In [4]: pip install numpy pandas matplotlib seaborn scikit-learn xgboost

Requirement already satisfied: numpy in c:\users\dgous\anaconda3\lib\site-pac kages (1.24.3)

Requirement already satisfied: pandas in c:\users\dgous\anaconda3\lib\site-pa ckages (1.5.3)

Requirement already satisfied: matplotlib in c:\users\dgous\anaconda3\lib\sit e-packages (3.7.1)

Requirement already satisfied: seaborn in c:\users\dgous\anaconda3\lib\site-p ackages (0.12.2)

Requirement already satisfied: scikit-learn in c:\users\dgous\anaconda3\lib\s ite-packages (1.4.1.post1)

Requirement already satisfied: xgboost in c:\users\dgous\anaconda3\lib\site-p ackages (2.0.3)

Requirement already satisfied: python-dateutil>=2.8.1 in c:\users\dgous\anaco nda3\lib\site-packages (from pandas) (2.8.2)

Requirement already satisfied: pytz>=2020.1 in c:\users\dgous\anaconda3\lib\s ite-packages (from pandas) (2022.7)

Requirement already satisfied: contourpy>=1.0.1 in c:\users\dgous\anaconda3\l ib\site-packages (from matplotlib) (1.0.5)

Requirement already satisfied: cycler>=0.10 in c:\users\dgous\anaconda3\lib\s ite-packages (from matplotlib) (0.11.0)

Requirement already satisfied: fonttools>=4.22.0 in c:\users\dgous\anaconda3 \lib\site-packages (from matplotlib) (4.25.0)

Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\dgous\anaconda3 \lib\site-packages (from matplotlib) (1.4.4)

Requirement already satisfied: packaging>=20.0 in c:\users\dgous\anaconda3\li b\site-packages (from matplotlib) (23.0)

Requirement already satisfied: pillow>=6.2.0 in c:\users\dgous\anaconda3\lib \site-packages (from matplotlib) (9.4.0)

Requirement already satisfied: pyparsing>=2.3.1 in c:\users\dgous\anaconda3\l ib\site-packages (from matplotlib) (3.0.9)

Requirement already satisfied: scipy>=1.6.0 in c:\users\dgous\anaconda3\lib\s ite-packages (from scikit-learn) (1.10.1)

Requirement already satisfied: joblib>=1.2.0 in c:\users\dgous\anaconda3\lib \site-packages (from scikit-learn) (1.2.0)

Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\dgous\anacond a3\lib\site-packages (from scikit-learn) (2.2.0)

Requirement already satisfied: six>=1.5 in c:\users\dgous\anaconda3\lib\site-packages (from python-dateutil>=2.8.1->pandas) (1.16.0)

Note: you may need to restart the kernel to use updated packages.

```
Untitled71 - Jupyter Notebook
In [5]:
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.model selection import train test split
        from sklearn.ensemble import RandomForestRegressor
        from xgboost import XGBRegressor
        from sklearn.decomposition import PCA
        from sklearn.linear model import LinearRegression
        from sklearn.preprocessing import StandardScaler
In [6]: np.random.seed(42)
        num_samples = 100 # Reduced from 500 to 100
        # Generate synthetic formulation data
        excipient_ratio = np.random.uniform(0.1, 1.0, num_samples)
        compression force = np.random.uniform(5, 50, num samples)
        granule_size = np.random.uniform(100, 500, num_samples)
        binder_percentage = np.random.uniform(1, 10, num_samples)
        # Target Variables (Dependent Variables)
        dissolution_profile = 10 + 3*excipient_ratio + 1.5*compression_force - 0.01*gr
        bioavailability = 20 + 4*excipient_ratio - 0.5*compression_force + 0.02*granul
        # Create DataFrame
        df = pd.DataFrame({
            "Excipient Ratio": excipient ratio,
            "Compression Force": compression_force,
            "Granule Size": granule_size,
            "Binder Percentage": binder percentage,
            "Dissolution Profile": dissolution profile,
            "Bioavailability": bioavailability
        })
        # Display first few rows
        print(df.head())
```

```
Excipient Ratio Compression Force Granule Size Binder Percentage \
0
         0.437086
                            6.414313
                                        356.812658
                                                             1.465135
1
         0.955643
                            33.638469
                                        133.655986
                                                             5.782192
2
         0.758795
                            19.146019
                                        164.651486
                                                             5.865716
3
         0.638793
                            27.885681
                                        459.421675
                                                             6.736869
4
         0.240417
                           45.840491
                                        342.571624
                                                             7.534822
  Dissolution Profile Bioavailability
0
            19.975559
                              26.674383
            62.030079
                              7.430997
1
2
            40.712803
                             21.408654
                              18.147787
3
            48.530149
```

8.430745

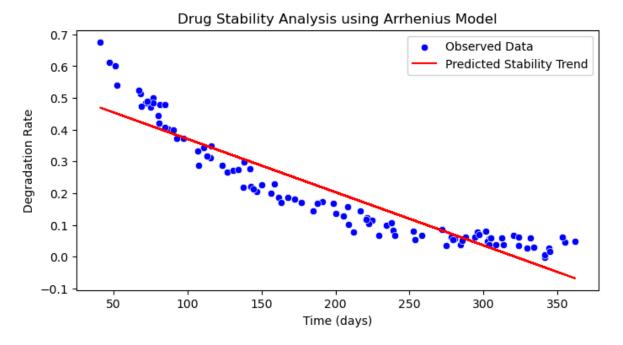
76.704604

4

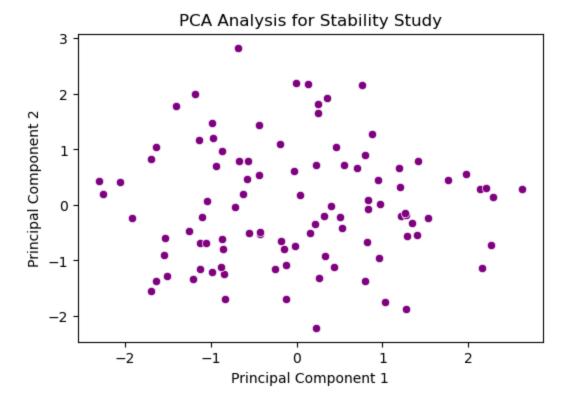
```
In [7]: X = df[["Excipient Ratio", "Compression Force", "Granule Size", "Binder Percer
         y_dissolution = df["Dissolution Profile"]
         y_bioavailability = df["Bioavailability"]
         # Split the data
         X_train, X_test, y_train_dissolution, y_test_dissolution = train_test_split(X,
         X_train, X_test, y_train_bioavailability, y_test_bioavailability = train_test_
 In [8]: rf_model = RandomForestRegressor(n_estimators=10, random_state=42) # Reduced
         rf model.fit(X train, y train dissolution)
         rf_pred = rf_model.predict(X_test)
         print("Random Forest Model trained successfully for Dissolution Profile Predid
         Random Forest Model trained successfully for Dissolution Profile Prediction
 In [9]: xgb_model = XGBRegressor(n_estimators=5, random_state=42) # Reduced estimator
         xgb_model.fit(X_train, y_train_bioavailability)
         xgb_pred = xgb_model.predict(X_test)
         print("XGBoost Model trained successfully for Bioavailability Prediction")
         XGBoost Model trained successfully for Bioavailability Prediction
In [10]: | scaler = StandardScaler()
         X scaled = scaler.fit transform(X)
         pca = PCA(n_components=2)
         X_pca = pca.fit_transform(X_scaled)
         df pca = pd.DataFrame(X pca, columns=["PC1", "PC2"])
         print("PCA Analysis Completed")
         PCA Analysis Completed
         stability time = np.random.uniform(30, 365, num samples)
In [11]:
         degradation_rate = np.exp(-0.01 * stability_time) + np.random.normal(0, 0.02,
         X_stability = stability_time.reshape(-1, 1)
         y_stability = degradation_rate
         reg model = LinearRegression()
         reg_model.fit(X_stability, y_stability)
         stability_pred = reg_model.predict(X_stability)
         print("Regression Model trained for Drug Stability Analysis")
```

Regression Model trained for Drug Stability Analysis

```
In [12]: plt.figure(figsize=(8,4))
    sns.scatterplot(x=stability_time, y=degradation_rate, label="Observed Data", c
    plt.plot(stability_time, stability_pred, color="red", label="Predicted Stability plt.xlabel("Time (days)")
    plt.ylabel("Degradation Rate")
    plt.title("Drug Stability Analysis using Arrhenius Model")
    plt.legend()
    plt.show()
```



```
In [13]: plt.figure(figsize=(6,4))
    sns.scatterplot(x=df_pca["PC1"], y=df_pca["PC2"], color="purple")
    plt.xlabel("Principal Component 1")
    plt.ylabel("Principal Component 2")
    plt.title("PCA Analysis for Stability Study")
    plt.show()
```



```
In [ ]:
```