```
# library loading
!pip install pandas
import pandas as pd
```

```
Requirement already satisfied: pandas in c:\users\silom\anaconda3\lib\site-packages (2.2.2)
Requirement already satisfied: numpy>=1.26.0 in c:\users\silom\anaconda3\lib\site-packages (from pandas) (1.26.4)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\silom\anaconda3\lib\site-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\users\silom\anaconda3\lib\site-packages (from pandas) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in c:\users\silom\anaconda3\lib\site-packages (from pandas) (2023.3)
Requirement already satisfied: six>=1.5 in c:\users\silom\anaconda3\lib\site-packages (from python-dateutil>=2.8.2->pandas) (1.1
```

```
""" name and code
customer_demographic - cd
transaction_history - th
customer_service - csv
online_activty - oa
churn_status - cs
"""

# uploading sheets
cd = pd.read_excel("Customer_Churn_Data_Large.xlsx", sheet_name = 0)
th = pd.read_excel("Customer_Churn_Data_Large.xlsx", sheet_name = 1)
csv = pd.read_excel("Customer_Churn_Data_Large.xlsx", sheet_name = 2)
oa = pd.read_excel("Customer_Churn_Data_Large.xlsx", sheet_name = 3)
cs = pd.read_excel("Customer_Churn_Data_Large.xlsx", sheet_name = 4)
```

```
#summary and description: customer demographic
print(cd.describe())
print(cd.head())
print("done")
```

```
        CustomerID          Age
count  1000.000000  1000.000000
mean    500.500000    43.267000
std     288.819436    15.242311
min       1.000000    18.000000
25%     250.750000    30.000000
50%     500.500000    43.000000
75%     750.250000    56.000000
max    1000.000000    69.000000
   CustomerID  Age Gender MaritalStatus IncomeLevel
0           1   62      M        Single         Low
1           2   65      M       Married         Low
2           3   18      M        Single         Low
3           4   21      M       Widowed         Low
4           5   21      M      Divorced      Medium
done
```

```
#summary and description: transaction history
print(th.describe())
print(th.head())
print("done")
```

```
        CustomerID  TransactionID                TransactionDate  AmountSpent
count  5054.000000    5054.000000                           5054  5054.000000
mean    501.424218    5510.538979  2022-07-01 19:25:37.158686208   250.707351
min       1.000000    1000.000000            2022-01-01 00:00:00     5.180000
25%     251.000000    3242.000000            2022-04-03 00:00:00   127.105000
50%     506.000000    5530.000000            2022-07-01 00:00:00   250.525000
75%     749.000000    7680.750000            2022-09-29 00:00:00   373.412500
max    1000.000000    9997.000000            2022-12-31 00:00:00   499.860000
std     285.172780    2582.088012                            NaN   142.250838
   CustomerID  TransactionID TransactionDate  AmountSpent ProductCategory
0           1           7194      2022-03-27       416.50     Electronics
1           2           7250      2022-08-08        54.96        Clothing
2           2           9660      2022-07-25       197.50     Electronics
3           2           2998      2022-01-25       101.31       Furniture
4           2           1228      2022-07-24       397.37        Clothing
done
```

```
#summary and description: customer service
print(csv.describe())
```

```
print(csv.head())
print("done")
```

```
        CustomerID  InteractionID                InteractionDate
count  1002.000000    1002.000000                           1002
mean    485.209581    5952.887226  2022-07-02 19:28:22.994011904
min       1.000000    2015.000000            2022-01-01 00:00:00
25%     238.250000    3991.500000            2022-04-07 00:00:00
50%     474.500000    5911.500000            2022-07-02 12:00:00
75%     735.750000    7908.250000            2022-09-30 00:00:00
max     995.000000    9997.000000            2022-12-30 00:00:00
std     287.030259    2305.819681                            NaN
   CustomerID  InteractionID InteractionDate InteractionType ResolutionStatus
0           1           6363      2022-03-31         Inquiry         Resolved
1           2           3329      2022-03-17         Inquiry         Resolved
2           3           9976      2022-08-24         Inquiry         Resolved
3           4           7354      2022-11-18         Inquiry         Resolved
4           4           5393      2022-07-03         Inquiry       Unresolved
done
```

```
#summary and description: online activity
print(oa.describe())
print(oa.head())
print("done")
```

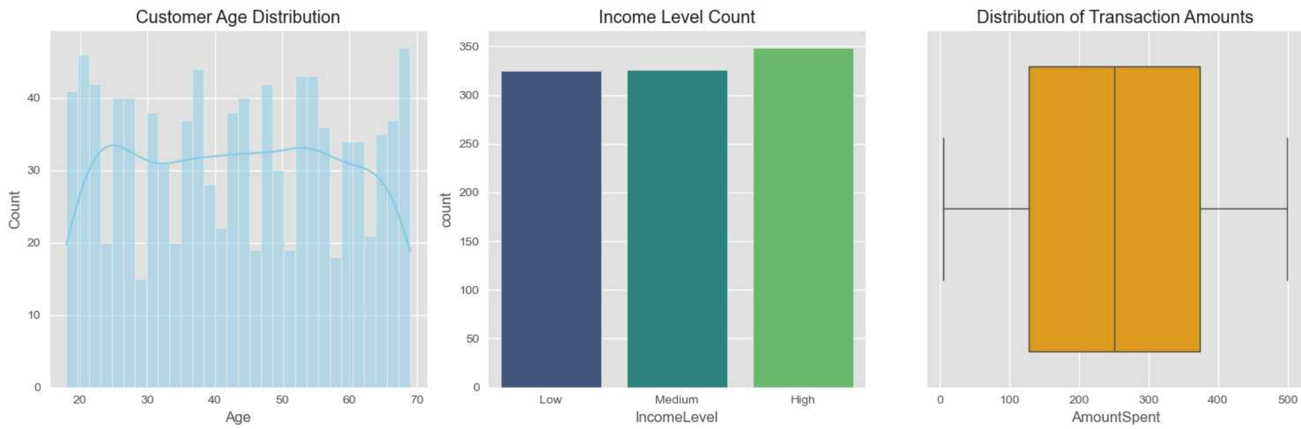
```
        CustomerID        LastLoginDate  LoginFrequency
count  1000.000000                 1000     1000.000000
mean    500.500000  2023-07-05 21:28:48       25.912000
min       1.000000  2023-01-01 00:00:00        1.000000
25%     250.750000  2023-04-08 00:00:00       13.750000
50%     500.500000  2023-07-10 12:00:00       27.000000
75%     750.250000  2023-10-01 06:00:00       38.000000
max    1000.000000  2023-12-31 00:00:00       49.000000
std     288.819436                  NaN       14.055953
   CustomerID LastLoginDate  LoginFrequency ServiceUsage
0           1    2023-10-21              34   Mobile App
1           2    2023-12-05               5      Website
2           3    2023-11-15               3      Website
3           4    2023-08-25               2      Website
4           5    2023-10-27              41      Website
done
```

```
#summary and description: churn status
print(cs.describe())
print(cs.head())
print("done")
```

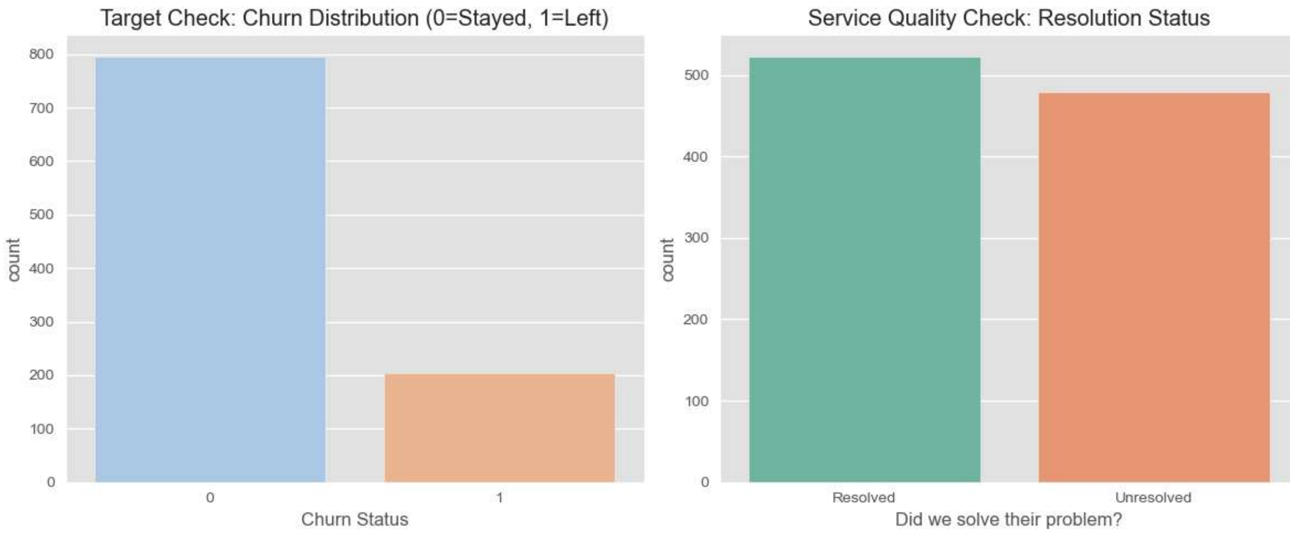
```
        CustomerID  ChurnStatus
count  1000.000000  1000.000000
mean    500.500000     0.204000
std     288.819436     0.403171
min       1.000000     0.000000
25%     250.750000     0.000000
50%     500.500000     0.000000
75%     750.250000     0.000000
max    1000.000000     1.000000
   CustomerID  ChurnStatus
0           1            0
1           2            1
2           3            0
3           4            0
4           5            0
done
```

```
# python packages for data visualisation
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Set visualization style
sns.set_style("whitegrid")
plt.style.use('ggplot')
%matplotlib inline

# Suppress warnings for cleaner output
import warnings
warnings.filterwarnings('ignore')
```

```
#visualising raw data - intial EDA

# Set up a figure with multiple subplots
plt.figure(figsize=(15, 5))

# 1. Age Distribution (Are there many young professionals?)
plt.subplot(1, 3, 1)
sns.histplot(cd['Age'], bins=30, kde=True, color='skyblue')
plt.title('Customer Age Distribution')

# 2. Income Levels
plt.subplot(1, 3, 2)
sns.countplot(x='IncomeLevel', data=cd, order=['Low', 'Medium', 'High'], palette='viridis')
plt.title('Income Level Count')

# 3. Transaction Amounts (Checking for outliers)
plt.subplot(1, 3, 3)
sns.boxplot(x=th['AmountSpent'], color='orange')
plt.title('Distribution of Transaction Amounts')

plt.tight_layout()
plt.show()
```




```
#churn and service visualisation

# Create a new figure for the missing categorical checks
plt.figure(figsize=(12, 5))

# 1. Check the Target: Churn Status
plt.subplot(1, 2, 1)
# We use the raw churn_df here
sns.countplot(x='ChurnStatus', data=cs, palette='pastel')
plt.title('Target Check: Churn Distribution (0=Stayed, 1=Left)')
plt.xlabel('Churn Status')

# 2. Check the Pain Point: Service Resolution
plt.subplot(1, 2, 2)
# We use the raw service_df here
sns.countplot(x='ResolutionStatus', data=csv, palette='Set2')
plt.title('Service Quality Check: Resolution Status')
plt.xlabel('Did we solve their problem?')

plt.tight_layout()
plt.show()
```




```
# Feature Engineering - Aggregating Transaction Data

# Group by CustomerID to get a single summary row per customer
trans_agg = th.groupby('CustomerID').agg(
    Total_Spend=('AmountSpent', 'sum'),              # Total money spent
    Avg_Transaction_Amt=('AmountSpent', 'mean'),     # Average purchase size
    Transaction_Count=('TransactionID', 'count'),    # How active are they?
    Latest_Transaction=('TransactionDate', 'max')    # When did they last buy?
).reset_index()

print("Transactions Aggregated:")
display(trans_agg.head())
```

Transactions Aggregated:

	CustomerID	Total_Spend	Avg_Transaction_Amt	Transaction_Count	Latest_Transaction
0	1	416.50	416.50000	1	2022-03-27
1	2	1547.42	221.06000	7	2022-11-19
2	3	1702.98	283.83000	6	2022-10-08
3	4	917.29	183.45800	5	2022-12-27
4	5	2001.49	250.18625	8	2022-12-21

```
# Feature Engineering - Customer Service Interaction Aggregation

# Group by CustomerID to summarize service history
service_agg = csv.groupby('CustomerID').agg(
    Total_Calls=('InteractionID', 'count'),
    # Calculate how many calls ended as 'Unresolved'
    Unresolved_Calls=('ResolutionStatus', lambda x: (x == 'Unresolved').sum())
).reset_index()

print("Service Interactions Aggregated:")
display(service_agg.head())
```

Service Interactions Aggregated:

	CustomerID	Total_Calls	Unresolved_Calls
0	1	1	0
1	2	1	0
2	3	1	0
3	4	2	1
4	6	1	0

```
# Master Data Table - merging all aggregated tables on the customer id attribute

# 1. Base Table: Demographics
df = cd.copy()

# 2. Join Churn Status
df = pd.merge(df, cs, on='CustomerID', how='left')

# 3. Join Online Activity
df = pd.merge(df, oa, on='CustomerID', how='left')

# 4. Join Aggregated Transactions
df = pd.merge(df, th, on='CustomerID', how='left')

# 5. Join Aggregated Service Data
df = pd.merge(df, csv, on='CustomerID', how='left')

# Fill NaN values with 0
# (If a customer isn't in the transaction table, it means they spent 0, not that the data is missing)
df.fillna({
    'Total_Spend': 0,
    'Avg_Transaction_Amt': 0,
    'Transaction_Count': 0,
    'Total_Calls': 0,
    'Unresolved_Calls': 0
}, inplace=True)

print(f"Final Master Dataset Shape: {df.shape}")
print(display(df.head()))
print(df.describe())
print(df.shape)
print("done")
```

```
Final Master Dataset Shape: (6812, 17)
```

	CustomerID	Age	Gender	MaritalStatus	IncomeLevel	ChurnStatus	LastLoginDate	LoginFrequency	ServiceUsage	TransactionID
0	1	62	M	Single	Low	0	2023-10-21	34	Mobile App	7194
1	2	65	M	Married	Low	1	2023-12-05	5	Website	7250
2	2	65	M	Married	Low	1	2023-12-05	5	Website	9660
3	2	65	M	Married	Low	1	2023-12-05	5	Website	2998
4	2	65	M	Married	Low	1	2023-12-05	5	Website	1228

```
None
        CustomerID          Age  ChurnStatus                  LastLoginDate  \
count  6812.000000  6812.000000  6812.000000                           6812
mean    500.169260    43.274516     0.198473  2023-07-06 04:56:47.633587712
min       1.000000    18.000000     0.000000            2023-01-01 00:00:00
25%     247.000000    30.000000     0.000000            2023-04-12 00:00:00
50%     505.500000    44.000000     0.000000            2023-07-13 00:00:00
75%     750.000000    56.000000     0.000000            2023-10-01 00:00:00
max    1000.000000    69.000000     1.000000            2023-12-31 00:00:00
std     286.704642    15.286788     0.398880                            NaN

       LoginFrequency  TransactionID                TransactionDate  \
count     6812.000000    6812.000000                           6812
mean        25.724310    5497.323253  2022-07-01 02:11:29.136817408
min          1.000000    1000.000000            2022-01-01 00:00:00
25%         14.000000    3223.500000            2022-04-02 00:00:00
50%         26.000000    5515.000000            2022-07-01 00:00:00
75%         38.000000    7675.250000            2022-09-30 00:00:00
max         49.000000    9997.000000            2022-12-31 00:00:00
std         14.062032    2584.768541                            NaN

       AmountSpent  InteractionID                InteractionDate
count  6812.000000    5204.000000                           5204
mean    251.620527    5921.861261  2022-07-01 16:31:10.561106944
min       5.180000    2015.000000            2022-01-01 00:00:00
25%     127.100000    3873.250000            2022-04-07 00:00:00
50%     251.845000    5903.000000            2022-07-02 00:00:00
75%     375.280000    7851.000000            2022-09-25 00:00:00
max     499.860000    9997.000000            2022-12-30 00:00:00
std     142.901693    2332.331260                            NaN
(6812, 17)
done
```

```
#MERGE AND Feature Engineering - Converting date format to number for machine learning part. models don't read dates but number

# --- PART 1: RE-MERGE (Ensuring columns exist) ---
# 1. Base Table: Demographics
df = cd.copy()

# 2. Join Churn Status
df = pd.merge(df, cs, on='CustomerID', how='left')

# 3. Join Online Activity (Contains 'LastLoginDate')
df = pd.merge(df, oa, on='CustomerID', how='left')

# 4. Join Aggregated Transactions (Contains 'Latest_Transaction')
df = pd.merge(df, th, on='CustomerID', how='left')

# 5. Join Aggregated Service Data
df = pd.merge(df, csv, on='CustomerID', how='left')

# Fill NaN values for numerical columns only
df.fillna({
    'Total_Spend': 0,
    'Avg_Transaction_Amt': 0,
    'Transaction_Count': 0,
    'Total_Calls': 0,
    'Unresolved_Calls': 0
}, inplace=True)

# --- PART 2: DATE ENGINEERING (The fix) ---

# 1. Convert to datetime (using errors='coerce' to handle any messy data safely)
df['LastLoginDate'] = pd.to_datetime(df['LastLoginDate'], errors='coerce')
df['TransactionDate'] = pd.to_datetime(df['TransactionDate'], errors='coerce')
df['InteractionDate'] = pd.to_datetime(df['InteractionDate'], errors='coerce')

# 2. Define Reference Date (Simulating "Today")
# We use the latest date in the entire dataset + 1 day
reference_date = df['LastLoginDate'].max() + pd.Timedelta(days=1)
print(f"Reference Date (Today): {reference_date}")

# 3. Calculate Days Since Last Event
df['Days_Since_Login'] = (reference_date - df['LastLoginDate']).dt.days
df['Days_Since_Transaction'] = (reference_date - df['TransactionDate']).dt.days
df['Days_Since_Interaction'] = (reference_date - df['InteractionDate']).dt.days

# 4. Handle NaNs for dates
# If Days_Since_Login is NaN, it means they never logged in. We set it to a high number (e.g., 365).
df['Days_Since_Login'].fillna(365, inplace=True)
df['Days_Since_Transaction'].fillna(365, inplace=True)
df['Days_Since_Interaction'].fillna(365, inplace=True)

# 5. Drop the original date columns (Cleanup)
df.drop(columns=['LastLoginDate', 'TransactionDate', 'InteractionDate'], inplace=True)

print("--- Date Engineering Successful ---")
print("New features 'Days_Since_Login' and 'Days_Since_Transaction, 'Days_Since_Interaction' created.")
display(df[['CustomerID', 'Days_Since_Login', 'Days_Since_Transaction', 'Days_Since_Interaction']].head())
```

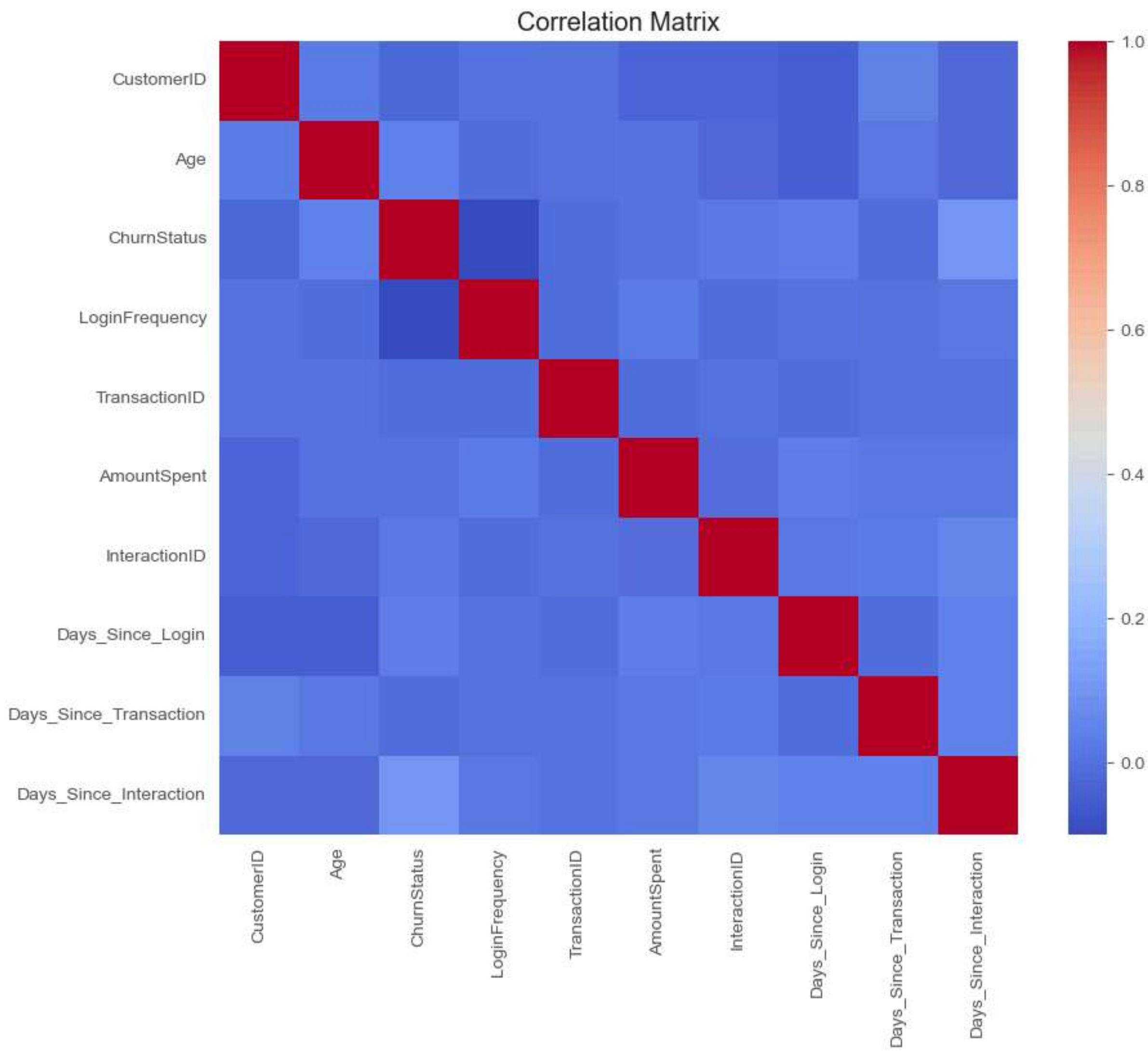
```
Reference Date (Today): 2024-01-01 00:00:00
--- Date Engineering Successful ---
New features 'Days_Since_Login' and 'Days_Since_Transaction, 'Days_Since_Interaction' created.
```

	CustomerID	Days_Since_Login	Days_Since_Transaction	Days_Since_Interaction
0	1	72	645	641.0
1	2	27	511	655.0
2	2	27	525	655.0
3	2	27	706	655.0
4	2	27	526	655.0

```
# Correlation with churn check

# Select only numeric columns for correlation
numeric_df = df.select_dtypes(include=[np.number])

# Calculate correlation with ChurnStatus
```

```
correlation = numeric_df.corr()['ChurnStatus'].sort_values(ascending=False)

print("Correlation with Churn Status:")
print(correlation)

# Visual Heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(numeric_df.corr(), cmap='coolwarm', annot=False)
plt.title("Correlation Matrix")
plt.show()
```

```
Correlation with Churn Status:
ChurnStatus               1.000000
Days_Since_Interaction    0.093400
Age                       0.045048
Days_Since_Login          0.031073
InteractionID             0.023130
AmountSpent               0.005113
Days_Since_Transaction   -0.006527
TransactionID            -0.008736
CustomerID               -0.025158
LoginFrequency           -0.100391
Name: ChurnStatus, dtype: float64
```




```
# Final Processing for machine learning and further parts in follow up steps

# 1. One-Hot Encode Categorical Variables
# This converts 'Gender' -> 'Gender_Male' (0 or 1)
df_model = pd.get_dummies(df, columns=['Gender', 'MaritalStatus', 'IncomeLevel', 'ServiceUsage'], drop_first=True)

# 2. Drop ID column (not useful for prediction)
df_model.drop(columns=['CustomerID'], inplace=True)

print("Final Data Ready for Modelling:")
```

```
display(df_model.head())

# 3. Save to CSV
df_model.to_csv('cleaned_lloyds_data.csv', index=False)
print("File 'cleaned_lloyds_data.csv' saved successfully!")
```

Final Data Ready for Modelling:

	Age	ChurnStatus	LoginFrequency	TransactionID	AmountSpent	ProductCategory	InteractionID	InteractionType	ResolutionStatu
0	62	0	34	7194	416.50	Electronics	6363.0	Inquiry	Resolve
1	65	1	5	7250	54.96	Clothing	3329.0	Inquiry	Resolve
2	65	1	5	9660	197.50	Electronics	3329.0	Inquiry	Resolve
3	65	1	5	2998	101.31	Furniture	3329.0	Inquiry	Resolve
4	65	1	5	1228	397.37	Clothing	3329.0	Inquiry	Resolve

File 'cleaned_lloyds_data.csv' saved successfully!

```
#Visualisation - final

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

# =======================================================
# 1. SETUP AND CONFIGURATION
# =======================================================

TARGET_COL = 'ChurnStatus'

# List of remaining numerical features (Confirmed in previous interaction)
INTENDED_NUMERICAL_COLS = [
    'Age',
    'LoginFrequency',
    'AmountSpent',
    'Days_Since_Login',
    'Days_Since_Transaction',
    'Days_Since_Interaction'
]

# The CORRECT list of one-hot encoded binary columns
INTENDED_BINARY_COLS = [
    'Gender_M',
    'MaritalStatus_Married',
    'MaritalStatus_Single',
    'MaritalStatus_Widowed',
    'IncomeLevel_Low',
    'IncomeLevel_Medium',
    'ServiceUsage_OnlineBanking', # <-- CORRECTED
    'ServiceUsage_Website'       # <-- CORRECTED
]
# =======================================================

# Load the processed DataFrame
try:
    df_model = pd.read_csv('cleaned_lloyds_data.csv')
except FileNotFoundError:
    print("Error: 'cleaned_lloyds_data.csv' not found. Please check your file path and ensure the file exists.")
    exit()

# --- ROBUSTNESS CHECK: Filter columns to only include those present in the DataFrame ---
df_cols = df_model.columns.tolist()
NUMERICAL_COLS = [col for col in INTENDED_NUMERICAL_COLS if col in df_cols]
BINARY_COLS = [col for col in INTENDED_BINARY_COLS if col in df_cols]

if TARGET_COL not in df_cols:
    print(f"\nFATAL ERROR: Target column '{TARGET_COL}' is missing from the data.")
    exit()

print(f"Loaded DataFrame with {len(df_cols)} columns.")
print(f"Numerical columns used: {NUMERICAL_COLS}")
print(f"Binary columns used: {BINARY_COLS}")
# =======================================================
```

```
# =======================================================
# 2. Target Variable Class Balance (Bar Plot)
# =======================================================

plt.figure(figsize=(6, 4))
sns.countplot(x=TARGET_COL, data=df_model, palette='viridis')
plt.title(f'Distribution of the Target Variable ({TARGET_COL})')
plt.xlabel(TARGET_COL)
plt.ylabel('Count')
plt.xticks([0, 1], ['No Churn (0)', 'Churn (1)'])
plt.savefig('2_target_balance_bar_plot.png')
plt.show()
plt.close()


# =======================================================
# 3. Correlation Heatmap
# =======================================================
# Identify multicollinearity and feature correlation with ChurnStatus.

relevant_cols = [TARGET_COL] + NUMERICAL_COLS + BINARY_COLS
corr_matrix = df_model[relevant_cols].corr()

plt.figure(figsize=(14, 12))
sns.heatmap(corr_matrix,
            annot=True,
            fmt=".2f",
            cmap='coolwarm',
            cbar=True,
            linewidths=.5,
            linecolor='black')
plt.title(f'Correlation Heatmap of Features vs. {TARGET_COL}')
plt.savefig('3_correlation_heatmap.png')
plt.show()
plt.close()


# =======================================================
# 4. Numerical Feature Distributions (Histograms)
# =======================================================
# Check for skewness and general distribution shape of continuous features.

n_plots = len(NUMERICAL_COLS)
n_cols = 3
n_rows = (n_plots + n_cols - 1) // n_cols

plt.figure(figsize=(15, 5 * n_rows))
for i, col in enumerate(NUMERICAL_COLS):
    plt.subplot(n_rows, n_cols, i + 1)
    sns.histplot(df_model[col], kde=True, bins=30, edgecolor='black')
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Frequency')

plt.tight_layout()
plt.savefig('4_numerical_distributions.png')
plt.show()
plt.close()


# =======================================================
# 5. Binary Features vs. Target (Exit Rate Bar Plots)
# =======================================================
# Visualize how the one-hot encoded groups influence the churn rate.

n_plots = len(BINARY_COLS)
n_cols = 3
n_rows = (n_plots + n_cols - 1) // n_cols

plt.figure(figsize=(15, 5 * n_rows))
for i, col in enumerate(BINARY_COLS):
    # Calculate the mean of the target column (ChurnStatus) for each binary feature class (0 or 1)
    temp_df = df_model.groupby(col)[TARGET_COL].mean().reset_index()

    plt.subplot(n_rows, n_cols, i + 1)
```

```
        sns.barplot(x=col, y=TARGET_COL, data=temp_df, palette='pastel')

        plt.title(f'Churn Rate by {col}')
        plt.xlabel(col)
        plt.ylabel(f'Mean {TARGET_COL} (Churn Rate)')
        plt.xticks([0, 1], ['No', 'Yes'])

    plt.tight_layout()
    plt.savefig('5_binary_vs_target_proportions.png')
    plt.show()
    plt.close()
```

```
Loaded DataFrame with 20 columns.
Numerical columns used: ['Age', 'LoginFrequency', 'AmountSpent', 'Days_Since_Login', 'Days_Since_Transaction', 'Days_Since_Inte
Binary columns used: ['Gender_M', 'MaritalStatus_Married', 'MaritalStatus_Single', 'MaritalStatus_Widowed', 'IncomeLevel_Low',
```