Exploratory Data Analysis (EDA)

Understanding Customer Behaviour and Churn

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What is EDA?

- EDA helps uncover **patterns**, **relationships**, and **trends** in the data.
- Critical for understanding which **features** influence customer churn.
- Sets the **foundation** for building predictive models.

1. Load and Explore the Dataset

We begin by loading the dataset to get an initial understanding of its structure and the nature of the data.

- Inspect the data to understand its structure, types, and completeness.
- Summarize key statistics of the dataset (mean, median, missing values).

1. Load and Explore the Dataset

```python
# Load the dataset
import pandas as pd
data = pd.read_csv('Customer Churn.csv')
data.head()
```

	Call Failure	Complains	Subscription Length	Charge Amount	Seconds of Use	Frequency of use	Frequency of SMS	Distinct Called Numbers	Age Group	Tariff Plan	Status	Age	Customer Value	Churn
0	8	0	38	0	4370	71	5	17	3	1	1	30	197.640	0
1	0	0	39	0	318	5	7	4	2	1	2	25	46.035	0
2	10	0	37	0	2453	60	359	24	3	1	1	30	1536.520	0
3	10	0	38	0	4198	66	1	35	1	1	1	15	240.020	0
4	3	0	38	0	2393	58	2	33	1	1	1	15	145.805	0

1. Load and Explore the Dataset

- The dataset contains **3150** rows and **14** columns.
- No missing values.
- Most columns are **integers** except for Customer Value, is a float.
- The **Churn** column is the **target** variable for **prediction**.

```
data.info()  # Check for data types and missing values
data.describe()  # Summary statistics
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3150 entries, 0 to 3149
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Call  Failure            3150 non-null   int64
 1   Complains                3150 non-null   int64
 2   Subscription  Length     3150 non-null   int64
 3   Charge  Amount           3150 non-null   int64
 4   Seconds of Use           3150 non-null   int64
 5   Frequency of use         3150 non-null   int64
 6   Frequency of SMS         3150 non-null   int64
 7   Distinct Called Numbers  3150 non-null   int64
 8   Age Group                3150 non-null   int64
 9   Tariff Plan              3150 non-null   int64
 10  Status                   3150 non-null   int64
 11  Age                      3150 non-null   int64
 12  Customer Value           3150 non-null   float64
 13  Churn                    3150 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 344.7 KB
```

1. Load and Explore the Dataset

	Call Failure	Complains	Subscription Length	Charge Amount	Seconds of Use	Frequency of use	Frequency of SMS	Distinct Called Numbers	Age Group
count	3150.000000	3150.000000	3150.000000	3150.000000	3150.000000	3150.000000	3150.000000	3150.000000	3150.000000
mean	7.627937	0.076508	32.541905	0.942857	4472.459683	69.460635	73.174921	23.509841	2.826032
std	7.263886	0.265851	8.573482	1.521072	4197.908687	57.413308	112.237560	17.217337	0.892555
min	0.000000	0.000000	3.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.000000
25%	1.000000	0.000000	30.000000	0.000000	1391.250000	27.000000	6.000000	10.000000	2.000000
50%	6.000000	0.000000	35.000000	0.000000	2990.000000	54.000000	21.000000	21.000000	3.000000
75%	12.000000	0.000000	38.000000	1.000000	6478.250000	95.000000	87.000000	34.000000	3.000000
max	36.000000	1.000000	47.000000	10.000000	17090.000000	255.000000	522.000000	97.000000	5.000000

2. Data Cleaning and Preparation

```
# Check for missing values
print("Missing values in each column:\n", data.isnull().sum())

# Check for duplicate rows
duplicate_rows = data.duplicated().sum()
print(f"\nNumber of duplicate rows: {duplicate_rows}")
```

```
Missing values in each column:
 Call  Failure              0
Complains                  0
Subscription  Length       0
Charge  Amount             0
Seconds of Use             0
Frequency of use           0
Frequency of SMS           0
Distinct Called Numbers    0
Age Group                  0
Tariff Plan                0
Status                     0
Age                        0
Customer Value             0
Churn                      0
dtype: int64

Number of duplicate rows: 300
```

- The data has **no missing values** but has **300 duplicate rows**.

2. Data Cleaning and Preparation

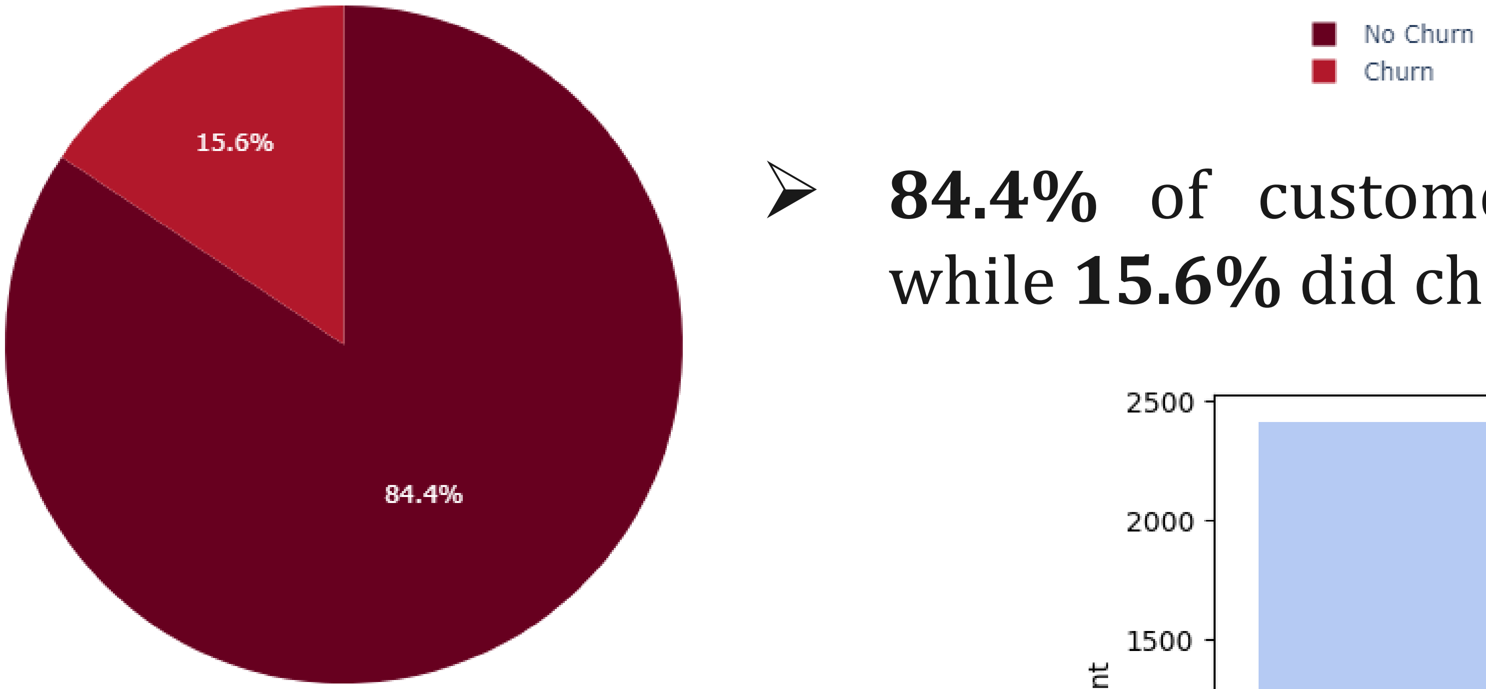
```
# Remove duplicate rows
data_cleaned = data.drop_duplicates()

# Verify that duplicates are removed
print(f'Number of rows after removing duplicates: {data_cleaned.shape[0]}')
```

```
Number of rows after removing duplicates: 2850
```

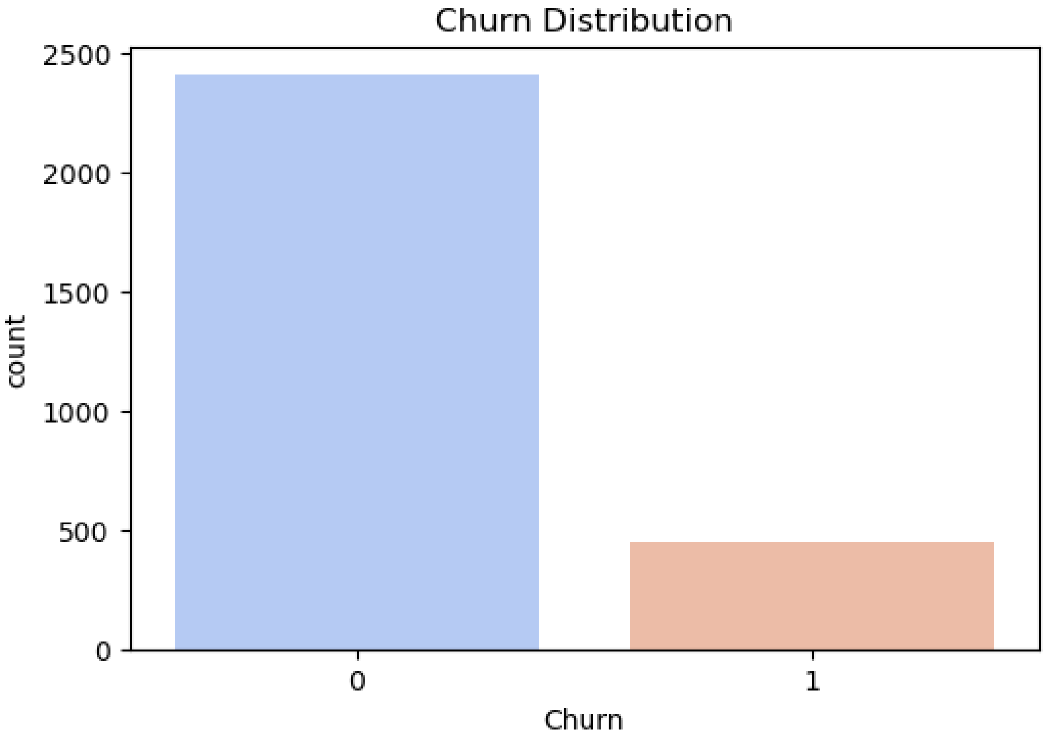
```
# Clean column names (remove extra spaces and strip them)
data_cleaned.columns = data_cleaned.columns.str.replace('  ', ' ').str.strip()

# Confirm cleaned column names
print("Cleaned column names:", data_cleaned.columns)
```

```
Cleaned column names: Index(['Call Failure', 'Complains', 'Subscription Length', 'Charge Amount',
       'Seconds of Use', 'Frequency of use', 'Frequency of SMS',
       'Distinct Called Numbers', 'Age Group', 'Tariff Plan', 'Status', 'Age',
       'Customer Value', 'Churn'],
      dtype='object')
```

Churn Rate Distribution:

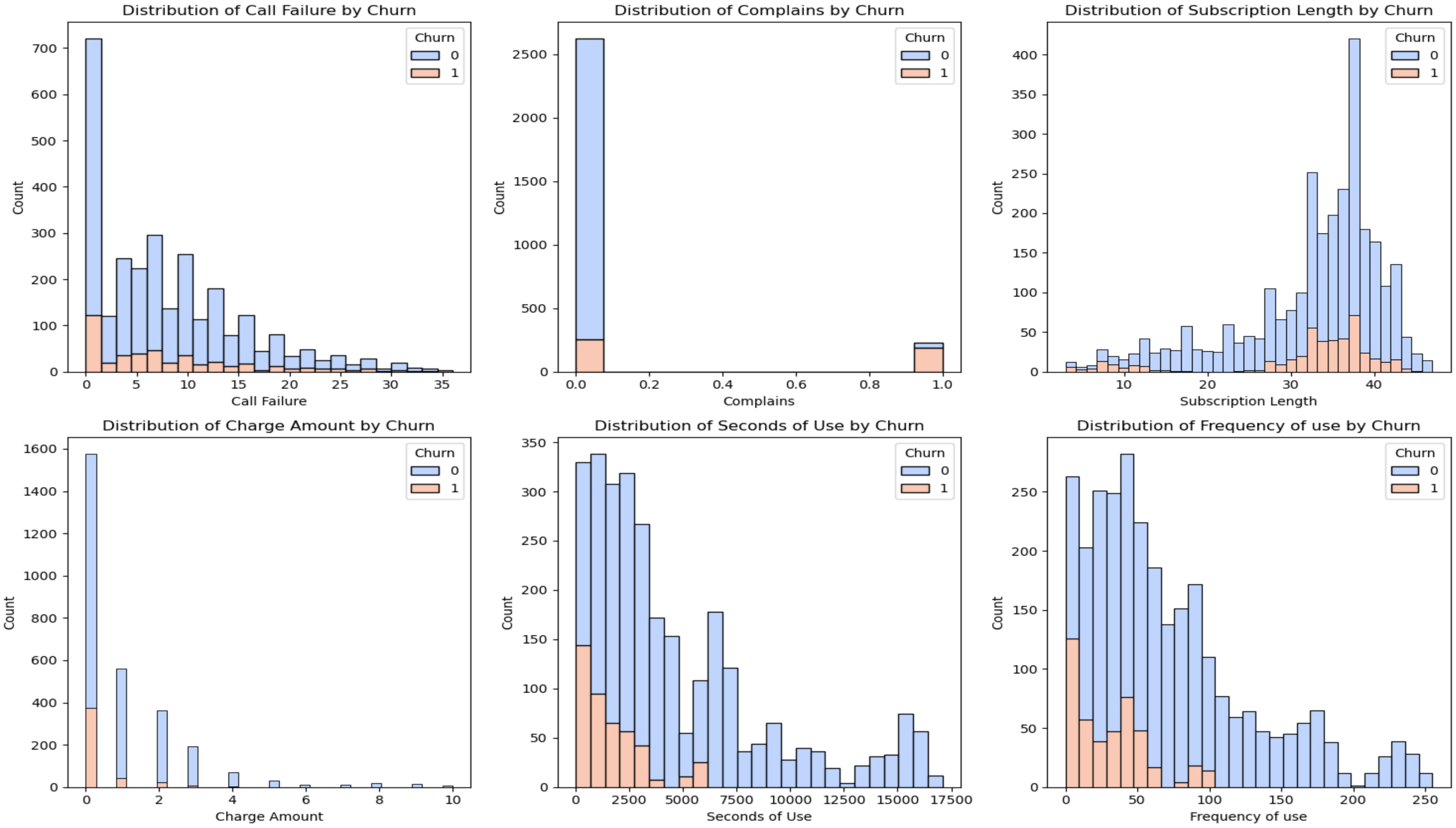


➢ **84.4%** of customers did not churn, while **15.6%** did churn.

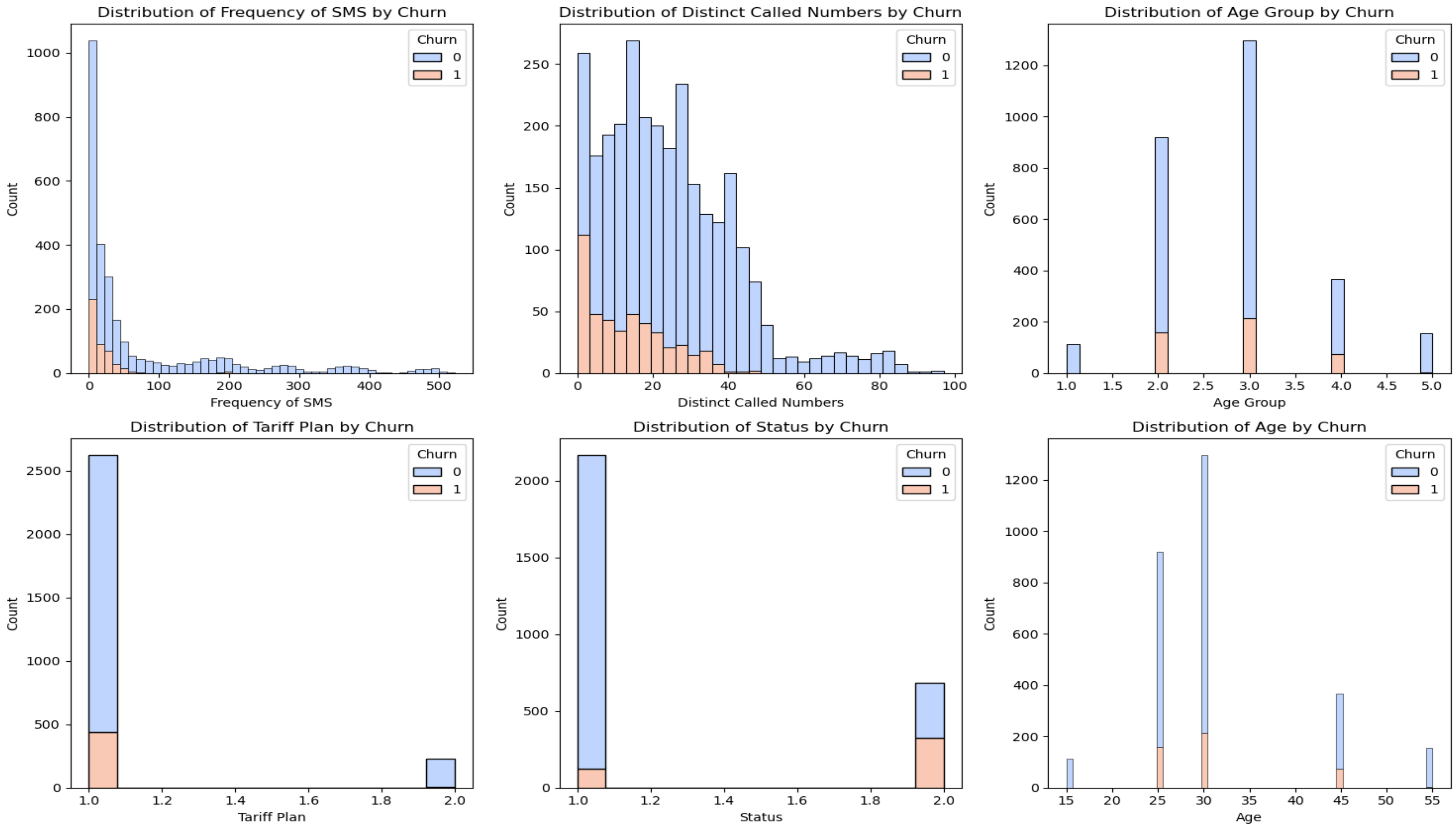


➢ Class **imbalance** observed, which could affect model performance.

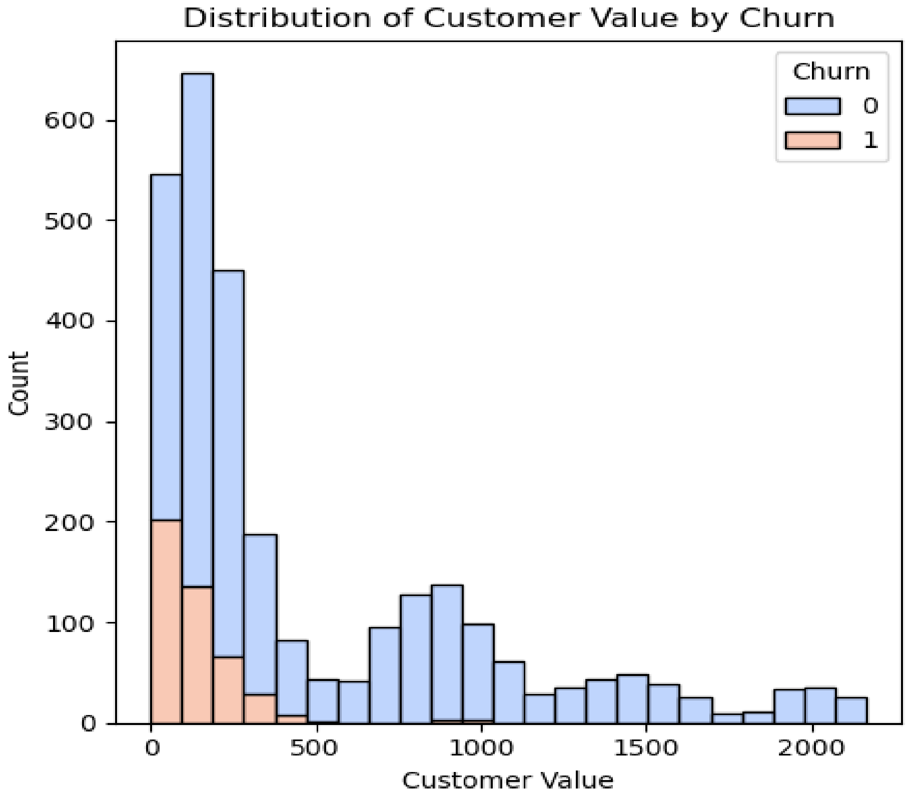
Histograms for Distributions

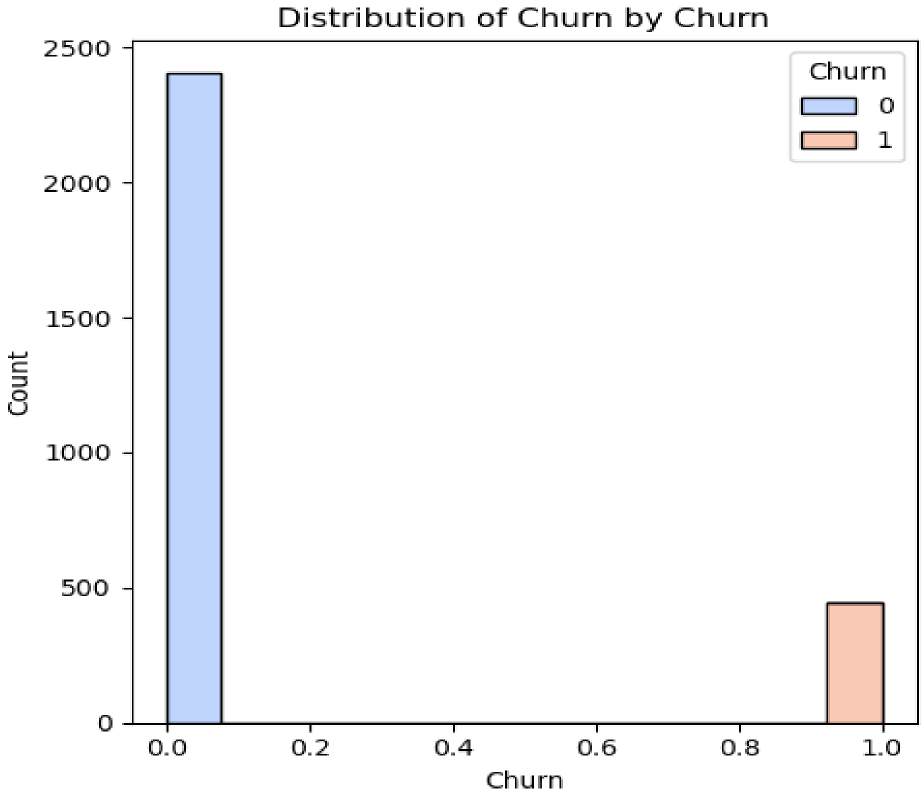


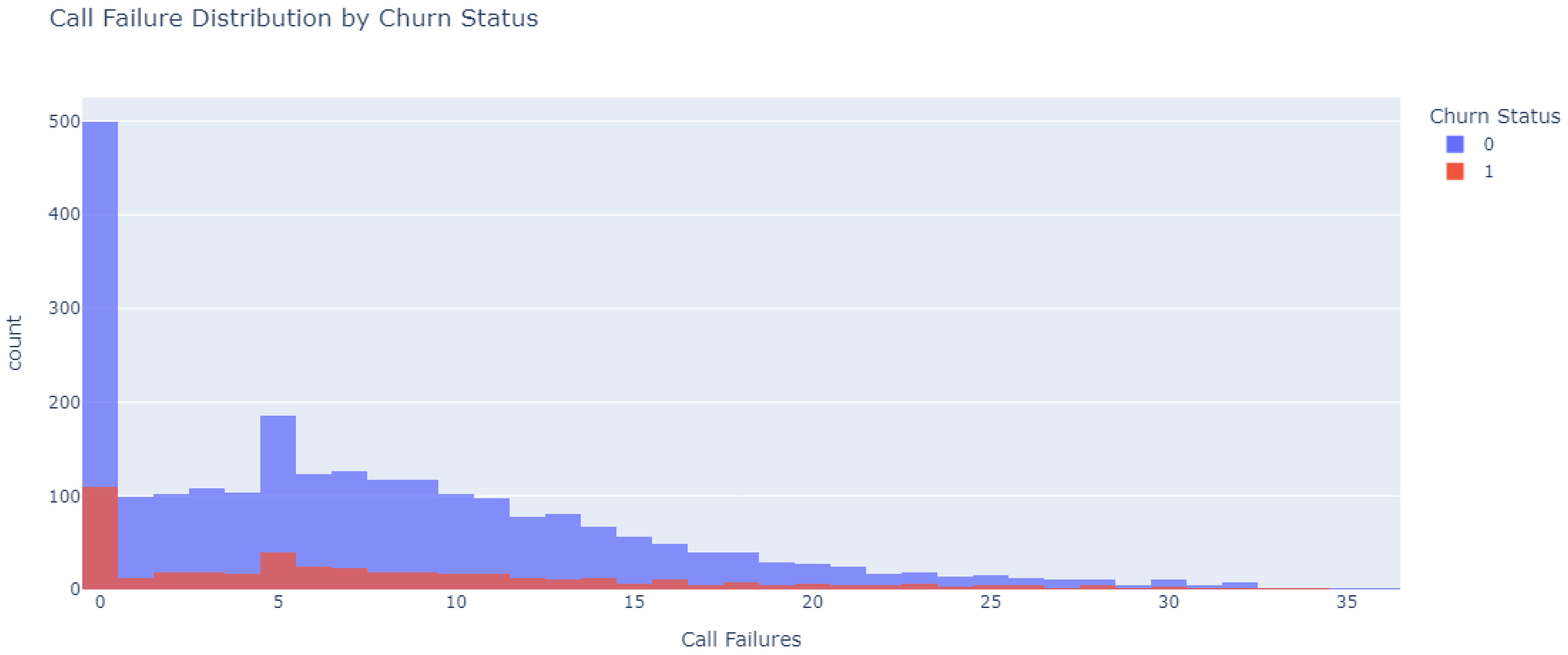
Histograms for Distributions



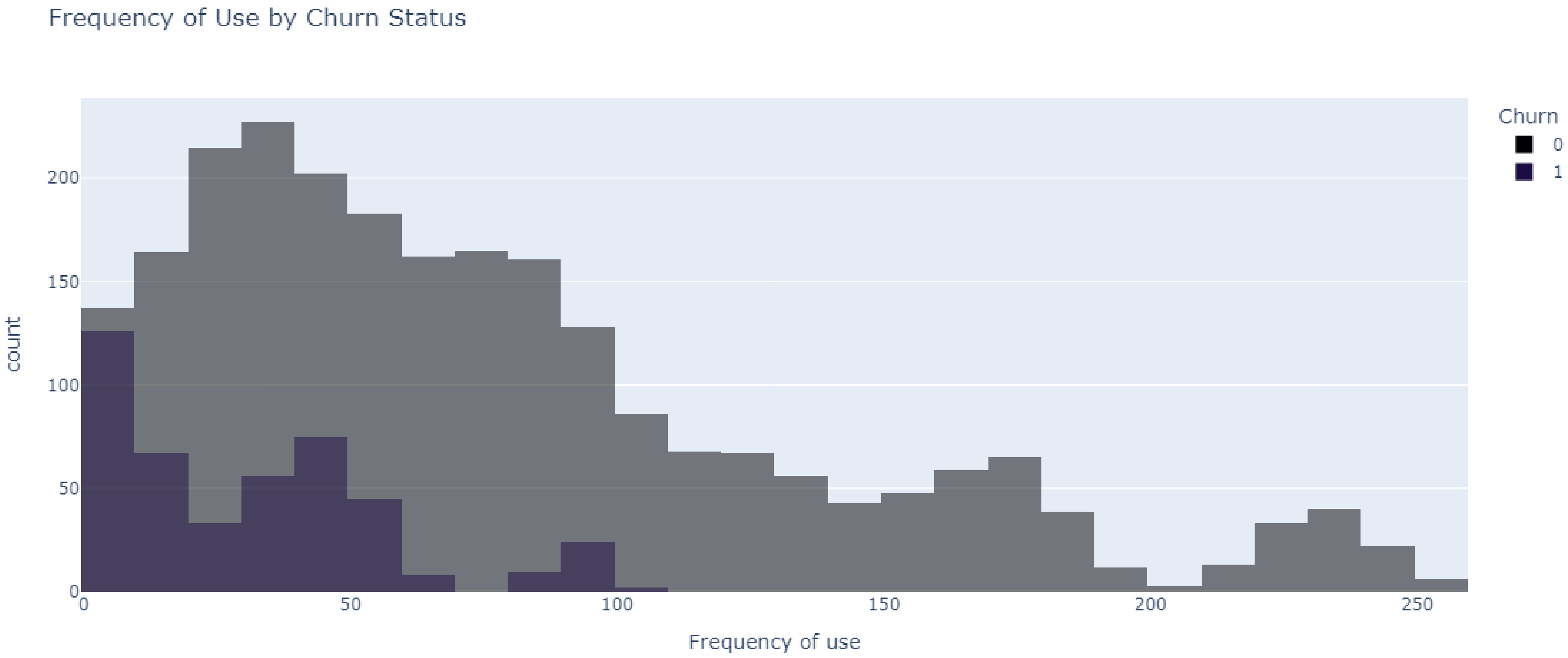
Histograms for Distributions



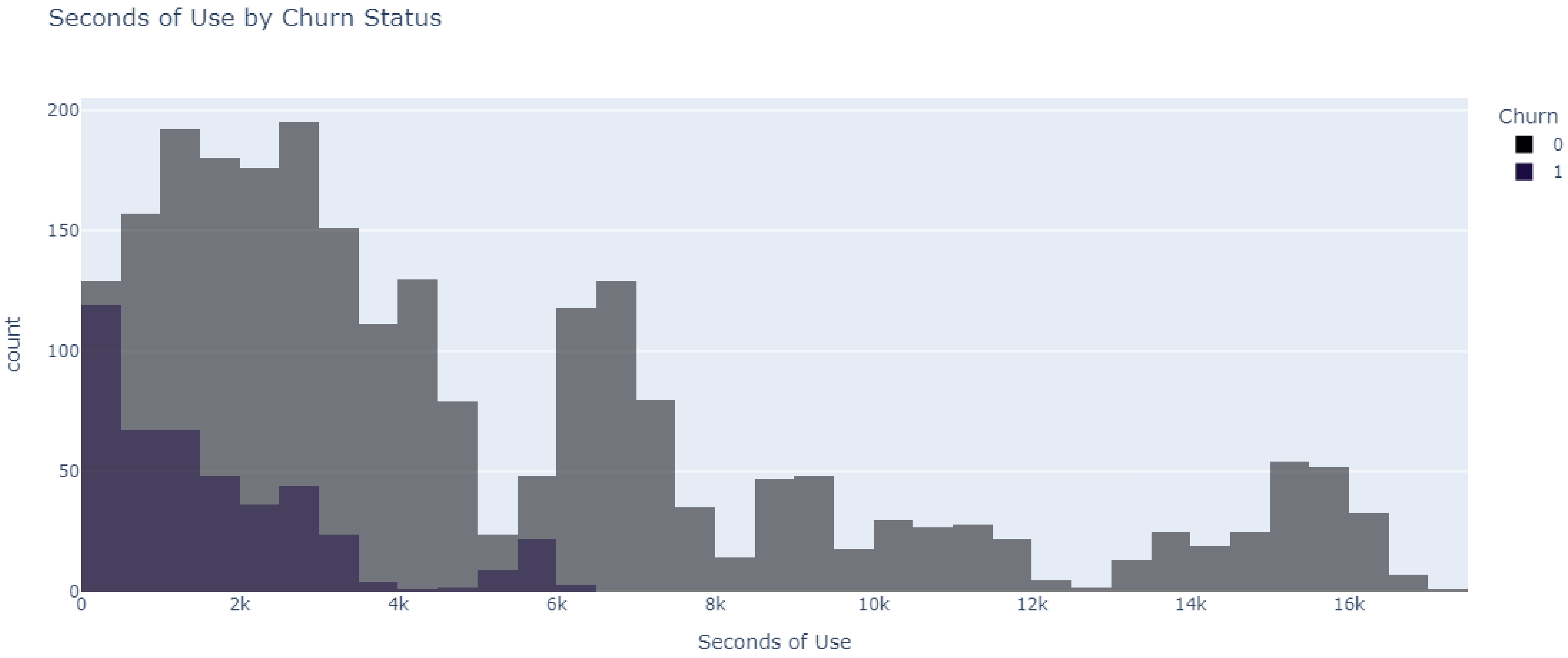




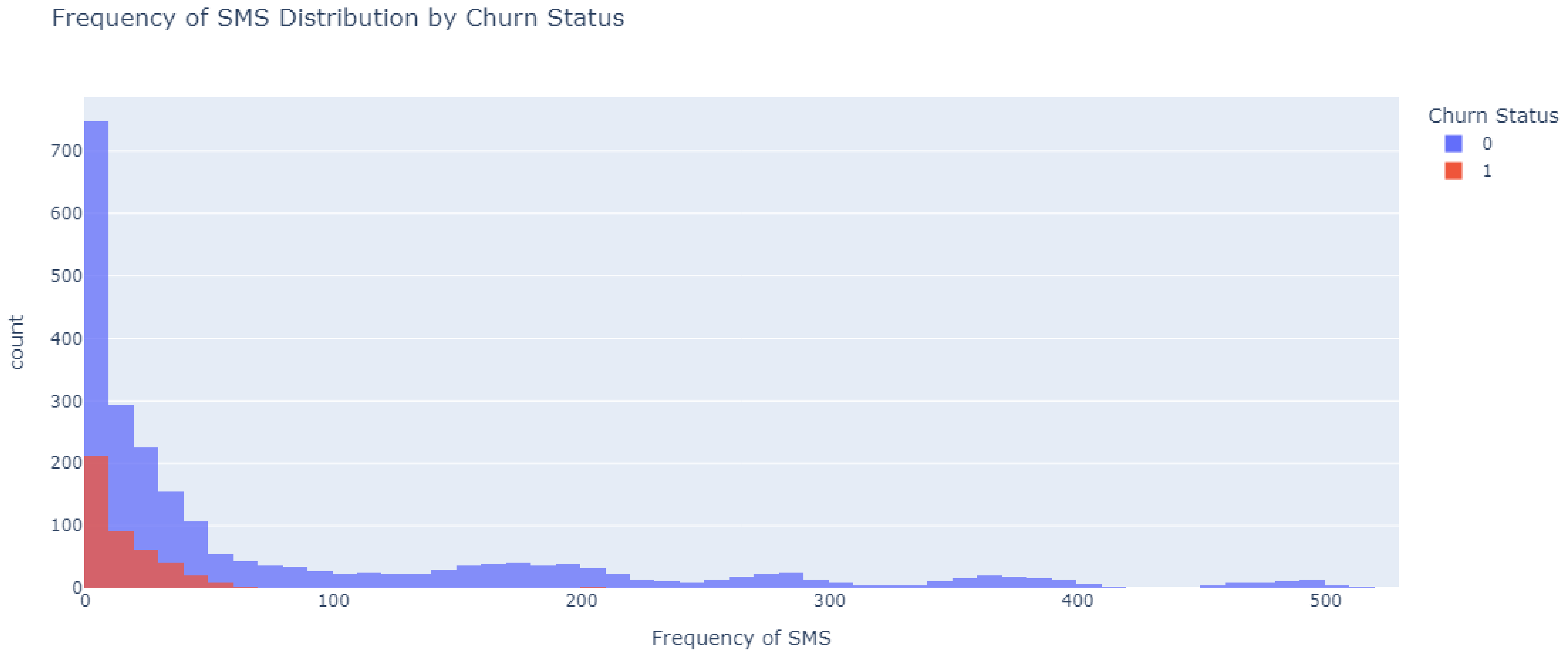
- A higher number of call failures correlates with increased churn rates.



- Customers with *fewer* **service interactions** are more likely to **churn**. *Higher* frequency users are generally **retained**.



- **Churners** generally spend ***less time on the service***. ***Longer engagement*** correlates with **retention**.



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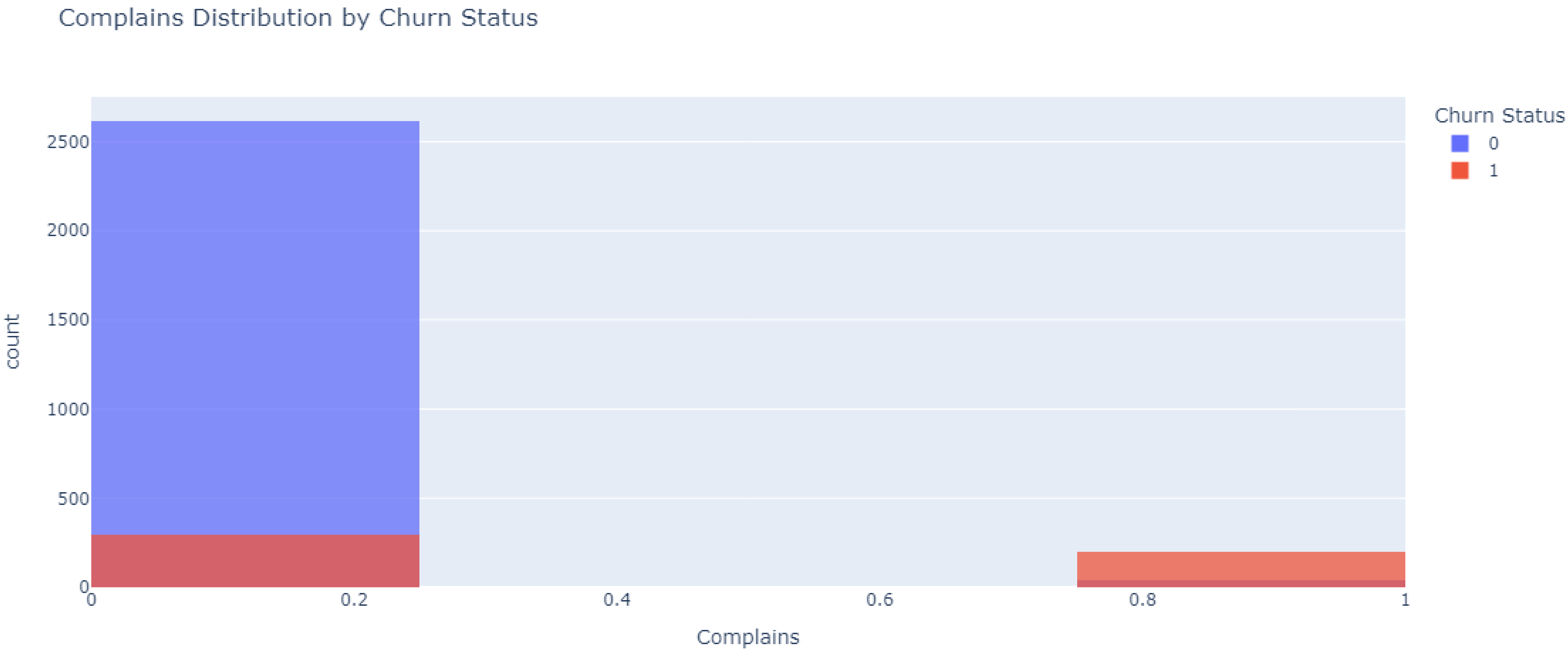
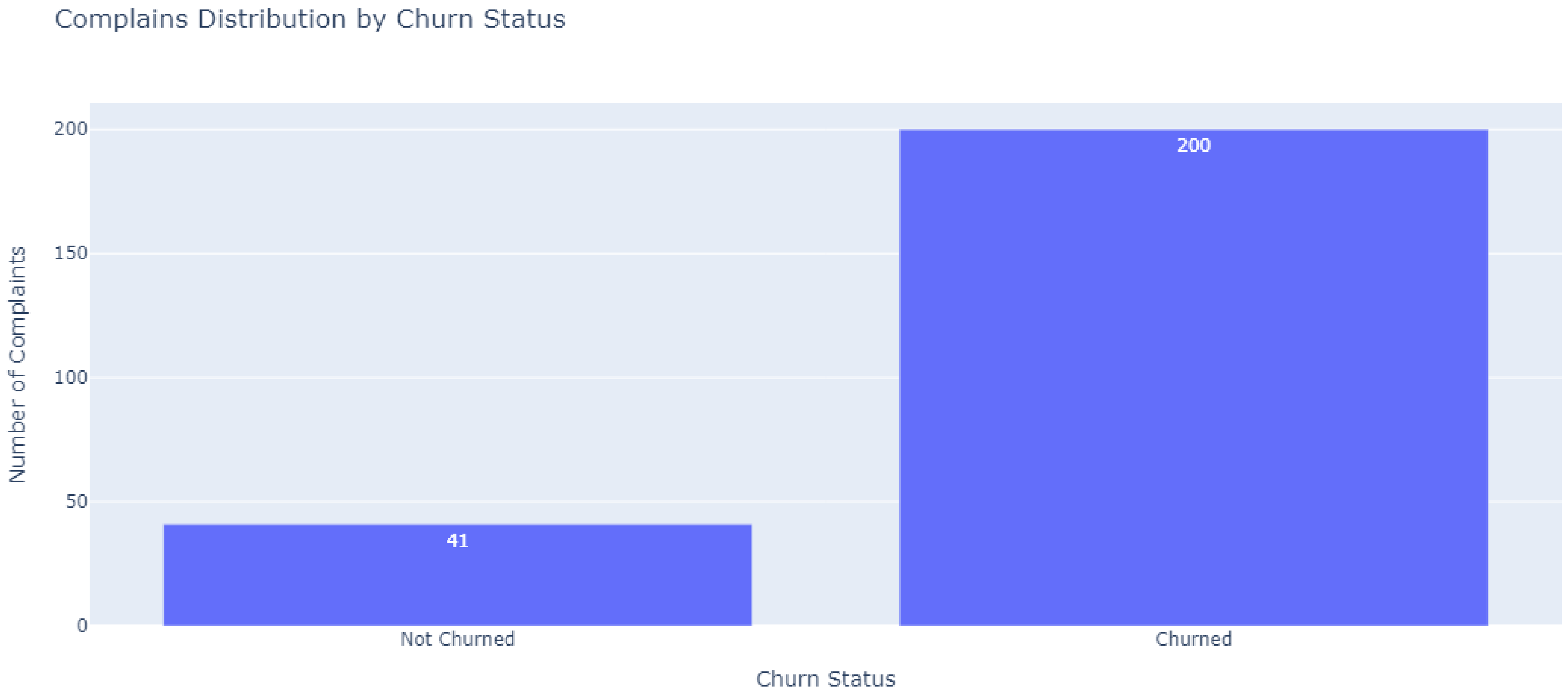
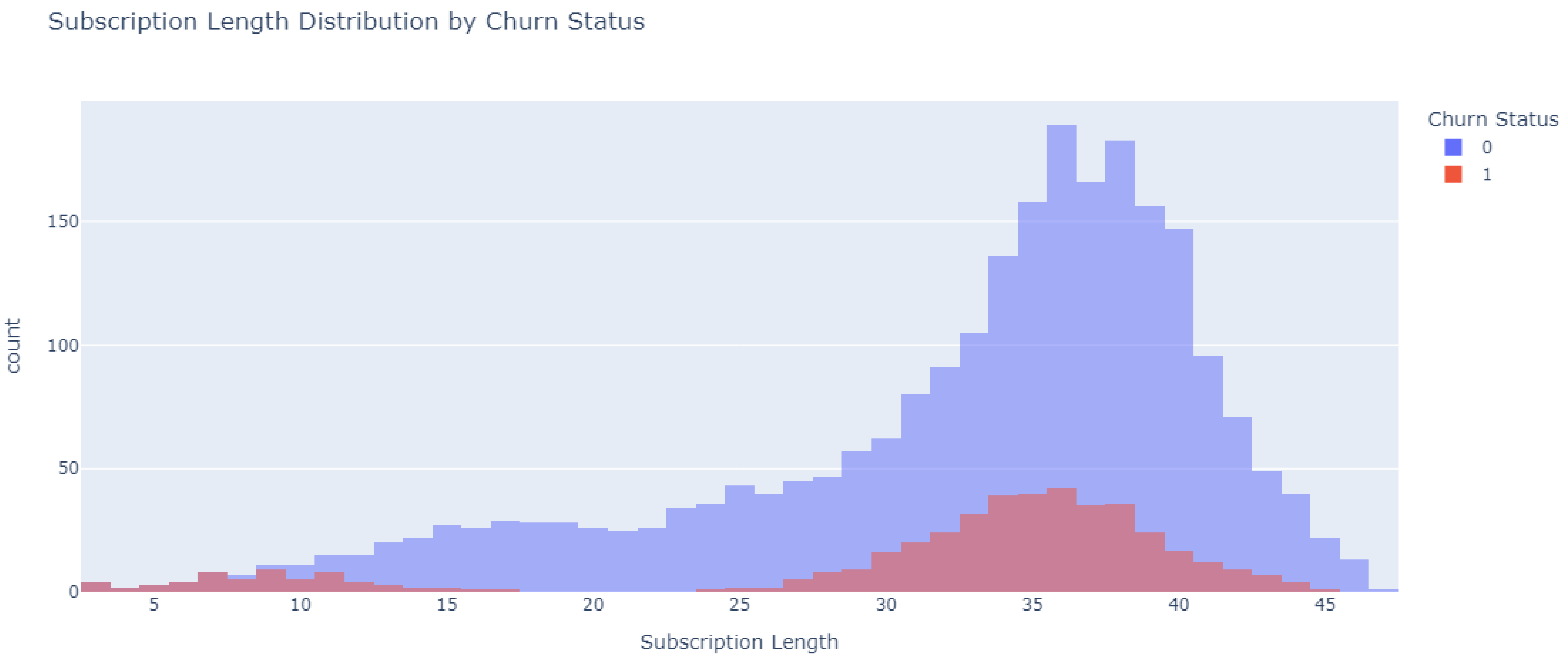


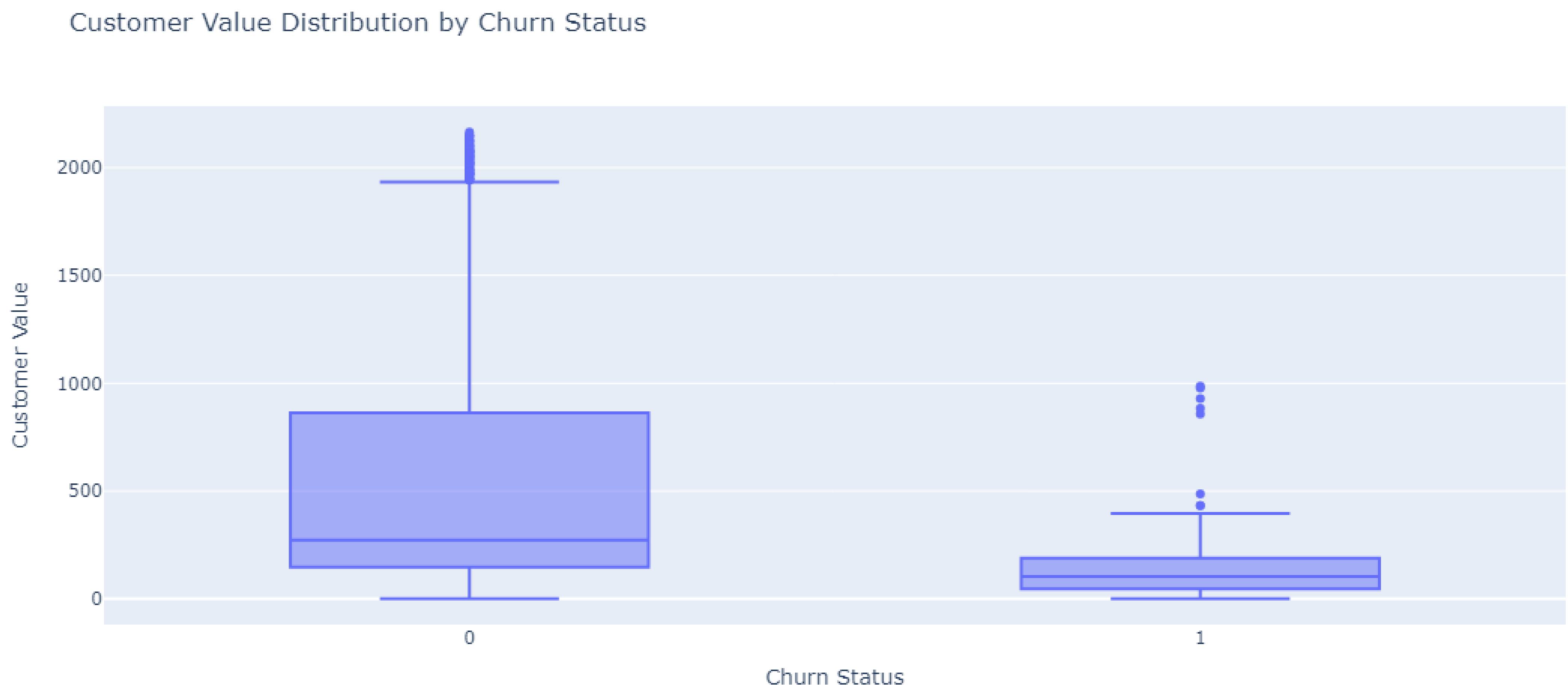
- Customers who register more complaints are more likely to churn.



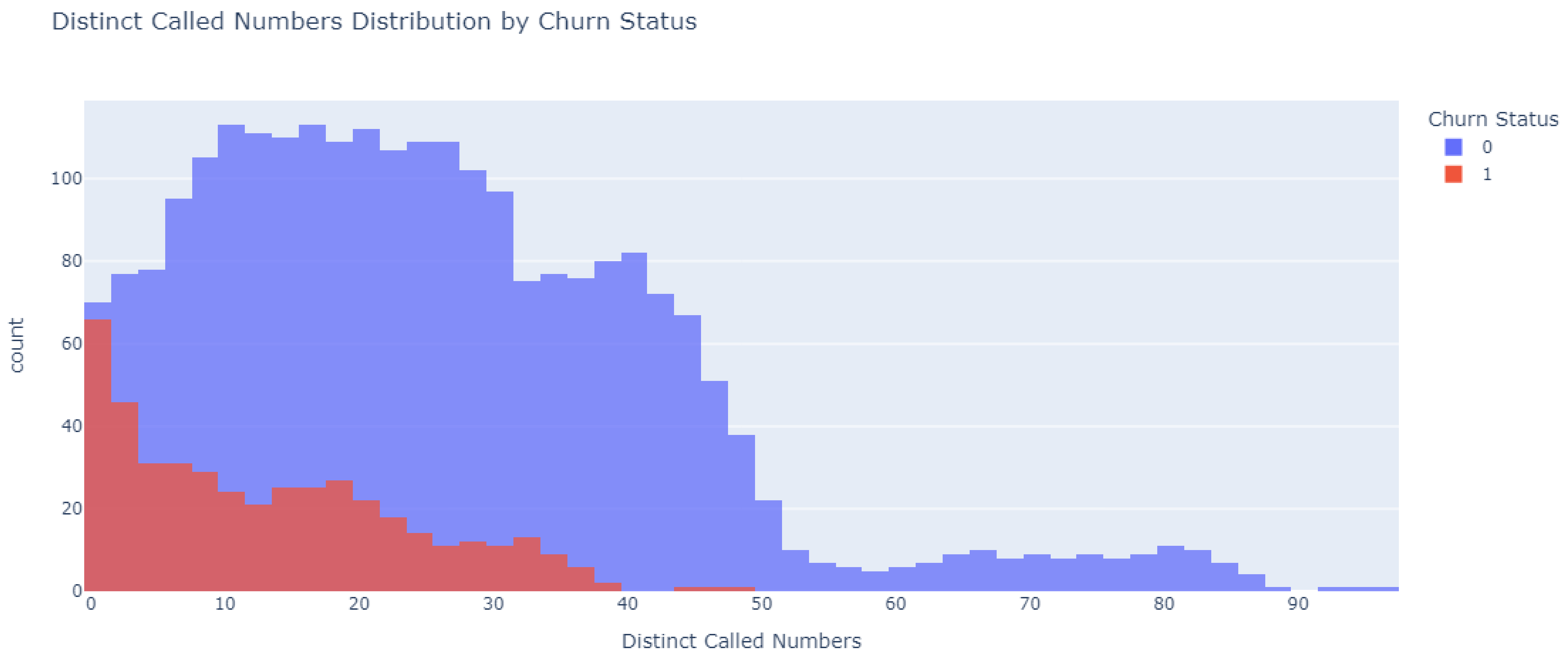
- Customers who register more complaints are more likely to churn.



- Longer subscription lengths are associated with lower churn rates.



➢ Non-churned customers have a higher overall customer value distribution compared to churned customers.



- Customers who engage with a broader range of contacts are less likely to churn.

Interactive Dashboard Using Plotly

This Dashboard visually highlights key metrics differentiating churned (in yellow) and non-churned (in blue) customers.

Summary of Findings

- Strong correlation between **usage frequency** and **churn** likelihood. ***Low engagement*** (frequency/seconds of use) *strongly correlates* with **churn**.
- EDA provided **actionable insights** for the predictive model.
- Insights were used to guide **key recommendations**.