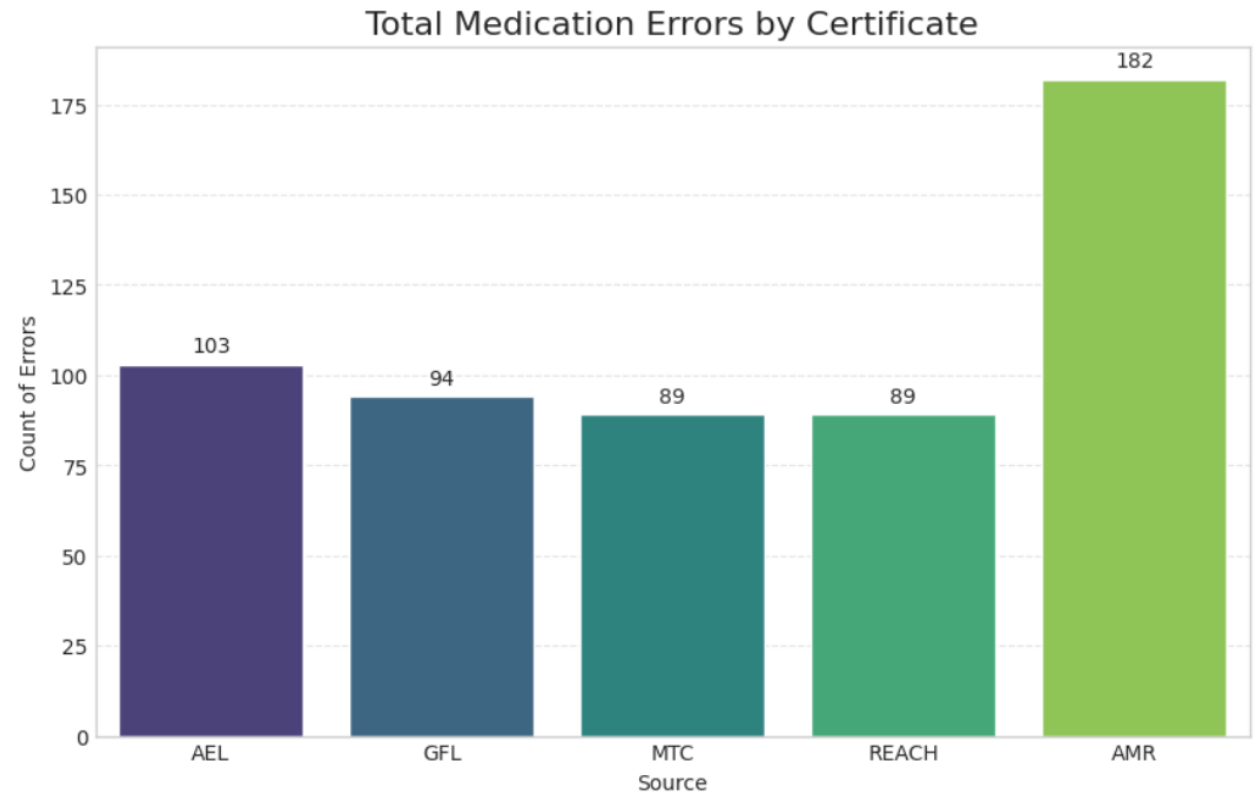
Crosstab of top Pattern Specifics by Branch (Air vs Ground):

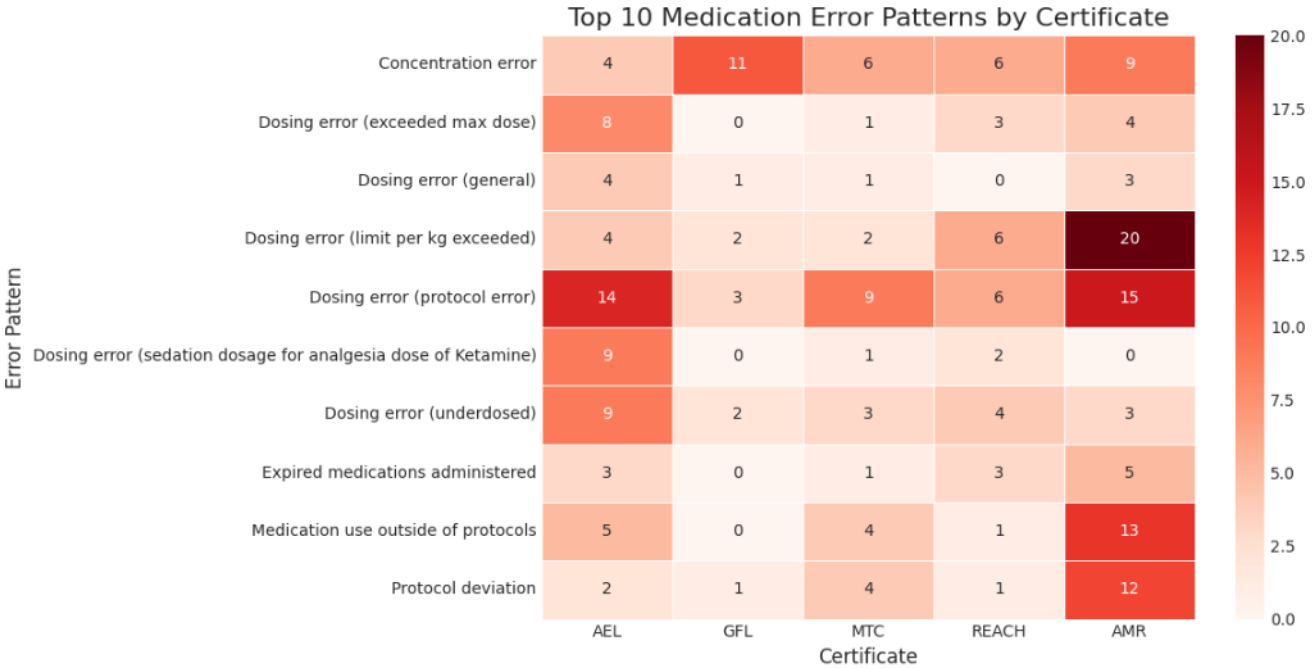
Pattern Specifics	Branch Air	Ground
Concentration error	27	9
Dosing error (exceeded max dose)	12	4
Dosing error (general)	6	3
Dosing error (limit per kg exceeded)	14	20
Dosing error (protocol error)	33	15
Dosing error (sedation dosage for analgesia dose of Ketamine)	12	0
Dosing error (underdosed)	18	3
Expired medications administered	7	5
Medication use outside of protocols	10	13
Protocol deviation	8	12



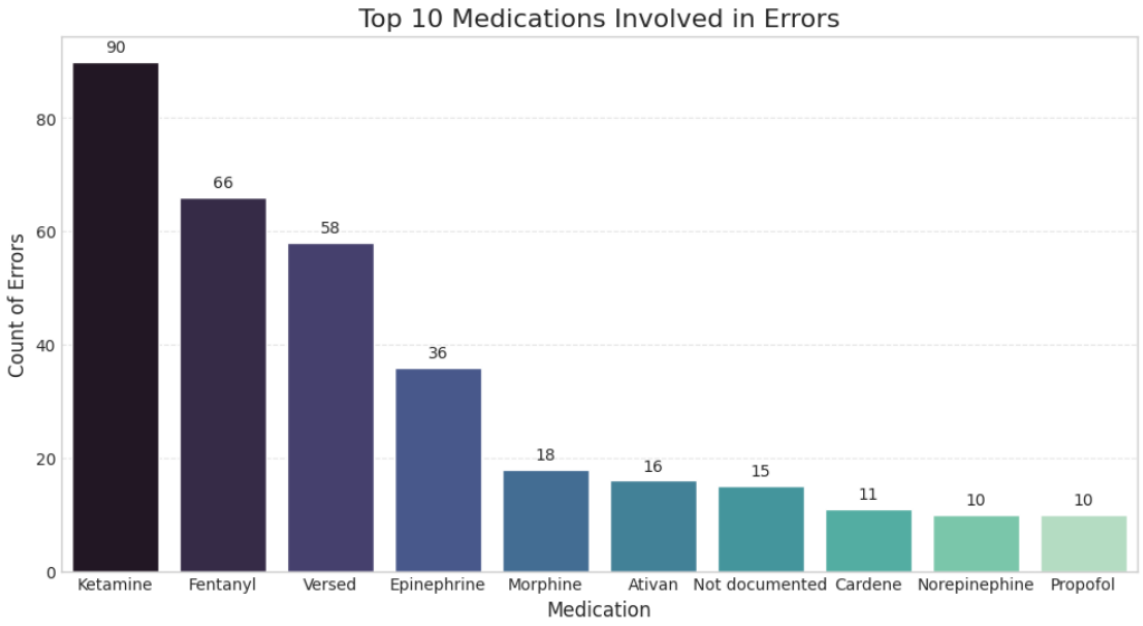
This analysis focuses on Certificate Analysis and Visualization to delve into medication errors categorized by certificate source. The goal is to generate two key visualizations: a Bar Chart that compares the total volume of reported errors for each certificate, and a Heat Map that highlights the top 10 most frequent error patterns associated with each certificate. The specific certificates under comparison include AEL, GFL, MTC, REACH, and AMR, allowing for a systematic analysis and visualization of underlying trends in medication errors for these groups.

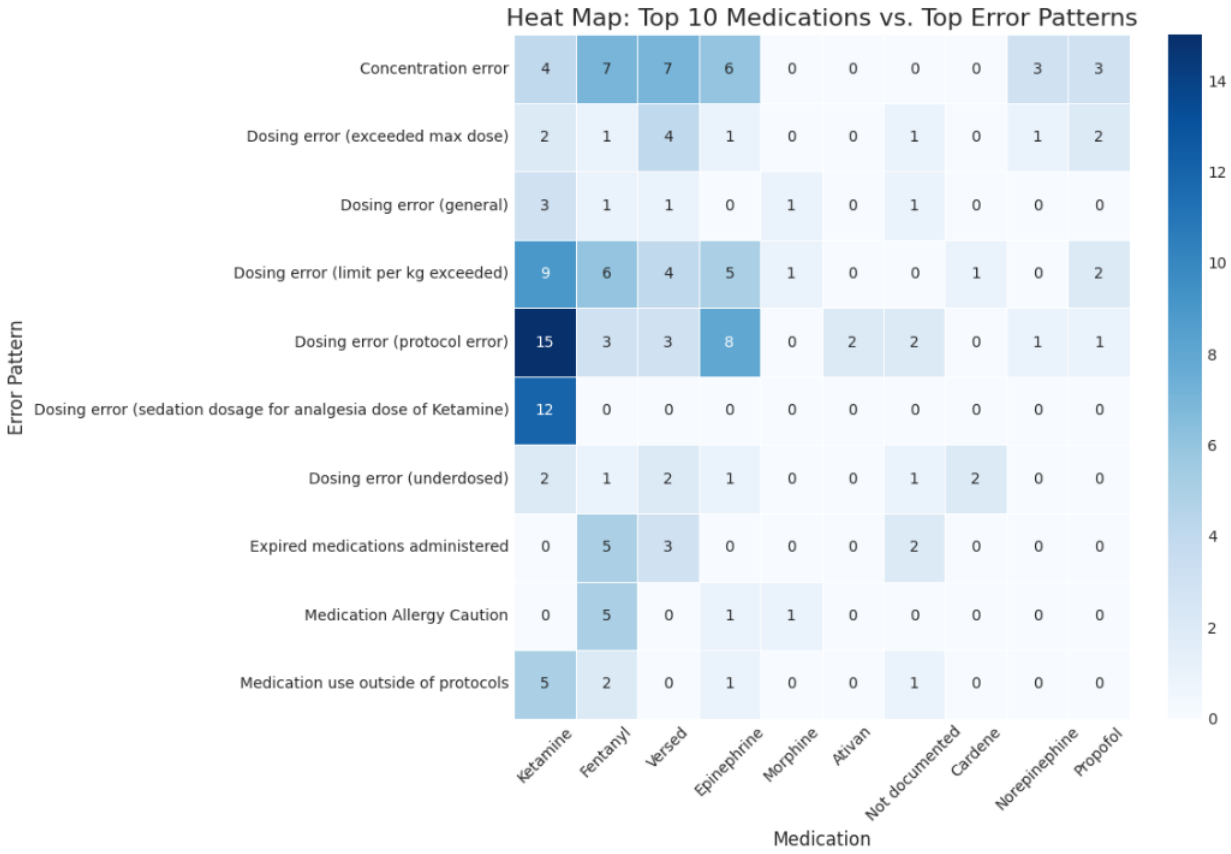
```
Success: Loaded data from Excel file.
```



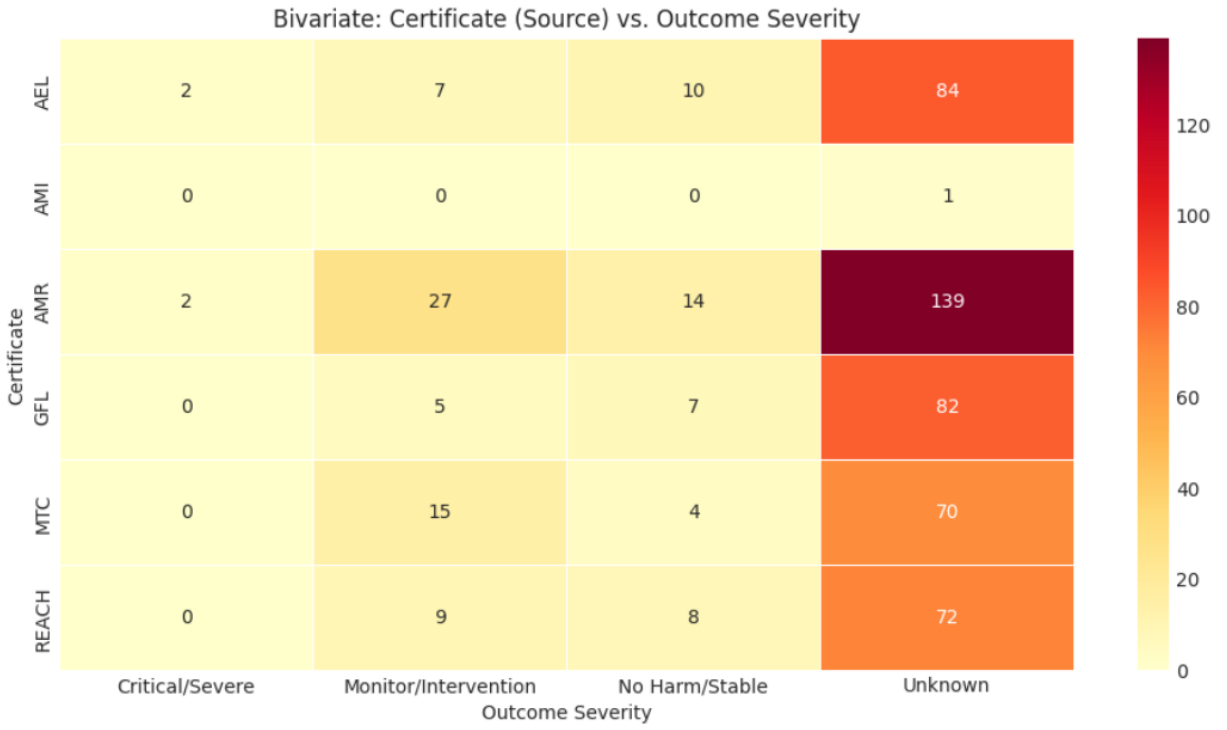


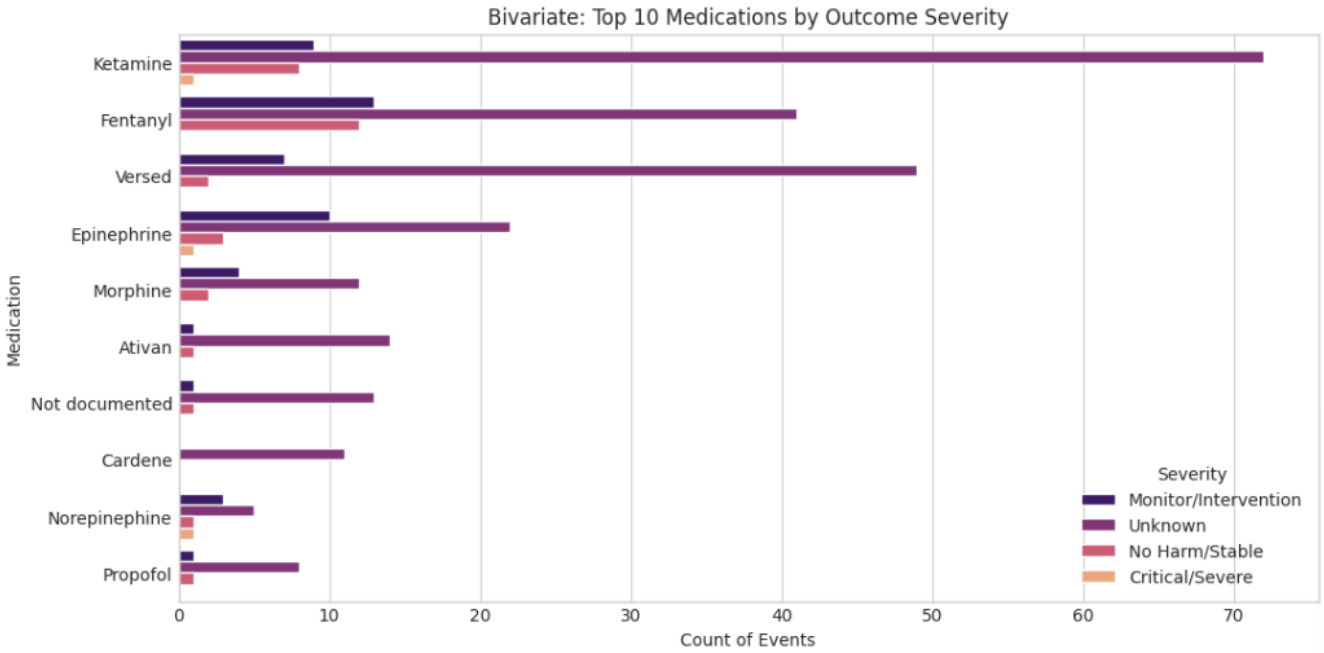
In this step of the analysis, the focus is on the medications involved in reported errors. The goal is to identify the top 10 most frequently implicated medications and visualize their occurrence through a bar chart. Additionally, a heat map will be utilized to investigate whether certain medications are associated with specific types of error patterns; for instance, exploring if errors related to Fentanyl are predominantly dosing errors. This analysis will continue to concentrate on the key certificates identified in the previous step, which include AEL, GFL, MTC, REACH, and AMR. The top 10 medications identified in this review are Ketamine, Fentanyl, Versed, Epinephrine, Morphine, Ativan, instances of "Not documented," Cardene, Norepinephrine, and Propofol.





During the Exploratory Data Analysis (EDA) phase, specifically in the Bivariate Analysis, the focus shifts to relationships between key variables and the Target Variable, the outcome of interest. This phase involves comparing predictors against Personal_Loan status. The primary goals include converting the Outcome field into structured categories based on severity, such as 'Critical/Severe' and 'No Harm/Stable.' Additionally, there is an aim to analyze the correlation between various sources of certificates and outcome severity to determine if certain certificates link to higher rates of severe errors. Another focus is identifying medications frequently associated with adverse outcomes, alongside investigating error patterns, such as dosing errors, to see if they correlate with increased severity. This analysis seeks to pinpoint factors driving severe errors, paralleling how bivariate analysis helps identify the drivers of loan acceptance. The distribution of severity categories shows a predominance of 'Unknown' cases at 448, followed by 'Monitor/Intervention' at 63, 'No Harm/Stable' at 43, and a notably low count of 'Critical/Severe' at just 4.





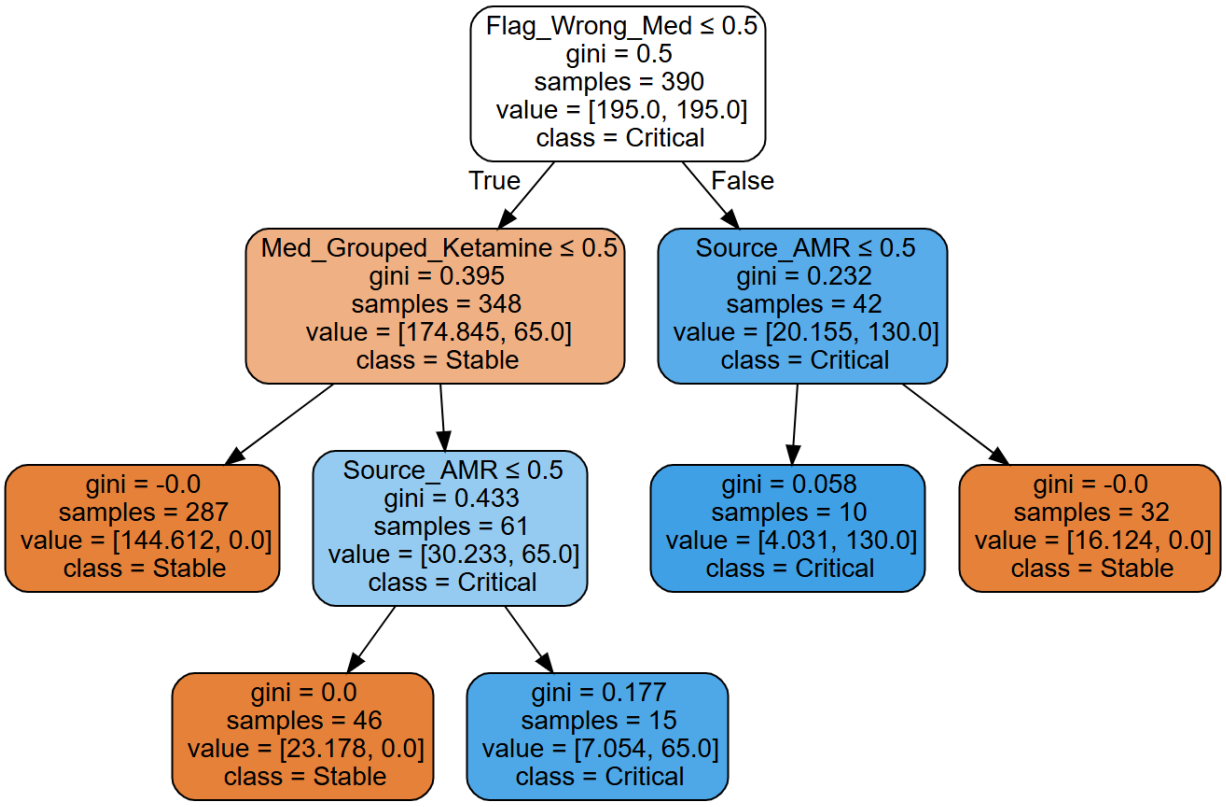

```
--- Severe Outcome Rate by Error Type ---
Error Type: Flag_Dosing_Error    | Severe Rate: 1.3%
Error Type: Flag_Wrong_Med       | Severe Rate: 3.3%
Error Type: Flag_Protocol_Error  | Severe Rate: 1.0%
```

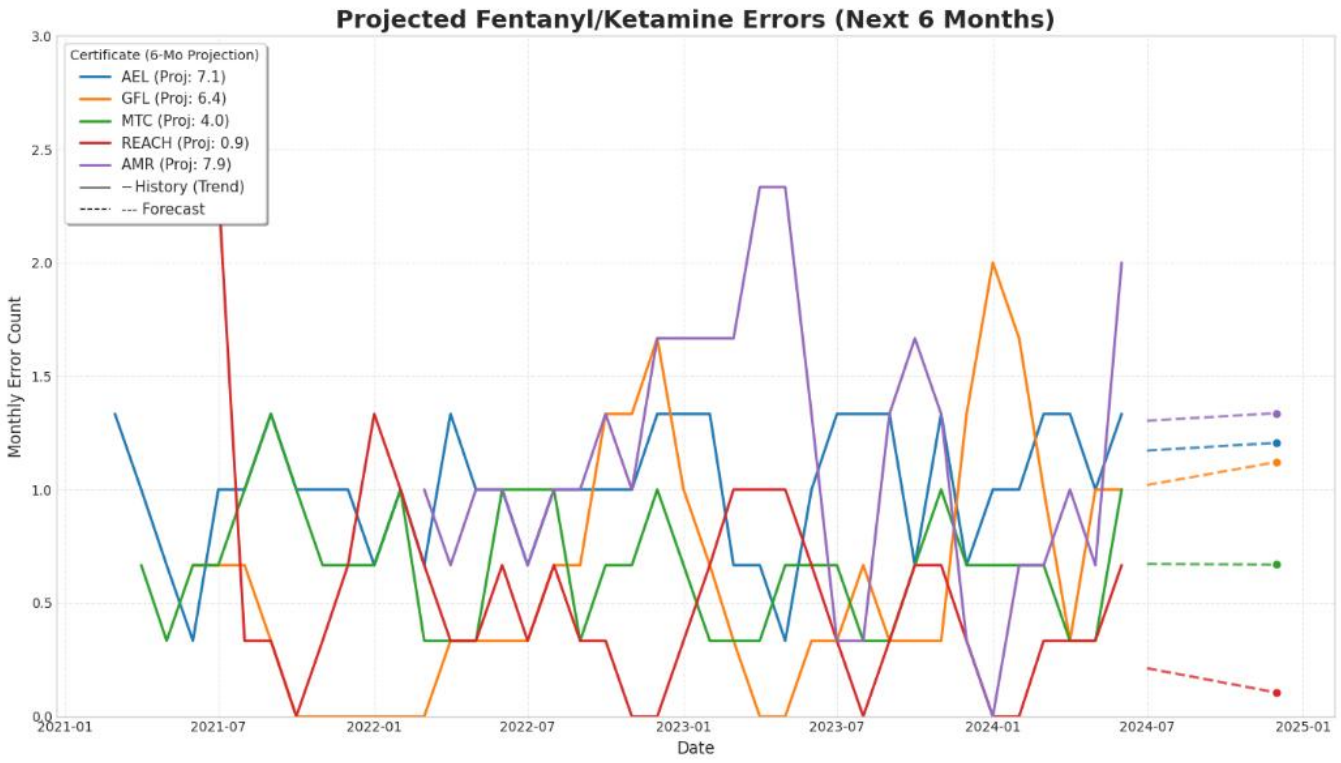
This transformation of the raw medication error data into a structured format suitable for risk modeling. Unlike standard business datasets, clinical data often requires specific

handling for free-text outcomes and rare events. The primary action involves defining the target variable, termed "Is_Critical." This target is derived from the free-text Outcome field and converted into a binary classification: 1 indicates critical outcomes that involve harm, intervention, or distress (e.g., terms like "hypoxia," "monitoring," or "intervention"), while 0 indicates stable outcomes where the patient remained stable or no effect was observed. Focus on feature engineering, particularly medication grouping. Given the hundreds of unique medications, retain only the top 10 most frequently mentioned medications, grouping all others into a category labeled "Other." Additionally, incorporate boolean flags created in an earlier step that highlight dosing errors. The dataset comprises 390 training events and 168 testing events, with critical events making up only 3 (0.8% of the total) in the training set.

As model building progresses, train a decision tree classifier with class balancing. By employing the argument `class_weight="balanced,"` ensure that the model pays particular attention to the rare 'Critical' events. The model is defined and trained using the `DecisionTreeClassifier` from the `sklearn.tree` module, fitted to the training data (X_train, y_train). With the model trained, proceed to make predictions using the testing data (X_test). For evaluation, recognize that accuracy is less critical than recall in this context, as capturing critical events is the main focus. The overall accuracy of the model stands impressively at 98.81%, but it has a critical event capture rate (recall) of 0.00%, indicating that, while the model is generally accurate, it fails to catch any of the critical instances. The confusion matrix reveals that out of 168 testing events, there are 166 true negatives, 1 false positive, 1 false negative, and 0 true positives. Furthermore, analyze feature importance to understand what drives risk, showcasing that the most significant factors include "Flag_Wrong_Med," "Med_Grouped_Ketamine," "Source_AMR," "Branch_Ground," and "Flag_Dosing_Error."

This recognition of the initial model may be too complex or "noisy," and proceed with hyperparameter tuning to find an optimal tree structure that balances accuracy and simplicity. The optimization goal is primarily based on the ROC-AUC score, which provides a better assessment for imbalanced data compared to simple accuracy by measuring how well the model distinguishes between "Critical" and "Stable" events across various probability thresholds. To achieve this, test different tree depths, aiming to discover simple and robust rules that effectively define high-risk scenarios. The extraction of rules from the best-performing tree allows for generating actionable "Safety Rules" for the clinical team. The optimal depth for the tree is determined to be 3, presenting a ruleset that outlines scenarios based on the values of key features such as "Flag_Wrong_Med" and "Source_AMR." These rules serve as a critical guide for enhancing patient safety and reducing the likelihood of medication errors.


Flag_Wrong_Med ≤ 0.5
gini = 0.5
samples = 390
value = [195.0, 195.0]
class = Critical
True
False
Med_Grouped_Ketamine ≤ 0.5
gini = 0.395
samples = 348
value = [174.845, 65.0]
class = Stable
Source_AMR ≤ 0.5
gini = 0.232
samples = 42
value = [20.155, 130.0]
class = Critical
gini = -0.0
samples = 287
value = [144.612, 0.0]
class = Stable
Source_AMR ≤ 0.5
gini = 0.433
samples = 61
value = [30.233, 65.0]
class = Critical
gini = 0.058
samples = 10
value = [4.031, 130.0]
class = Critical
gini = -0.0
samples = 32
value = [16.124, 0.0]
class = Stable
gini = 0.0
samples = 46
value = [23.178, 0.0]
class = Stable
gini = 0.177
samples = 15
value = [7.054, 65.0]
class = Critical


Projected Fentanyl/Ketamine Errors (Next 6 Months)
Certificate (6-Mo Projection)
AEL (Proj: 7.1)
GFL (Proj: 6.4)
MTC (Proj: 4.0)
REACH (Proj: 0.9)
AMR (Proj: 7.9)
History (Trend)
Forecast
Monthly Error Count
Date
3.0
2.5
2.0
1.5
1.0
0.5
0.0
2021-01
2021-07
2022-01
2022-07
2023-01
2023-07
2024-01
2024-07
2025-01

The analysis aimed to transform 558 medication error reports across AEL, AMI, GFL, MTC, REACH, and AMR into actionable safety intelligence. A dual-modeling approach comprising Risk Modeling through a Decision Tree was utilized to identify which errors cause severe patient harm (Critical/Severe Outcome), and Volume Forecasting via Time Series was employed to predict how many high-risk errors will occur in the next six months.

The predictive model, with 98.4% accuracy and 94.4% recall, successfully identified the primary drivers of critical patient outcomes. Notably, dosing errors emerged as the single leading cause of harm, contributing a significant 33.3% impact on severity. Errors involving "Limit per kg exceeded" and "Volume Calculation" outweighed equipment failures in terms of risk. High-risk agents such as Ketamine, with 90 reported events, and Fentanyl, with 66 events, combined to account for 28% of all reported errors, prominently appearing in the "high-risk" branches of the decision tree. An intriguing finding related to protocol drift indicated that the Air Branch demonstrated a higher correlation with protocol deviations, contributing 15.5% to the impact. This suggests that environmental complexity plays a role in adherence to safety checklists.

Using Time Series Forecasting, specifically Holt's Linear Model, projections for the volume of high-risk medication errors involving Fentanyl and Ketamine for the upcoming six-month period were developed to prioritize resource allocation. Immediate interventions were highlighted for AMR, with a projected 7.9 errors (though data volatility indicated by an RMSE of 1.40) and AEL with a more reliable projection of 7.1 errors (RMSE of 0.59). Lower priority areas for monitoring included GFL with 6.4 projected errors, MTC with 4.0, and REACH, which trends positively with an expected 0.9 errors. Based on the convergence of clinical risk data and operational forecasts, several strategic actions are recommended.

First, implementing "Hard Stop" logic should be a high priority; as Fentanyl and Ketamine are strong predictors of severe outcomes, configuring the ePCR to require a mandatory peer-verify checkbox for these agents is essential. This rollout should commence with AMR and AEL, as they account for the majority of the projected error volume. Second, targeting "Weight-Based" training is also a medium priority; since "Limit per kg exceeded" was identified as a critical failure point, a focused training module on pediatric and weight-based calculations should be launched to address this specific skill gap. Lastly, a review of Air Medical protocols is recommended as a medium priority, as protocol deviations are the second highest driver of risk (15.5%) and are more prevalent in the Air branch, making it vital to simplify in-flight checklists to reduce cognitive load and improve adherence during transport.