```python
import pandas as pd

train_df = pd.read_csv('/content/customer_churn_dataset-training-master[1].csv')
test_df = pd.read_csv('/content/customer_churn_dataset-testing-master[1].csv')

print("Training DataFrame - Head:")
print(train_df.head())
```

```
Training DataFrame - Head:
   CustomerID   Age  Gender  Tenure  Usage Frequency  Support Calls  \
0         2.0  30.0  Female    39.0             14.0            5.0
1         3.0  65.0  Female    49.0              1.0           10.0
2         4.0  55.0  Female    14.0              4.0            6.0
3         5.0  58.0    Male    38.0             21.0            7.0
4         6.0  23.0    Male    32.0             20.0            5.0

   Payment Delay Subscription Type Contract Length  Total Spend  \
0           18.0          Standard          Annual        932.0
1            8.0             Basic         Monthly        557.0
2           18.0             Basic       Quarterly        185.0
3            7.0          Standard         Monthly        396.0
4            8.0             Basic         Monthly        617.0

   Last Interaction  Churn
0              17.0    1.0
1               6.0    1.0
2               3.0    1.0
3              29.0    1.0
4              20.0    1.0
```

```python
print("\nTraining DataFrame - Info:")
train_df.info()

print("\nTraining DataFrame - Description:")
print(train_df.describe())

print("\nTraining DataFrame - Missing Values:")
print(train_df.isnull().sum())
```

```
 2   Gender             440832 non-null  object
 3   Tenure             440832 non-null  float64
 4   Usage Frequency    440832 non-null  float64
 5   Support Calls      440832 non-null  float64
 6   Payment Delay      440832 non-null  float64
 7   Subscription Type  440832 non-null  object
 8   Contract Length    440832 non-null  object
 9   Total Spend        440832 non-null  float64
 10  Last Interaction   440832 non-null  float64
 11  Churn              440832 non-null  float64
dtypes: float64(9), object(3)
memory usage: 40.4+ MB

Training DataFrame - Description:
          CustomerID            Age         Tenure  Usage Frequency  \
count  440832.000000  440832.000000  440832.000000    440832.000000
mean   225398.667955      39.373153      31.256336        15.807494
std    129531.918550      12.442369      17.255727         8.586242
min         2.000000      18.000000       1.000000         1.000000
25%    113621.750000      29.000000      16.000000         9.000000
50%    226125.500000      39.000000      32.000000        16.000000
75%    337739.250000      48.000000      46.000000        23.000000
max    449999.000000      65.000000      60.000000        30.000000

       Support Calls  Payment Delay    Total Spend  Last Interaction  \
count  440832.000000  440832.000000  440832.000000     440832.000000
mean        3.604437      12.965722     631.616223         14.480868
std         3.070218       8.258063     240.803001          8.596208
```

```
min          0.000000
25%          0.000000
50%          1.000000
75%          1.000000
max          1.000000

Training DataFrame - Missing Values:
CustomerID           1
Age                  1
Gender               1
Tenure               1
Usage Frequency      1
Support Calls        1
Payment Delay        1
Subscription Type    1
Contract Length      1
Total Spend          1
Last Interaction     1
Churn                1
dtype: int64
```

```python
print("\nTesting DataFrame - Head:")
print(test_df.head())

print("\nTesting DataFrame - Info:")
test_df.info()

print("\nTesting DataFrame - Description:")
print(test_df.describe())

print("\nTesting DataFrame - Missing Values:")
print(test_df.isnull().sum())
```

```
 2   Gender             64374 non-null  object
 3   Tenure             64374 non-null  int64
 4   Usage Frequency    64374 non-null  int64
 5   Support Calls      64374 non-null  int64
 6   Payment Delay      64374 non-null  int64
 7   Subscription Type  64374 non-null  object
 8   Contract Length    64374 non-null  object
 9   Total Spend        64374 non-null  int64
 10  Last Interaction   64374 non-null  int64
 11  Churn              64374 non-null  int64
dtypes: int64(9), object(3)
memory usage: 5.9+ MB

Testing DataFrame - Description:
```

```
CustomerID           0
Age                  0
Gender               0
Tenure               0
Usage Frequency      0
Support Calls        0
Payment Delay        0
Subscription Type    0
Contract Length      0
Total Spend          0
Last Interaction     0
Churn                0
dtype: int64
```

```
print("Shape of train_df before dropping missing values:", train_df.shape)
train_df.dropna(inplace=True)
print("Shape of train_df after dropping missing values:", train_df.shape)

print("\nMissing values in train_df after dropping:")
print(train_df.isnull().sum())
```

```
Shape of train_df before dropping missing values: (440833, 12)
Shape of train_df after dropping missing values: (440832, 12)

Missing values in train_df after dropping:
CustomerID           0
Age                  0
Gender               0
Tenure               0
Usage Frequency      0
Support Calls        0
Payment Delay        0
Subscription Type    0
Contract Length      0
Total Spend          0
Last Interaction     0
Churn                0
dtype: int64
```

```
import pandas as pd

categorical_cols = ['Gender', 'Subscription Type', 'Contract Length']

# Apply One-Hot Encoding to training data
train_df_encoded = pd.get_dummies(train_df, columns=categorical_cols, drop_first=False)
print("Shape of train_df after One-Hot Encoding:", train_df_encoded.shape)

# Apply One-Hot Encoding to testing data, ensuring consistent columns with training data
test_df_encoded = pd.get_dummies(test_df, columns=categorical_cols, drop_first=False)

# Align columns - this is crucial to ensure both dataframes have the same columns after encoding
train_cols = set(train_df_encoded.columns)
test_cols = set(test_df_encoded.columns)

missing_in_test = list(train_cols - test_cols)
for col in missing_in_test:
    test_df_encoded[col] = 0

missing_in_train = list(test_cols - train_cols)
for col in missing_in_train:
    train_df_encoded[col] = 0

test_df_encoded = test_df_encoded[train_df_encoded.columns]

train_df = train_df_encoded
test_df = test_df_encoded

print("Shape of test_df after One-Hot Encoding and column alignment:", test_df.shape)
print("First 5 rows of train_df after encoding:")
print(train_df.head())
```

```
Shape of train_df after One-Hot Encoding: (440832, 17)
Shape of test_df after One-Hot Encoding and column alignment: (64374, 17)
First 5 rows of train_df after encoding:
   CustomerID   Age  Tenure  Usage Frequency  Support Calls  Payment Delay  \
0         2.0  30.0    39.0             14.0            5.0           18.0
```

```
1         3.0  65.0    49.0              1.0          10.0           8.0
2         4.0  55.0    14.0              4.0           6.0          18.0
3         5.0  58.0    38.0             21.0           7.0           7.0
4         6.0  23.0    32.0             20.0           5.0           8.0

   Total Spend  Last Interaction  Churn  Gender_Female  Gender_Male  \
0        932.0              17.0    1.0           True        False
1        557.0               6.0    1.0           True        False
2        185.0               3.0    1.0           True        False
3        396.0              29.0    1.0          False         True
4        617.0              20.0    1.0          False         True

   Subscription Type_Basic  Subscription Type_Premium  \
0                    False                      False
1                     True                      False
2                     True                      False
3                    False                      False
4                     True                      False

   Subscription Type_Standard  Contract Length_Annual  \
0                        True                    True
1                       False                   False
2                       False                   False
3                        True                   False
4                       False                   False

   Contract Length_Monthly  Contract Length_Quarterly
0                    False                      False
1                     True                      False
2                    False                       True
3                     True                      False
4                     True                      False
```

```
from sklearn.preprocessing import StandardScaler

# Identify numerical columns to be scaled (excluding CustomerID and Churn for now)
numerical_cols = ['Age', 'Tenure', 'Usage Frequency', 'Support Calls', 'Payment Delay', 'Total Spend', 'Last In

# Initialize StandardScaler
scaler = StandardScaler()

# Apply StandardScaler to training data (fit and transform)
train_df[numerical_cols] = scaler.fit_transform(train_df[numerical_cols])

# Apply StandardScaler to testing data (transform only)
test_df[numerical_cols] = scaler.transform(test_df[numerical_cols])

# Drop 'CustomerID' column from both dataframes
train_df.drop('CustomerID', axis=1, inplace=True)
test_df.drop('CustomerID', axis=1, inplace=True)

print("First 5 rows of train_df after scaling numerical features and dropping CustomerID:")
print(train_df.head())
print("\nFirst 5 rows of test_df after scaling numerical features and dropping CustomerID:")
print(test_df.head())
```

```
4    -0.060698          0.642043    1.0          False         True

   Subscription Type_Basic  Subscription Type_Premium  \
0                    False                      False
1                     True                      False
2                     True                      False
3                    False                      False
4                     True                      False
```

```
First 5 rows of test_df after scaling numerical features and dropping CustomerID:
        Age    Tenure  Usage Frequency  Support Calls  Payment Delay  \
0 -1.396291 -0.362566        -0.210511       0.128839       1.699466
1  0.130751 -0.188711         1.420007       1.105969       0.004151
2  0.612974 -0.246662        -0.676373      -0.522581       1.941654
3 -0.351473 -1.289796        -0.443442       0.454549       0.488527
4  1.095198  1.549845         0.954145       1.757390      -1.327882

   Total Spend  Last Interaction  Churn  Gender_Female  Gender_Male  \
0    -0.139601         -0.637592      1           True        False
1    -0.197740          0.642043      0           True        False
2     0.520691          0.758374      0          False         True
3    -1.659517          0.409382      0          False         True
4    -0.409531          0.409382      0           True        False

   Subscription Type_Basic  Subscription Type_Premium  \
0                     True                      False
1                    False                      False
2                    False                       True
3                    False                       True
4                    False                      False

   Subscription Type_Standard  Contract Length_Annual  \
0                       False                   False
1                        True                   False
2                       False                    True
3                       False                   False
4                        True                    True

   Contract Length_Monthly  Contract Length_Quarterly
0                     True                      False
1                     True                      False
2                    False                      False
3                    False                       True
4                    False                      False
```

```python
X = train_df.drop('Churn', axis=1)
y = train_df['Churn']

print("Shape of X (features):")
print(X.shape)
print("Shape of y (target):")
print(y.shape)
```

```
Shape of X (features):
(440832, 15)
Shape of y (target):
(440832,)
```

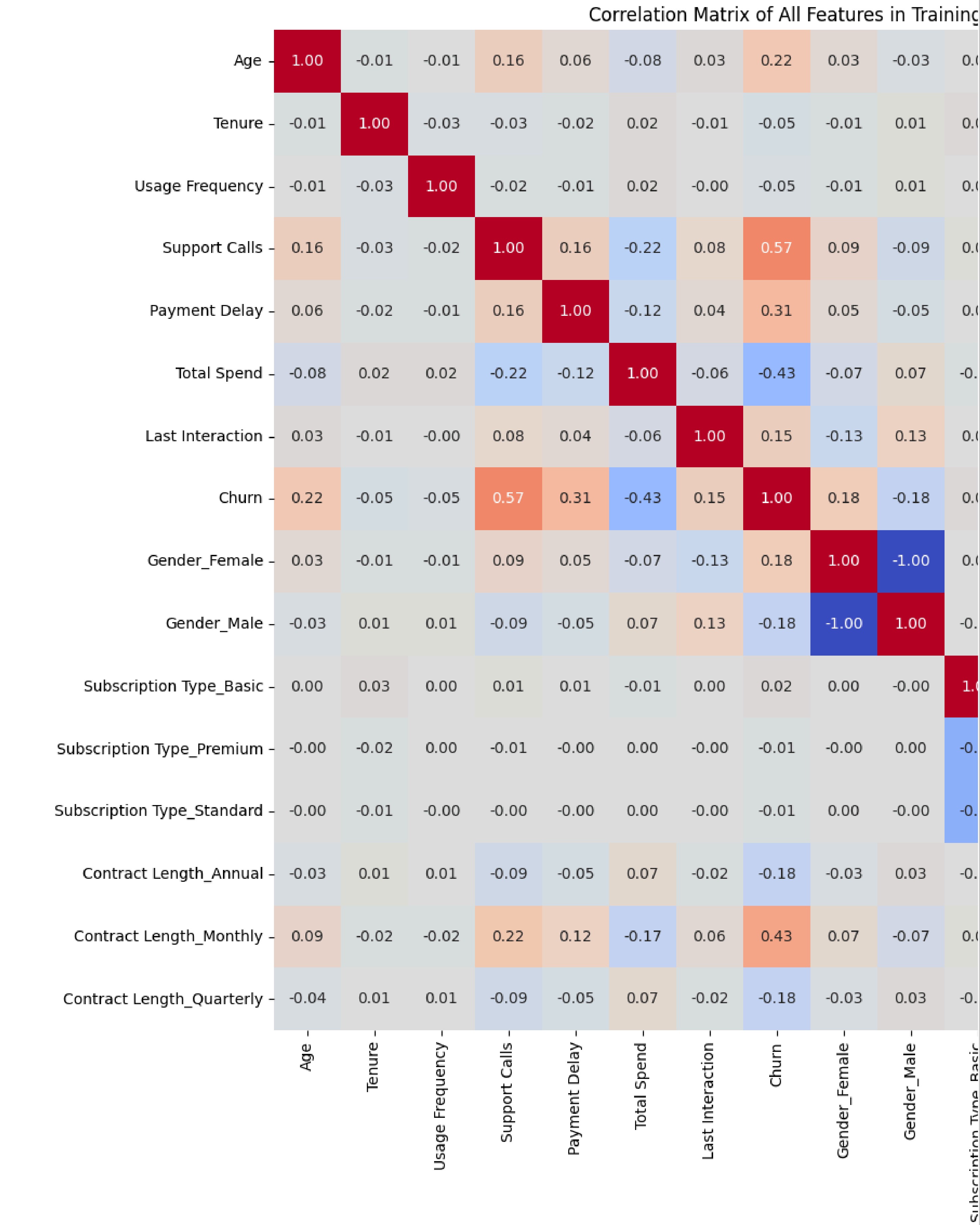
```python
from sklearn.model_selection import train_test_split

X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.2, random_state=42)

print("Shape of X_train:", X_train.shape)
print("Shape of X_val:", X_val.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_val:", y_val.shape)
```

```
Shape of X_train: (352665, 15)
Shape of X_val: (88167, 15)
Shape of y_train: (352665,)
Shape of y_val: (88167,)
```

```python
import matplotlib.pyplot as plt
import seaborn as sns

print("Libraries matplotlib.pyplot and seaborn imported successfully.")
```

```
Libraries matplotlib.pyplot and seaborn imported successfully.
```

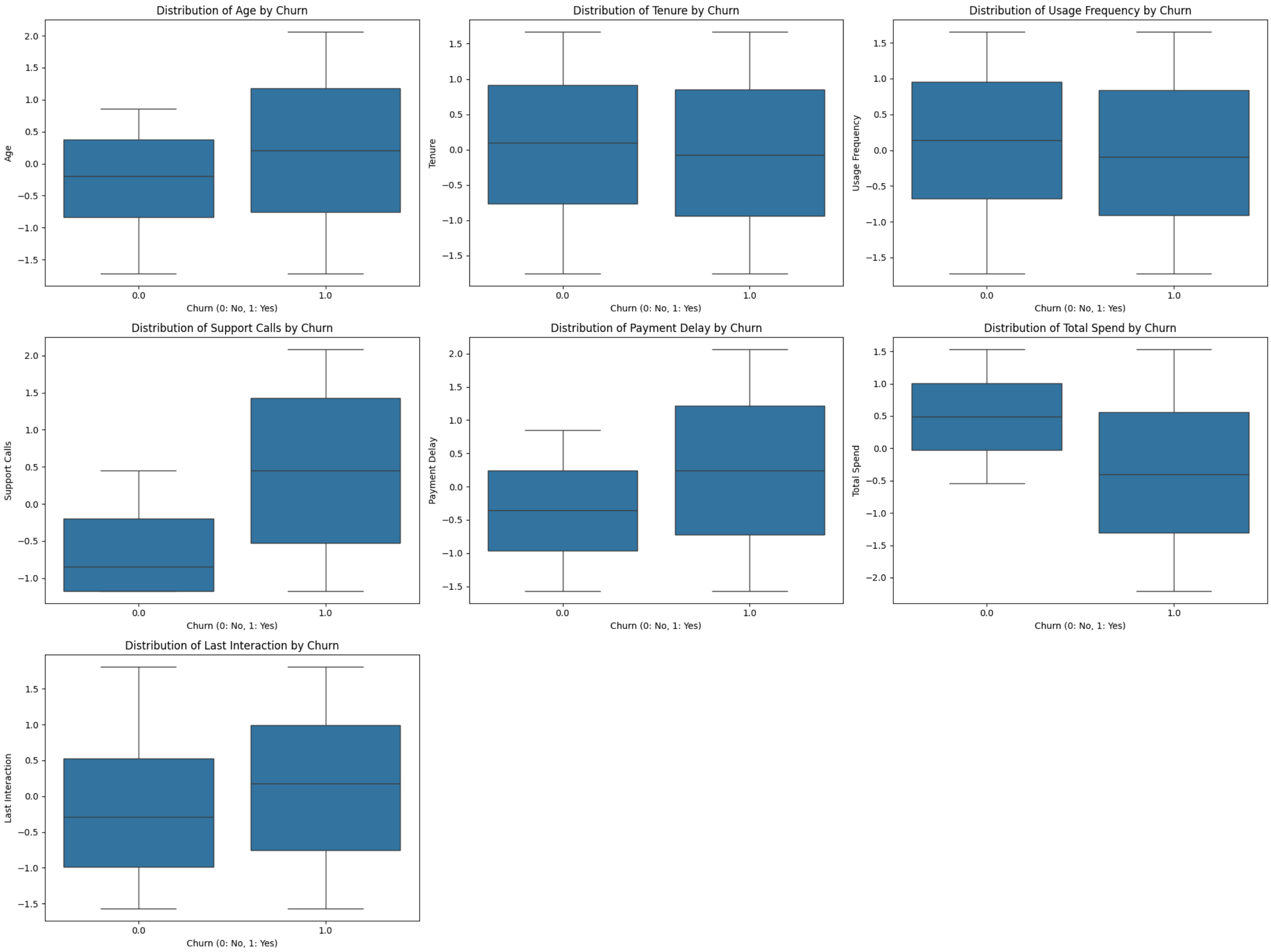
```python
plt.figure(figsize=(16, 12))
sns.heatmap(train_df.corr(numeric_only=True), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix of All Features in Training Data')
plt.show()
```



Interpretation of Correlation Heatmap:
The correlation heatmap provides insights into the linear relationships between all features, including the 'Churn'
- **Positive Correlation with Churn**: Features like `Payment Delay`, `Support Calls`, and `Usage Frequency` show a
- **Negative Correlation with Churn**: `Tenure` and `Total Spend` exhibit moderate negative correlations with 'Chur
- **Inter-feature Correlations**: There are some notable correlations between independent features. For instance, `
- **Categorical Features**: The one-hot encoded categorical features (Gender, Subscription Type, Contract Length) s

This heatmap serves as a good starting point for further investigation into specific relationships with box plots a

```
numerical_cols_for_boxplot = ['Age', 'Tenure', 'Usage Frequency', 'Support Calls', 'Payment Delay', 'Total Spen

plt.figure(figsize=(20, 15))
for i, col in enumerate(numerical_cols_for_boxplot):
    plt.subplot(3, 3, i + 1) # Adjust subplot grid based on number of numerical columns
    sns.boxplot(x='Churn', y=col, data=train_df)
    plt.title(f'Distribution of {col} by Churn')
    plt.xlabel('Churn (0: No, 1: Yes)')
    plt.ylabel(col)
plt.tight_layout()
plt.show()
```



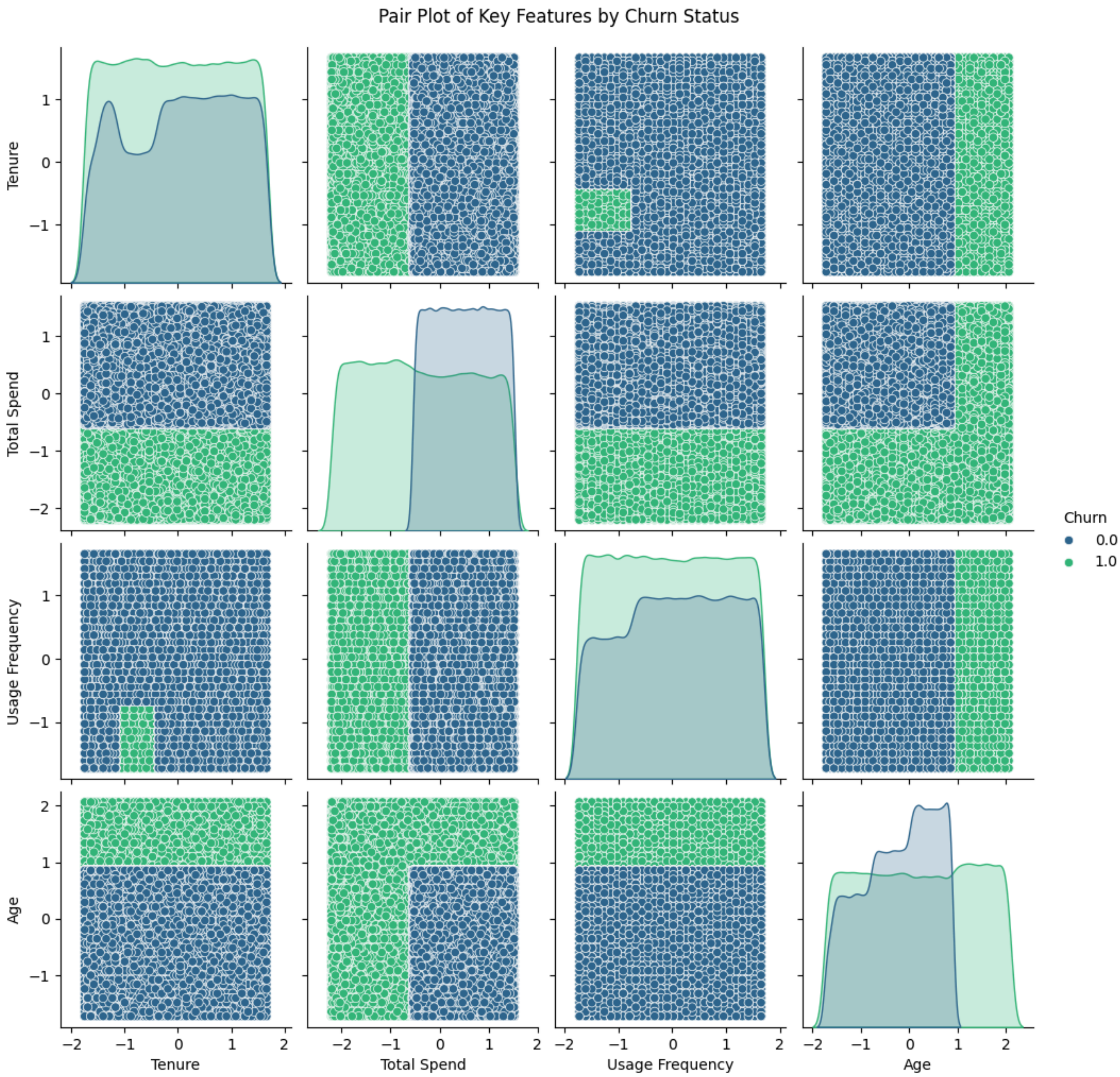
Interpretation of Box Plots (Numerical Features vs. Churn):

The box plots illustrate the distribution of each numerical feature for customers who churned (1) and those who did

- **Age**: The median age appears similar for both churned and non-churned customers, indicating age might not be a
- **Tenure**: Non-churned customers tend to have a higher median tenure and a wider distribution towards longer ten
- **Usage Frequency**: Churned customers seem to have a slightly higher median and spread for usage frequency, whic
- **Support Calls**: Churned customers exhibit a higher median and range for support calls, implying that frequent
- **Payment Delay**: There's a noticeable difference, with churned customers generally having higher payment delays
- **Total Spend**: Non-churned customers show a higher median total spend and a larger interquartile range, indicat
- **Last Interaction**: The distributions for last interaction seem somewhat similar between churned and non-churne

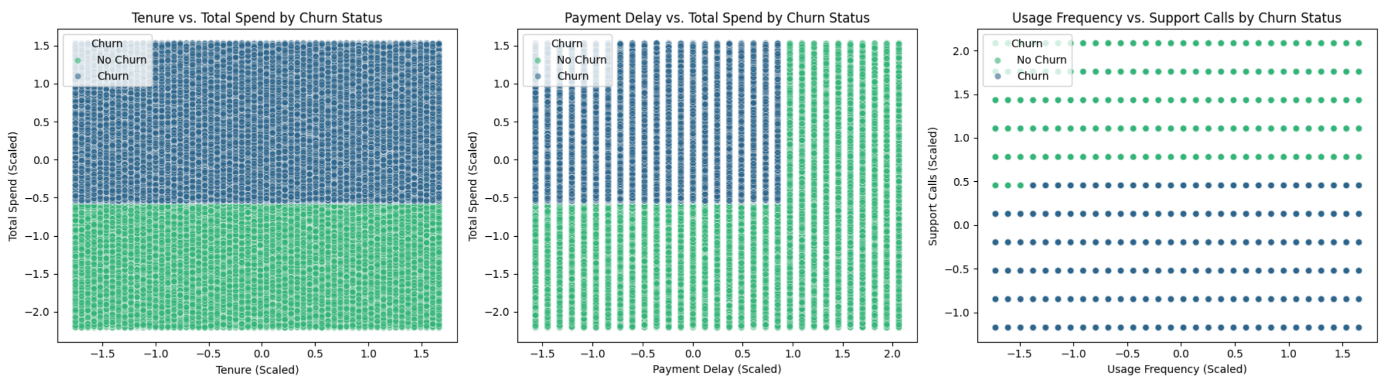
Overall, features like `Tenure`, `Payment Delay`, `Support Calls`, and `Total Spend` show distinct differences in t

```
key_features_for_pairplot = ['Tenure', 'Total Spend', 'Usage Frequency', 'Age', 'Churn']
sns.pairplot(train_df[key_features_for_pairplot], hue='Churn', palette='viridis', diag_kind='kde')
plt.suptitle('Pair Plot of Key Features by Churn Status', y=1.02) # Adjust suptitle position
plt.show()
```



```
**Interpretation of Pair Plots:**
The pair plots provide a matrix of scatter plots for each combination of the selected key numerical features, with
- **Tenure vs. Total Spend**: There's a clear positive correlation, as expected. Customers with higher `Tenure` gen
- **Usage Frequency vs. Tenure/Total Spend**: `Usage Frequency` doesn't show a very strong linear relationship with
- **Age vs. Other Features**: `Age` generally shows a mild positive correlation with `Tenure` and `Total Spend`. Th
- **Diagonal (KDE Plots)**: The diagonal plots show the density distribution for each feature, separated by churn s

Overall, the pair plots confirm that `Tenure` and `Total Spend` are important indicators, with lower values in both
```

```python
plt.figure(figsize=(18, 5))

# Scatter Plot 1: Tenure vs. Total Spend
plt.subplot(1, 3, 1)
sns.scatterplot(x='Tenure', y='Total Spend', hue='Churn', data=train_df, palette='viridis', alpha=0.6)
plt.title('Tenure vs. Total Spend by Churn Status')
plt.xlabel('Tenure (Scaled)')
plt.ylabel('Total Spend (Scaled)')
plt.legend(title='Churn', loc='upper left', labels=['No Churn', 'Churn'])

# Scatter Plot 2: Payment Delay vs. Total Spend
plt.subplot(1, 3, 2)
sns.scatterplot(x='Payment Delay', y='Total Spend', hue='Churn', data=train_df, palette='viridis', alpha=0.6)
plt.title('Payment Delay vs. Total Spend by Churn Status')
plt.xlabel('Payment Delay (Scaled)')
plt.ylabel('Total Spend (Scaled)')
plt.legend(title='Churn', loc='upper left', labels=['No Churn', 'Churn'])

# Scatter Plot 3: Usage Frequency vs. Support Calls
plt.subplot(1, 3, 3)
sns.scatterplot(x='Usage Frequency', y='Support Calls', hue='Churn', data=train_df, palette='viridis', alpha=0.
plt.title('Usage Frequency vs. Support Calls by Churn Status')
plt.xlabel('Usage Frequency (Scaled)')
plt.ylabel('Support Calls (Scaled)')
plt.legend(title='Churn', loc='upper left', labels=['No Churn', 'Churn'])

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




```
**Interpretation of Scatter Plots:**
The scatter plots provide a more detailed view of the relationships between specific pairs of features, colored by
- **Tenure vs. Total Spend by Churn Status**: This plot clearly shows a region where most churned customers (orange
- **Payment Delay vs. Total Spend by Churn Status**: Churned customers tend to have higher `Payment Delay` values,
- **Usage Frequency vs. Support Calls by Churn Status**: This plot is interesting because both features are positiv
```

These scatter plots highlight specific customer segments that are more prone to churn and provide visual evidence f

```
from sklearn.linear_model import LinearRegression

# Select 'Tenure' as the key numerical predictor
X_simple_lr_train = X_train[['Tenure']]
X_simple_lr_val = X_val[['Tenure']]

# Instantiate LinearRegression model
linear_model = LinearRegression()

# Train the model
linear_model.fit(X_simple_lr_train, y_train)

print("Linear Regression model trained successfully with 'Tenure' as the predictor.")
print(f"Model coefficients: {linear_model.coef_[0]:.4f}")
print(f"Model intercept: {linear_model.intercept_:.4f}")
```

```
Linear Regression model trained successfully with 'Tenure' as the predictor.
Model coefficients: -0.0257
Model intercept: 0.5668
```

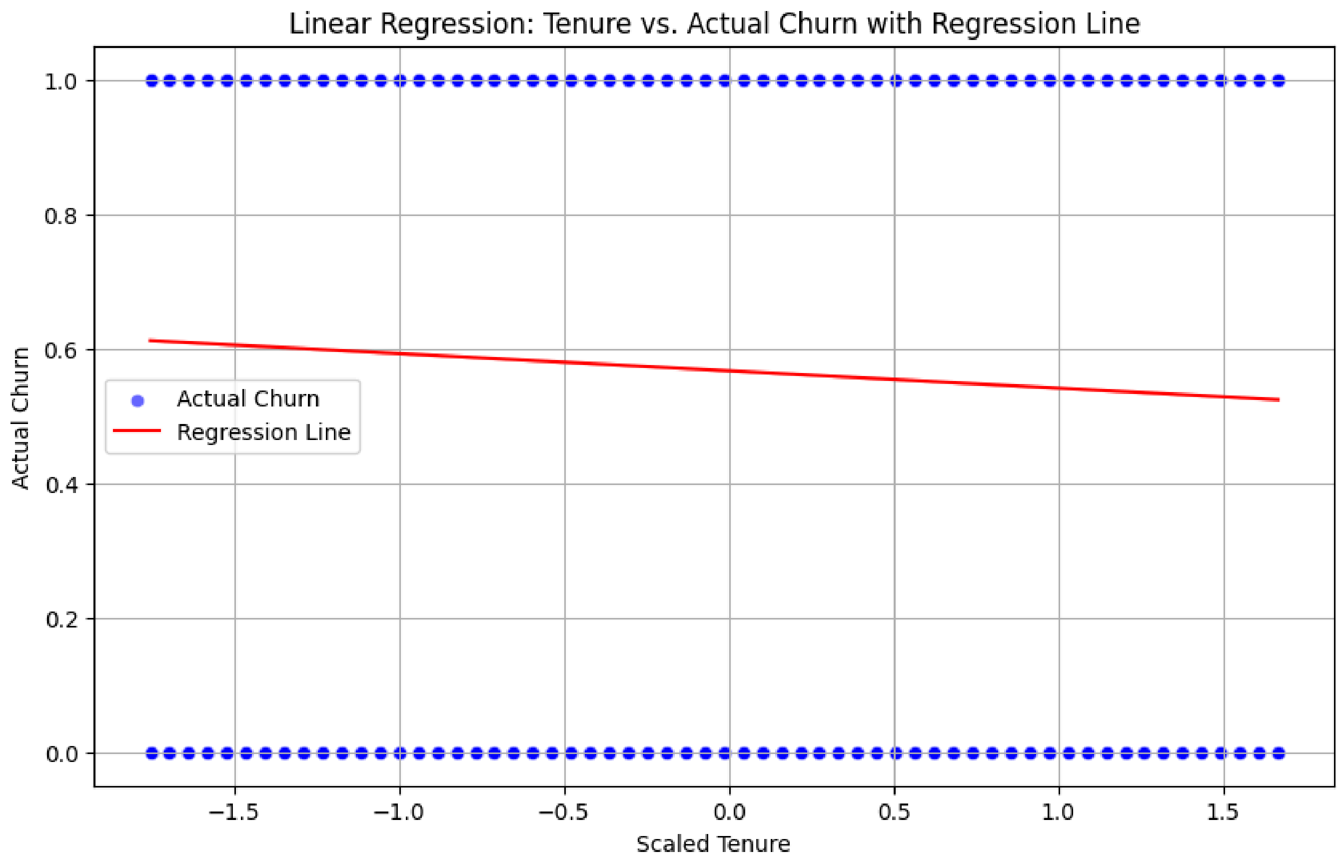
```
X_test_lr = test_df[['Tenure']]

# Generate predictions on the validation set
y_val_pred_lr = linear_model.predict(X_simple_lr_val)

# Generate predictions on the test set
y_test_pred_lr = linear_model.predict(X_test_lr)

print("Predictions generated for validation and test sets.")
```

```
Predictions generated for validation and test sets.
```

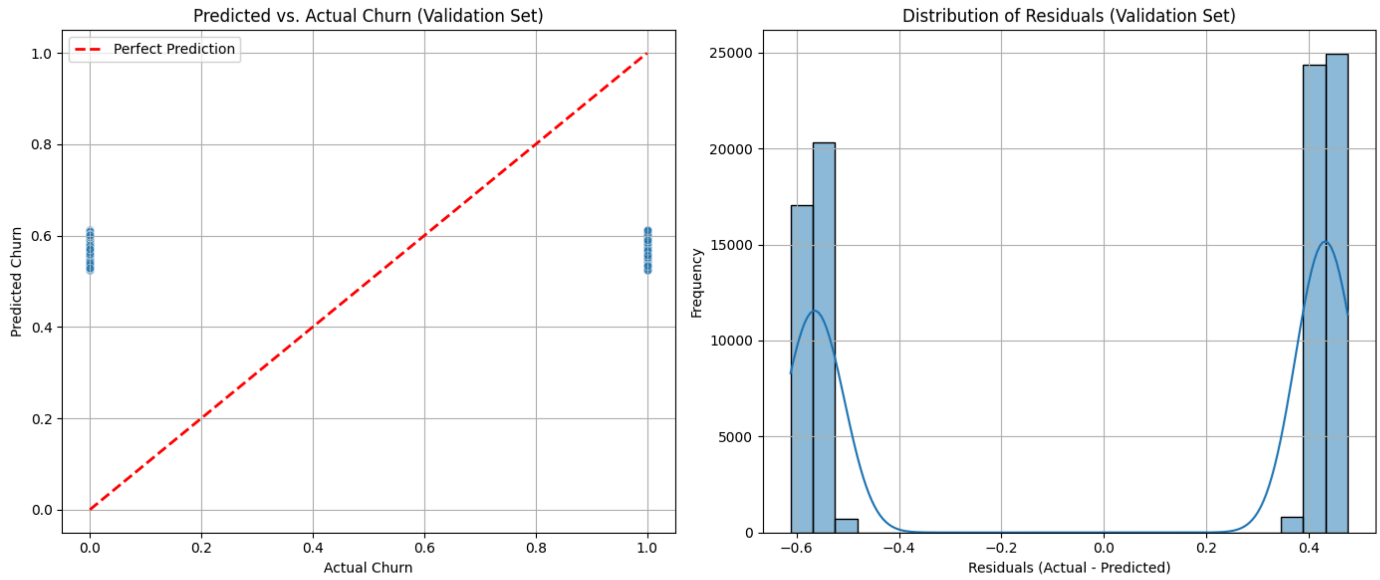
```
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error

# Extract 'Churn' target from test_df for evaluation
y_test = test_df['Churn']

# Evaluate on Validation Set
r2_val = r2_score(y_val, y_val_pred_lr)
mae_val = mean_absolute_error(y_val, y_val_pred_lr)
mse_val = mean_squared_error(y_val, y_val_pred_lr)

print("Validation Set Evaluation:")
print(f"  R-squared: {r2_val:.4f}")
print(f"  Mean Absolute Error (MAE): {mae_val:.4f}")
print(f"  Mean Squared Error (MSE): {mse_val:.4f}")

# Evaluate on Test Set
r2_test = r2_score(y_test, y_test_pred_lr)
mae_test = mean_absolute_error(y_test, y_test_pred_lr)
mse_test = mean_squared_error(y_test, y_test_pred_lr)

print("\nTest Set Evaluation:")
print(f"  R-squared: {r2_test:.4f}")
print(f"  Mean Absolute Error (MAE): {mae_test:.4f}")
print(f"  Mean Squared Error (MSE): {mse_test:.4f}")
```

```
Validation Set Evaluation:
  R-squared: 0.0028
  Mean Absolute Error (MAE): 0.4895
  Mean Squared Error (MSE): 0.2447

Test Set Evaluation:
  R-squared: -0.0565
  Mean Absolute Error (MAE): 0.5084
  Mean Squared Error (MSE): 0.2634
```

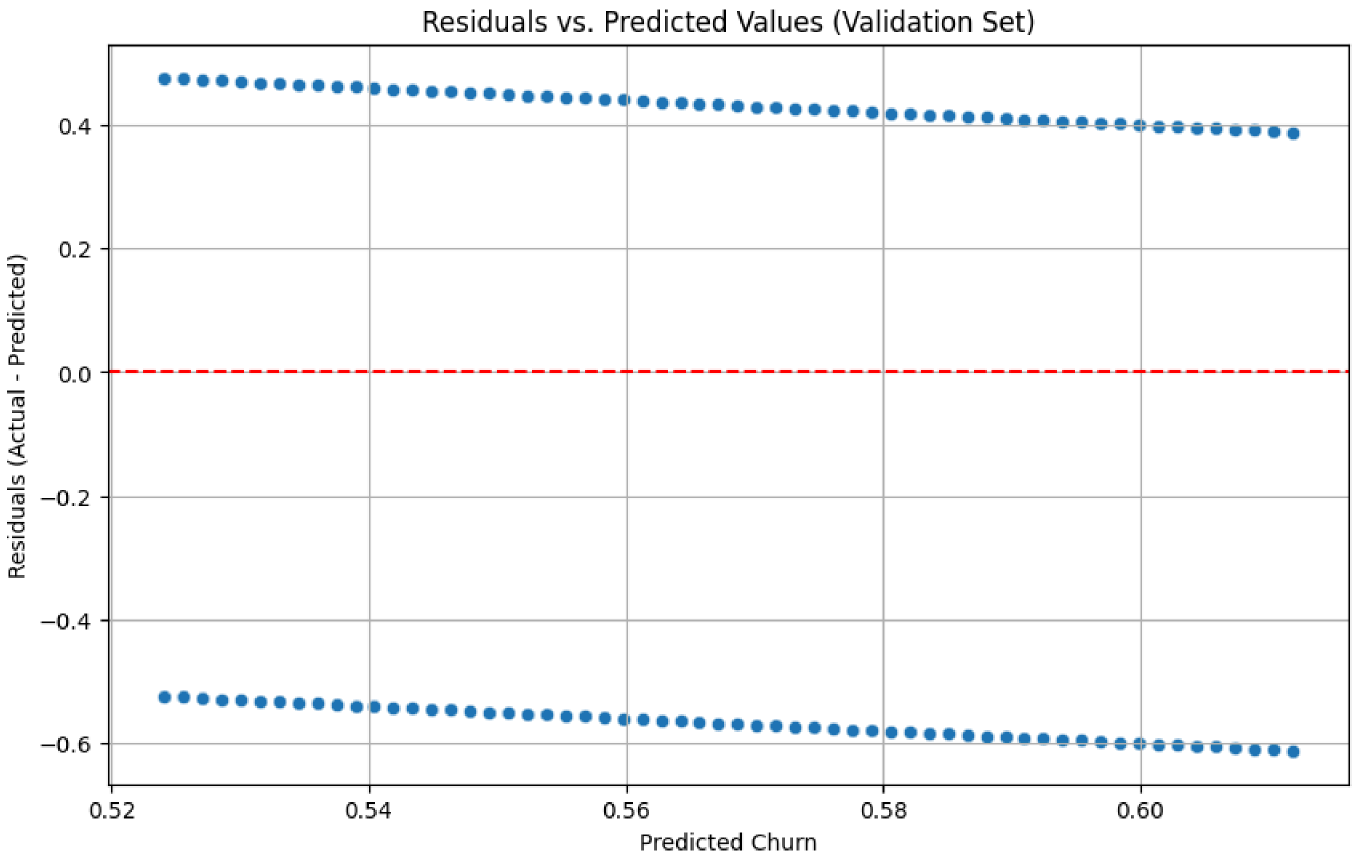
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x=X_simple_lr_val['Tenure'], y=y_val, label='Actual Churn', color='blue', alpha=0.6)
sns.lineplot(x=X_simple_lr_val['Tenure'], y=y_val_pred_lr, color='red', label='Regression Line')
plt.title('Linear Regression: Tenure vs. Actual Churn with Regression Line')
plt.xlabel('Scaled Tenure')
plt.ylabel('Actual Churn')
plt.legend()
plt.grid(True)
plt.show()
```




```
plt.figure(figsize=(14, 6))

# Predicted vs Actual Churn values
plt.subplot(1, 2, 1)
sns.scatterplot(x=y_val, y=y_val_pred_lr, alpha=0.6)
plt.plot([y_val.min(), y_val.max()], [y_val.min(), y_val.max()], 'r--', lw=2, label='Perfect Prediction')
plt.title('Predicted vs. Actual Churn (Validation Set)')
plt.xlabel('Actual Churn')
plt.ylabel('Predicted Churn')
plt.legend()
plt.grid(True)

# Distribution of Residuals
residuals = y_val - y_val_pred_lr
plt.subplot(1, 2, 2)
sns.histplot(residuals, kde=True)
plt.title('Distribution of Residuals (Validation Set)')
plt.xlabel('Residuals (Actual - Predicted)')
plt.ylabel('Frequency')
plt.grid(True)

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

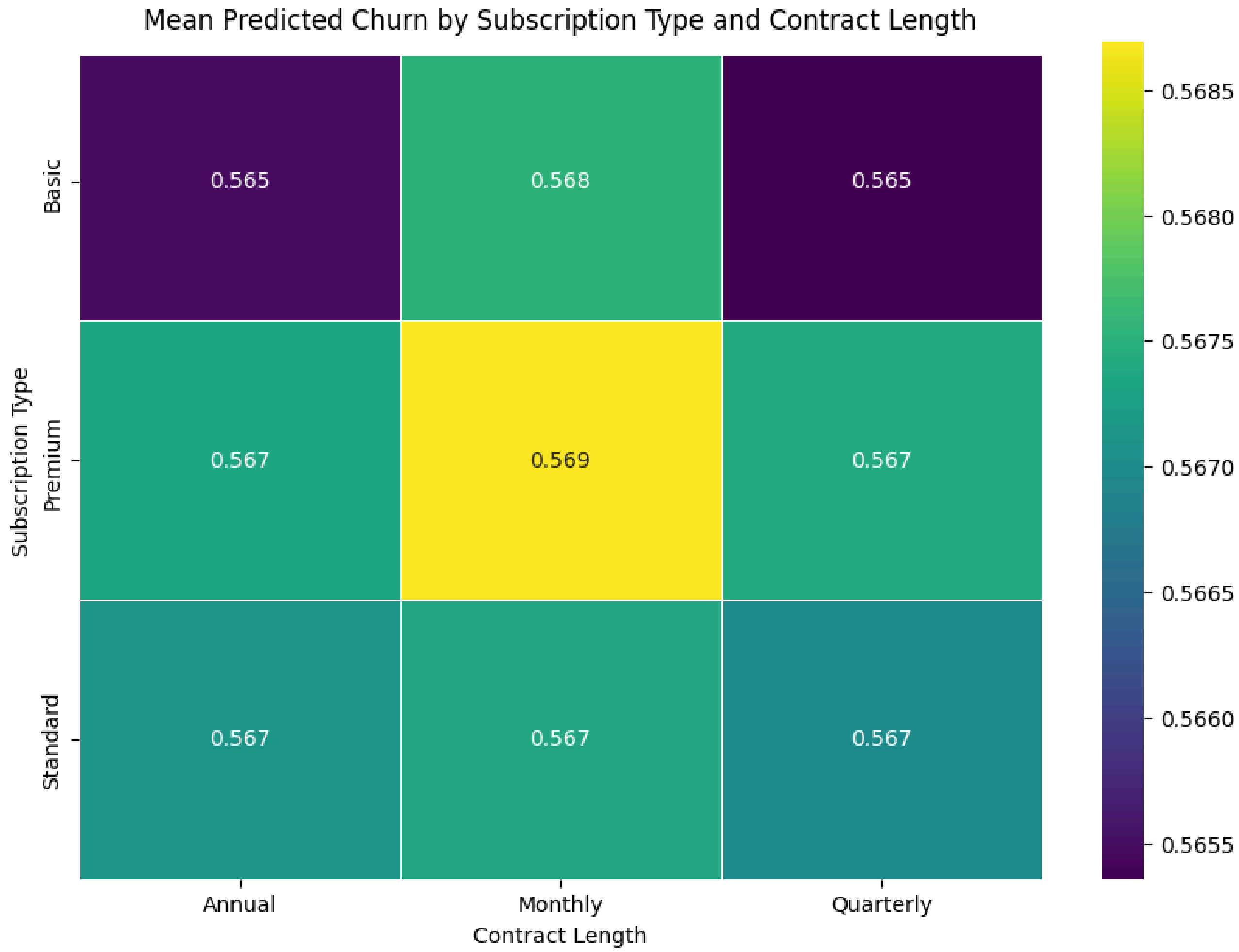



```python
plt.figure(figsize=(10, 6))
sns.scatterplot(x=y_val_pred_lr, y=residuals, alpha=0.6)
plt.axhline(y=0, color='r', linestyle='--')
plt.title('Residuals vs. Predicted Values (Validation Set)')
plt.xlabel('Predicted Churn')
plt.ylabel('Residuals (Actual - Predicted)')
plt.grid(True)
plt.show()
```




```python
def reconstruct_categorical(df, prefix):
    cols = [col for col in df.columns if col.startswith(prefix)]
```

```
        if cols:
            # Find the column that is True (1) for each row and extract its suffix
            return df[cols].idxmax(axis=1).apply(lambda x: x.split('_')[1])
        return None

    # Create a temporary DataFrame for validation set analysis
    val_analysis_df = X_val.copy()
    val_analysis_df['Predicted_Churn'] = y_val_pred_lr

    # Reconstruct original categorical columns for grouping
    val_analysis_df['Subscription Type'] = reconstruct_categorical(val_analysis_df, 'Subscription Type_')
    val_analysis_df['Contract Length'] = reconstruct_categorical(val_analysis_df, 'Contract Length_')

    # Create a pivot table to get the mean predicted churn for each group
    heatmap_data = val_analysis_df.pivot_table(index='Subscription Type', columns='Contract Length', values='Predic

    plt.figure(figsize=(10, 7))
    sns.heatmap(heatmap_data, annot=True, cmap='viridis', fmt=".3f", linewidths=.5)
    plt.title('Mean Predicted Churn by Subscription Type and Contract Length')
    plt.ylabel('Subscription Type')
    plt.xlabel('Contract Length')
    plt.show()
```



Interpretation of Simple Linear Regression Model:

The simple linear regression model was trained using 'Tenure' as the sole predictor for 'Churn'.

- **Model Coefficients:** The coefficient for 'Tenure' was approximately **-0.0257**, and the intercept was around **0.5668**.
- **Trend Interpretation:**
  - The negative coefficient for 'Tenure' indicates an inverse relationship between 'Tenure' and 'Churn'. Specifically, for every one-unit increase in `Scaled Tenure`, the predicted 'Churn' probability **decreases by approximately 0.0257**.
  - The intercept of 0.5668 can be interpreted as the predicted churn probability when `Scaled Tenure` is zero. Since 'Churn' is a binary variable (0 or 1), this can be seen as a baseline probability.

  - This trend aligns with our EDA findings, where longer tenure was associated with a lower likelihood of churn. However, given that churn is a binary outcome, a linear regression attempts to fit a straight line through points that are only 0 or 1, which isn't ideal.

- **Implications for Predicting Churn:** The model suggests that `Tenure` is a statistically significant predictor, as its coefficient is non-zero. The negative sign confirms that customers with longer relationships (higher tenure) are less likely to churn. However, the magnitude of the coefficient (-0.0257) is relatively small, suggesting that `Tenure` alone might not be a very strong predictor of individual churn probability in a linear sense. The model will predict continuous values for churn, which then need to be thresholded to get a binary classification. This can lead to issues, as the predicted values can fall outside the meaningful range of 0 to 1.

Limitations of Simple Linear Regression for Binary Classification:

Using a simple linear regression model for a binary classification target like 'Churn' (0 for no churn, 1 for churn) comes with several inherent limitations, which are clearly reflected in the evaluation metrics:

- **Non-binary Predictions:** Linear regression models predict continuous numerical values. When applied to a binary target, the model can output predictions outside the meaningful range of [0, 1]. For example, the model might predict a 'churn probability' of -0.2 or 1.3, which are nonsensical in the context of probability. To convert these to a binary outcome, a threshold must be applied, which is an additional step not inherently handled by the model.
- **Assumptions Violation:** Linear regression assumes a linear relationship between the independent and dependent variables, and that the residuals are normally distributed with constant variance (homoscedasticity). For a binary dependent variable, these assumptions are almost always violated. The relationship is inherently non-linear (an S-curve for probabilities), and the residuals will not be normally distributed or homoscedastic (they will concentrate at 0 and 1).
- **Poor Performance Metrics:**
  - **Low R-squared (0.0028 for validation, -0.0565 for test):** R-squared measures the proportion of variance in the dependent variable that is predictable from the independent variable(s). A very low or negative R-squared value, as observed here, indicates that 'Tenure' explains almost none of the variability in 'Churn'. A negative R-squared suggests that the model performs worse than simply predicting the mean of the dependent variable.
  - **High Mean Absolute Error (MAE) and Mean Squared Error (MSE):** While MAE (0.4895 validation, 0.5084 test) and MSE (0.2447 validation, 0.2634 test) provide a sense of prediction error, their interpretation is less straightforward for a binary target. An MAE of ~0.5 indicates that, on average, the model's predictions are about 0.5 units away from the true binary labels. Given the target is 0 or 1, this means predictions are often quite far off.
- **Difficulty in Interpretation:** While the coefficient indicates a negative trend, interpreting the output as a 'probability' is inaccurate due to the continuous nature of the predictions and the violated assumptions. The model struggles to differentiate between the two classes effectively, often predicting values around the mean churn rate, as observed in the scatter plot of actual vs. predicted churn values.