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

# Load all sheet names
excel_path = "Customer_Churn_Data_Large.xlsx"
xls = pd.ExcelFile(excel_path)
sheet_names = xls.sheet_names  # List of all sheet names
print("Available sheets:", sheet_names)

# Load each sheet into a dictionary of DataFrames
dataframes = {sheet: xls.parse(sheet) for sheet in sheet_names}

# Access example:
df_main = dataframes['Customer_Demographics']  # Replace with actual
sheet name
df_main.head()
```

```
Available sheets: ['Customer_Demographics', 'Transaction_History',
'Customer_Service', 'Online_Activity', 'Churn_Status']

   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
```

```python
def show_all_df_info(dataframes):
    for name, df in dataframes.items():
        print(f"\n=== {name} ===")
        print(df.info())
show_all_df_info(dataframes)
```

```

=== Customer_Demographics ===
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   CustomerID     1000 non-null   int64
 1   Age            1000 non-null   int64
 2   Gender         1000 non-null   object
 3   MaritalStatus  1000 non-null   object
 4   IncomeLevel    1000 non-null   object
dtypes: int64(2), object(3)
memory usage: 39.2+ KB
None
```

```
=== Transaction_History ===
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5054 entries, 0 to 5053
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CustomerID       5054 non-null   int64
 1   TransactionID    5054 non-null   int64
 2   TransactionDate  5054 non-null   datetime64[ns]
 3   AmountSpent      5054 non-null   float64
 4   ProductCategory  5054 non-null   object
dtypes: datetime64[ns](1), float64(1), int64(2), object(1)
memory usage: 197.6+ KB
None

=== Customer_Service ===
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1002 entries, 0 to 1001
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   CustomerID        1002 non-null   int64
 1   InteractionID     1002 non-null   int64
 2   InteractionDate   1002 non-null   datetime64[ns]
 3   InteractionType   1002 non-null   object
 4   ResolutionStatus  1002 non-null   object
dtypes: datetime64[ns](1), int64(2), object(2)
memory usage: 39.3+ KB
None

=== Online_Activity ===
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   CustomerID      1000 non-null   int64
 1   LastLoginDate   1000 non-null   datetime64[ns]
 2   LoginFrequency  1000 non-null   int64
 3   ServiceUsage    1000 non-null   object
dtypes: datetime64[ns](1), int64(2), object(1)
memory usage: 31.4+ KB
None

=== Churn_Status ===
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 2 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
```

```
 0   CustomerID   1000 non-null   int64
 1   ChurnStatus  1000 non-null   int64
dtypes: int64(2)
memory usage: 15.8 KB
None
```

□ Join Strategy Explanation

To build a comprehensive dataset for churn prediction, we need to consolidate customer information from all available sources. Each of the provided sheets contributes a different dimension of behavioral, demographic, or outcome data. Here's the logic behind our join strategy:

1. `Customer_Demographics`

This sheet provides static customer attributes such as age, gender, marital status, and income level. It serves as our **primary base table**, as each entry represents a unique customer (`CustomerID`).

2. `Transaction_History`

Each customer can have **multiple transactions**, making this a one-to-many relationship. Therefore, we **aggregate** this table by `CustomerID` to extract useful features such as:

- Total amount spent
- Average transaction value
- Number of transactions

3. `Customer_Service`

Similar to transaction history, each customer can have **multiple interactions** with customer service. Thus, we also **aggregate** this table, capturing features such as:

- Number of interactions
- Most common resolution type

4. `Online_Activity`

This data contains one row per customer, showing their **most recent login**, **login frequency**, and **digital product usage**. It can be **joined directly** on `CustomerID` without aggregation.

5. `Churn_Status`

This is our **target variable**, indicating whether the customer has churned. Since it has a one-to-one mapping with `CustomerID`, it can also be **joined directly**.

By merging these tables using `CustomerID` as the key, we construct a unified dataset containing demographic, transactional, service, digital behavior, and churn outcome data—ideal for performing EDA and training a predictive model.

```python
# 1. Aggregating Transaction_History
agg_trans = 
dataframes['Transaction_History'].groupby('CustomerID').agg({
    'AmountSpent': ['sum', 'mean', 'count'],
}).reset_index()
agg_trans.columns = ['CustomerID', 'TotalSpent', 'AvgSpent', 
'NumTransactions']

# 2. Aggregating Customer_Service
agg_service = 
dataframes['Customer_Service'].groupby('CustomerID').agg({
    'InteractionID': 'count',
    'ResolutionStatus': lambda x: x.value_counts().idxmax()  # most 
common resolution
}).reset_index()
agg_service.columns = ['CustomerID', 'NumInteractions', 
'MostCommonResolution']

# 3. Merging all
df_merged = dataframes['Customer_Demographics'] \
    .merge(agg_trans, on='CustomerID', how='left') \
    .merge(agg_service, on='CustomerID', how='left') \
    .merge(dataframes['Online_Activity'], on='CustomerID', how='left') 
\
    .merge(dataframes['Churn_Status'], on='CustomerID', how='left')

df_merged.head()
```

```
   CustomerID  Age Gender MaritalStatus IncomeLevel  TotalSpent  
AvgSpent  \
0           1   62      M        Single         Low      416.50  
416.50000   
1           2   65      M       Married         Low     1547.42  
221.06000   
2           3   18      M        Single         Low     1702.98  
283.83000   
3           4   21      M       Widowed         Low      917.29  
183.45800   
4           5   21      M      Divorced      Medium     2001.49  
250.18625   

   NumTransactions  NumInteractions MostCommonResolution LastLoginDate 
\
0                1              1.0             Resolved    2023-10-21   

1                7              1.0             Resolved    2023-12-05
```

```
2                 6              1.0               Resolved    2023-11-15

3                 5              2.0               Resolved    2023-08-25

4                 8              NaN                    NaN    2023-10-27


   LoginFrequency ServiceUsage  ChurnStatus
0              34   Mobile App            0
1               5      Website            1
2               3      Website            0
3               2      Website            0
4              41      Website            0
```

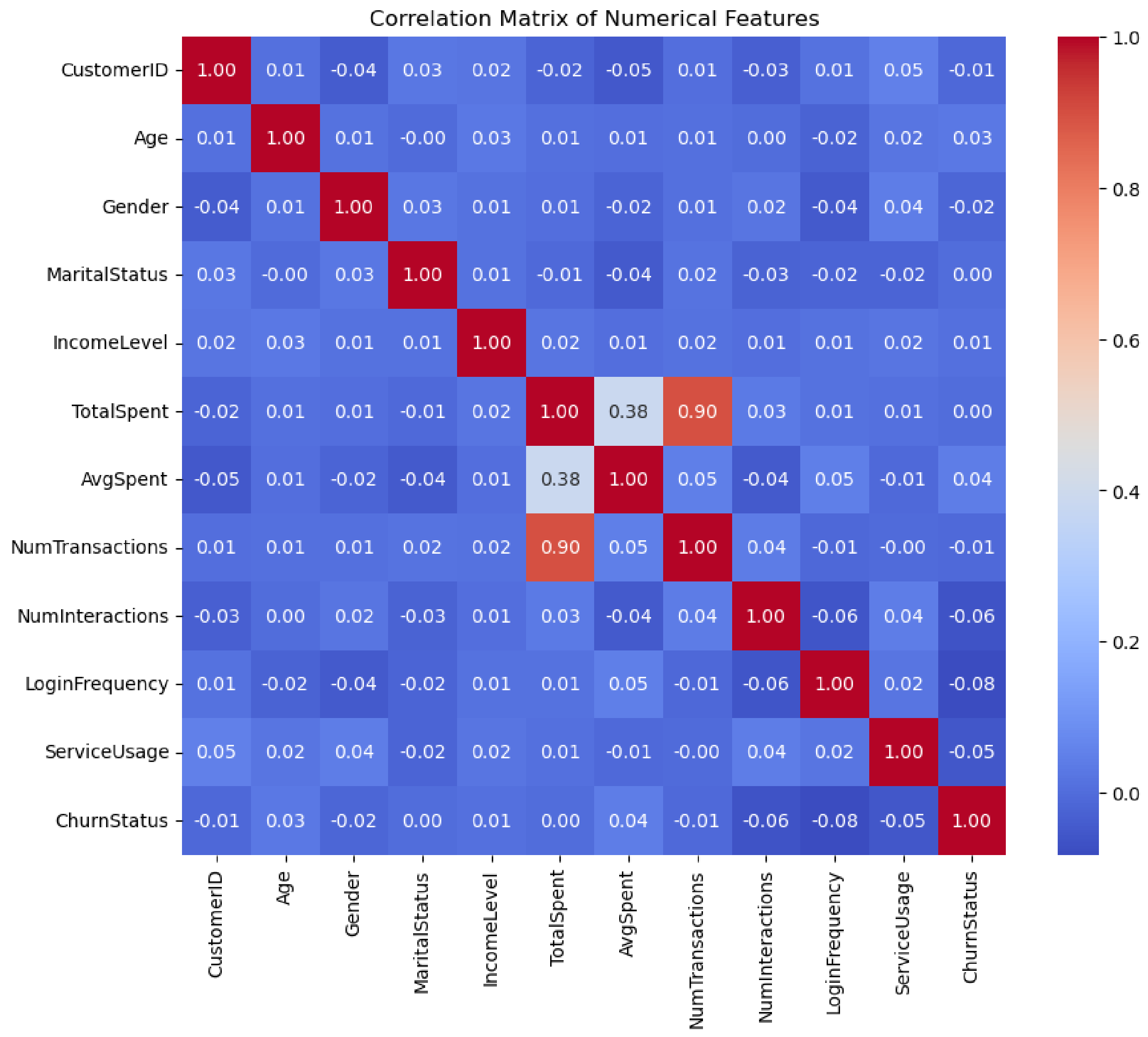
```
df_merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 14 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   CustomerID             1000 non-null   int64
 1   Age                    1000 non-null   int64
 2   Gender                 1000 non-null   object
 3   MaritalStatus          1000 non-null   object
 4   IncomeLevel            1000 non-null   object
 5   TotalSpent             1000 non-null   float64
 6   AvgSpent               1000 non-null   float64
 7   NumTransactions        1000 non-null   int64
 8   NumInteractions        668 non-null    float64
 9   MostCommonResolution   668 non-null    object
 10  LastLoginDate          1000 non-null   datetime64[ns]
 11  LoginFrequency         1000 non-null   int64
 12  ServiceUsage           1000 non-null   object
 13  ChurnStatus            1000 non-null   int64
dtypes: datetime64[ns](1), float64(3), int64(5), object(5)
memory usage: 109.5+ KB
```

Correlation Analysis

```
# Copy and convert categorical columns explicitly
df_corr = df_merged.copy()

# Map gender if it's still object dtype
if df_corr['Gender'].dtype == 'object':
    df_corr['Gender'] = df_corr['Gender'].map({'M': 0, 'F': 1})

# Also convert other categorical columns if you'd like to include them
```

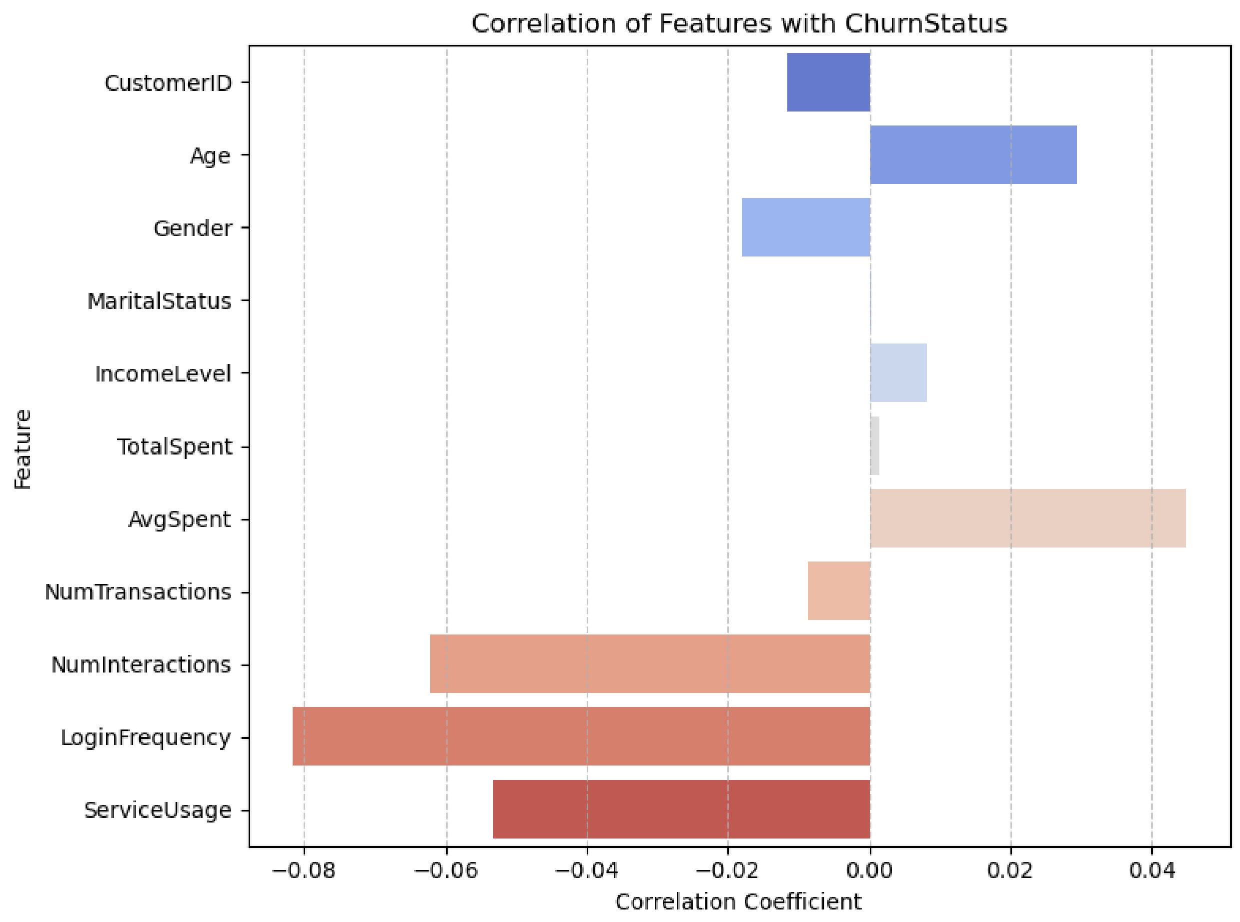
```
df_corr['ServiceUsage'] =
df_corr['ServiceUsage'].astype('category').cat.codes
df_corr['MaritalStatus'] =
df_corr['MaritalStatus'].astype('category').cat.codes
df_corr['IncomeLevel'] =
df_corr['IncomeLevel'].astype('category').cat.codes

# Then plot again
plt.figure(figsize=(10, 8))
corr_matrix = df_corr.corr(numeric_only=True)
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```



	CustomerID	Age	Gender	MaritalStatus	IncomeLevel	TotalSpent	AvgSpent	NumTransactions	NumInteractions	LoginFrequency	ServiceUsage	ChurnStatus
CustomerID	1.00	0.01	-0.04	0.03	0.02	-0.02	-0.05	0.01	-0.03	0.01	0.05	-0.01
Age	0.01	1.00	0.01	-0.00	0.03	0.01	0.01	0.01	0.00	-0.02	0.02	0.03
Gender	-0.04	0.01	1.00	0.03	0.01	0.01	-0.02	0.01	0.02	-0.04	0.04	-0.02
MaritalStatus	0.03	-0.00	0.03	1.00	0.01	-0.01	-0.04	0.02	-0.03	-0.02	-0.02	0.00
IncomeLevel	0.02	0.03	0.01	0.01	1.00	0.02	0.01	0.02	0.01	0.01	0.02	0.01
TotalSpent	-0.02	0.01	0.01	-0.01	0.02	1.00	0.38	0.90	0.03	0.01	0.01	0.00
AvgSpent	-0.05	0.01	-0.02	-0.04	0.01	0.38	1.00	0.05	-0.04	0.05	-0.01	0.04
NumTransactions	0.01	0.01	0.01	0.02	0.02	0.90	0.05	1.00	0.04	-0.01	-0.00	-0.01
NumInteractions	-0.03	0.00	0.02	-0.03	0.01	0.03	-0.04	0.04	1.00	-0.06	0.04	-0.06
LoginFrequency	0.01	-0.02	-0.04	-0.02	0.01	0.01	0.05	-0.01	-0.06	1.00	0.02	-0.08
ServiceUsage	0.05	0.02	0.04	-0.02	0.02	0.01	-0.01	-0.00	0.04	0.02	1.00	-0.05
ChurnStatus	-0.01	0.03	-0.02	0.00	0.01	0.00	0.04	-0.01	-0.06	-0.08	-0.05	1.00

```
# Copy and encode if needed
df_focus = df_merged.copy()
df_focus['Gender'] = df_focus['Gender'].map({'M': 0, 'F': 1})
df_focus['ServiceUsage'] =
df_focus['ServiceUsage'].astype('category').cat.codes
df_focus['MaritalStatus'] =
df_focus['MaritalStatus'].astype('category').cat.codes
df_focus['IncomeLevel'] =
df_focus['IncomeLevel'].astype('category').cat.codes

# Compute correlations
correlations = df_focus.corr(numeric_only=True)
['ChurnStatus'].drop('ChurnStatus')

# Plot
plt.figure(figsize=(8, 6))
sns.barplot(x=correlations.values, y=correlations.index,
palette='coolwarm')
plt.title('Correlation of Features with ChurnStatus')
plt.xlabel('Correlation Coefficient')
plt.ylabel('Feature')
plt.grid(True, axis='x', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

# Correlation with ChurnStatus (numerical output)
correlations = df_focus.corr(numeric_only=True)
['ChurnStatus'].drop('ChurnStatus')
correlations_sorted = correlations.sort_values(ascending=False)
print(correlations_sorted)
```

```
C:\Users\Kasandika Andariefli\AppData\Local\Temp\
ipykernel_4548\1141302335.py:13: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=correlations.values, y=correlations.index,
palette='coolwarm')
```



```
AvgSpent           0.044811
Age                0.029407
IncomeLevel        0.008134
TotalSpent         0.001324
MaritalStatus      0.000270
NumTransactions   -0.008598
CustomerID        -0.011528
Gender            -0.018132
ServiceUsage      -0.053155
NumInteractions   -0.062044
LoginFrequency    -0.081615
Name: ChurnStatus, dtype: float64
```

Feature Correlation with ChurnStatus (Updated)

This visualization and summary highlight how each feature correlates with the target variable `ChurnStatus`, where a value of **1 represents a churned customer**. Understanding this directionality is key:

- **Positive correlation** → associated with **higher likelihood of churn**
- **Negative correlation** → associated with **lower likelihood of churn**

Interpretation:

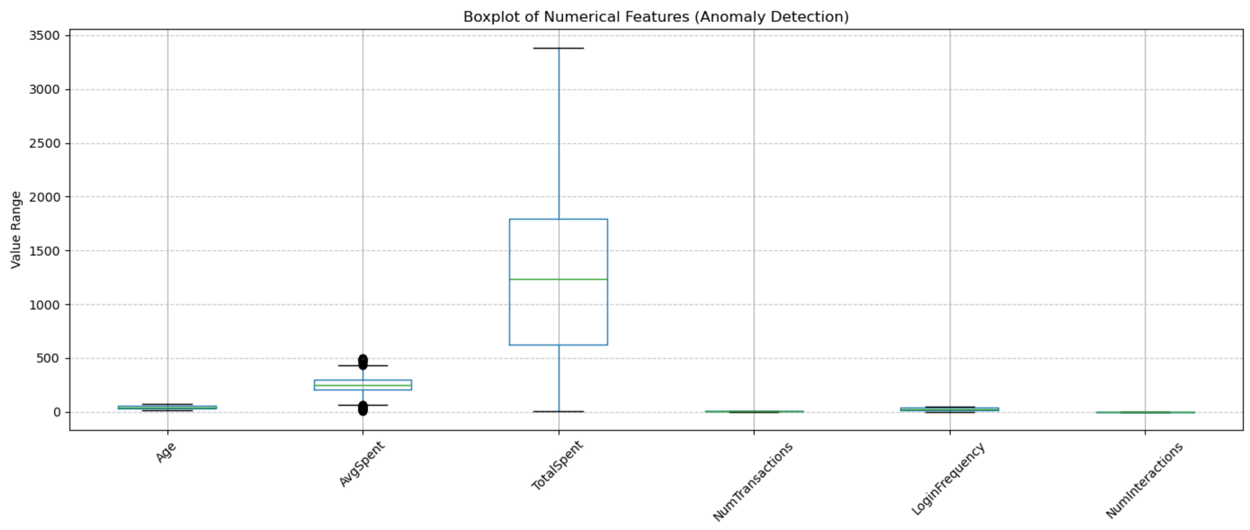
- **LoginFrequency (-0.0816)** shows the strongest inverse correlation with churn, suggesting customers who log in frequently are more likely to **stay**.
- **NumInteractions (-0.0620)** and **ServiceUsage (-0.0532)** follow a similar trend—highlighting that **engagement and support usage reduce churn risk**.
- **Gender (-0.0181)**, now correctly encoded, suggests that **males (0)** may churn slightly more than females (1), though the effect is weak.
- **AvgSpent (+0.0448)** and **Age (+0.0294)** have small positive correlations, hinting that higher spending and older age might slightly increase churn—but this could indicate dissatisfaction or changing needs.
- **TotalSpent**, **IncomeLevel**, and **MaritalStatus** show near-zero correlation and likely require cross-feature interaction analysis for deeper insight.

Takeaway:

The top features negatively correlated with churn relate to **digital behavior and service usage**. These should be prioritized in model design and retention strategies. No single feature is dominant—supporting the use of a multivariate predictive model to capture subtle patterns.

Anomaly Detection

```python
from scipy.stats import zscore

# Select numeric columns (excluding target)
numeric_cols = ['Age', 'AvgSpent', 'TotalSpent', 'NumTransactions',
                'LoginFrequency', 'NumInteractions']

plt.figure(figsize=(14, 6))
df_merged[numeric_cols].boxplot()
plt.title('Boxplot of Numerical Features (Anomaly Detection)')
plt.ylabel('Value Range')
plt.xticks(rotation=45)
plt.grid(True, axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()

# Compute z-scores
z_scores = df_merged[numeric_cols].apply(zscore)

# Count outliers (Z-score > 3 or < -3)
outlier_counts = (z_scores.abs() > 3).sum()
print("Outliers (|z| > 3) per feature:")
print(outlier_counts)
```



```
Outliers (|z| > 3) per feature:
Age                 0
AvgSpent            6
TotalSpent          0
NumTransactions     0
LoginFrequency      0
NumInteractions     0
dtype: int64
```

⚠ Anomaly Detection (Z-Score & Boxplot Analysis)

To detect unusual values that may indicate **data quality issues** or **rare behavioral patterns**, we applied **Z-score based anomaly detection** and visualized the results using boxplots.

Z-Score Summary:

Only **`AvgSpent`** exhibits significant outliers — 6 customers had unusually high or low average spending patterns.

Boxplot Insights:

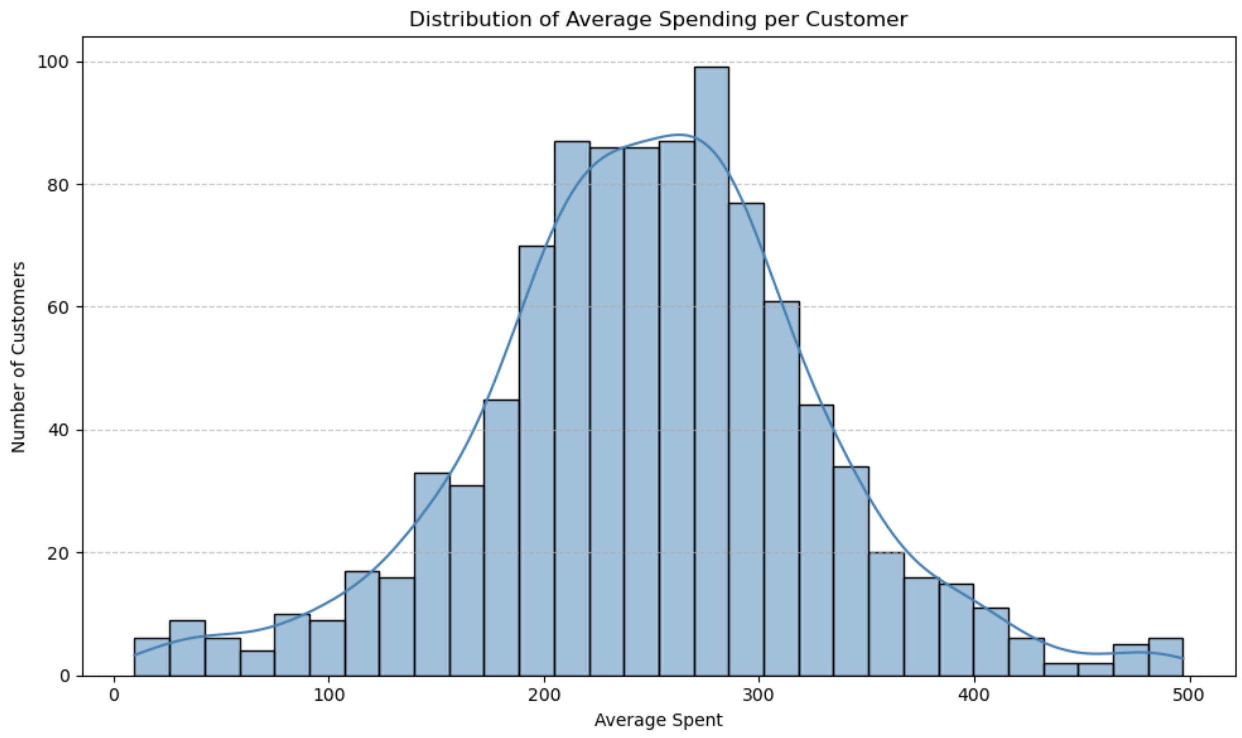
- **AvgSpent** shows clear outliers and a fairly wide spread, suggesting variability in spending behavior. This may capture high-value or low-engagement customer extremes.
- **TotalSpent**, despite its large range, shows no statistical outliers by Z-score — possibly due to its spread being normalized across the population.
- Other features like **Age**, **LoginFrequency**, and **NumTransactions** are tightly distributed with no significant anomalies.

Interpretation:

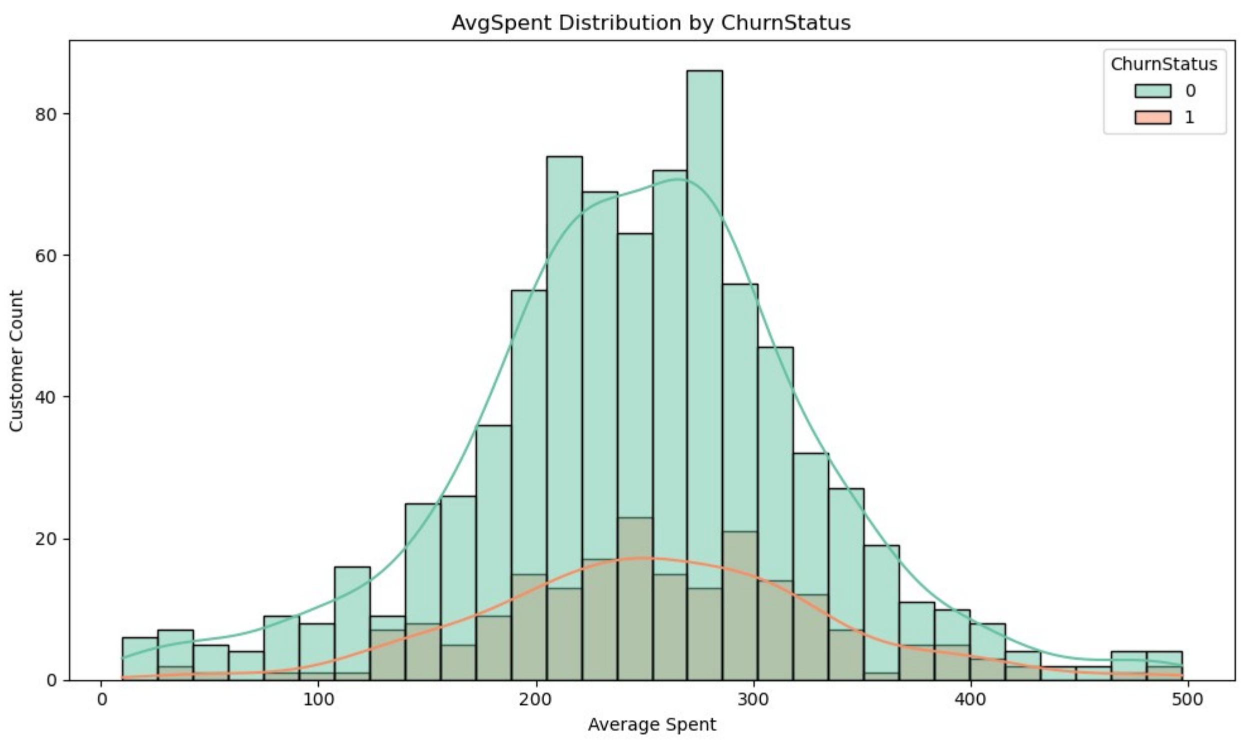
- The outliers in `AvgSpent` should be reviewed carefully:

  - Are they data entry errors?
  - Or do they represent key behavioral patterns (e.g., high-value churn risks)?
- Since no other features show high-anomaly frequency, we **do not recommend removing these outliers at this stage**, but instead flagging them for potential stratified analysis or robust modeling.

```python
plt.figure(figsize=(10, 6))
sns.histplot(df_merged['AvgSpent'], bins=30, kde=True,
color='steelblue')
plt.title('Distribution of Average Spending per Customer')
plt.xlabel('Average Spent')
plt.ylabel('Number of Customers')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



```python
plt.figure(figsize=(10, 6))
sns.histplot(data=df_merged, x='AvgSpent', hue='ChurnStatus', bins=30,
kde=True, palette='Set2')
plt.title('AvgSpent Distribution by ChurnStatus')
plt.xlabel('Average Spent')
plt.ylabel('Customer Count')
plt.tight_layout()
plt.show()
```



```python
high_spenders = df_merged[df_merged['AvgSpent'] >
df_merged['AvgSpent'].quantile(0.95)]
print("High spenders who churned:")
print(high_spenders[high_spenders['ChurnStatus'] == 1])
```

```
High spenders who churned:
     CustomerID  Age Gender MaritalStatus IncomeLevel  TotalSpent
AvgSpent  \
136         137   21      F       Married        High      431.47
431.470000
143         144   45      F       Married         Low      419.85
419.850000
236         237   61      M      Divorced         Low      398.99
398.990000
260         261   27      M       Married         Low      489.07
489.070000
281         282   42      M        Single        High     2016.68
403.336000
487         488   28      F       Married      Medium      393.84
393.840000
497         498   45      F        Single         Low      763.91
381.955000
509         510   30      M        Single      Medium      392.10
392.100000
564         565   69      M        Single         Low     2436.25
406.041667
613         614   64      F       Married        High     1239.16
```

```
413.053333
629          630   61       F        Married       Medium       942.44
471.220000
826          827   42       M        Married          Low      2317.93
386.321667
923          924   23       M         Single         High       760.13
380.065000
924          925   54       F       Divorced       Medium      1930.41
386.082000
989          990   37       F        Widowed         High       483.50
483.500000

     NumTransactions  NumInteractions MostCommonResolution
LastLoginDate  \
136                1              NaN                  NaN    2023-06-
19
143                1              1.0             Resolved    2023-02-
18
236                1              NaN                  NaN    2023-01-
13
260                1              1.0           Unresolved    2023-05-
29
281                5              1.0             Resolved    2023-07-
22
487                1              NaN                  NaN    2023-06-
14
497                2              NaN                  NaN    2023-06-
28
509                1              1.0           Unresolved    2023-07-
04
564                6              2.0             Resolved    2023-04-
22
613                3              1.0             Resolved    2023-03-
25
629                2              1.0           Unresolved    2023-08-
17
826                6              NaN                  NaN    2023-10-
09
923                2              1.0           Unresolved    2023-03-
25
924                5              NaN                  NaN    2023-01-
20
989                1              2.0             Resolved    2023-06-
07

     LoginFrequency    ServiceUsage  ChurnStatus
136              38  Online Banking            1
143              39  Online Banking            1
236              16  Online Banking            1
```

```
260                49  Online Banking            1
281                 3  Online Banking            1
487                33      Mobile App            1
497                 5         Website            1
509                31      Mobile App            1
564                30         Website            1
613                24      Mobile App            1
629                44         Website            1
826                38  Online Banking            1
923                41         Website            1
924                38      Mobile App            1
989                49      Mobile App            1
```

AvgSpent vs. ChurnStatus

The distribution of `AvgSpent` reveals a **slightly right-skewed curve** with a central cluster between $150–$300. When split by `ChurnStatus`, both churned and retained customers show similar spread, but a **slightly higher proportion of churners exists in the upper-middle spend range**.

Insight:

- High spend does **not guarantee loyalty**. A subset of churners are high spenders, potentially indicating dissatisfaction or lack of personalization despite high engagement.
- This segment should be considered for **targeted retention strategies**, such as loyalty rewards, concierge support, or exclusive financial products.