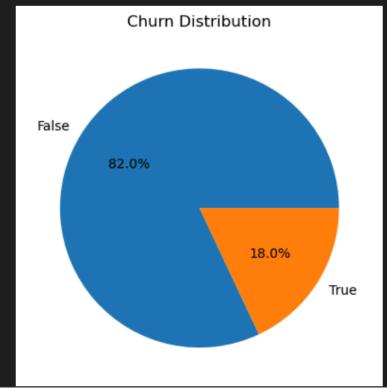
#### **DESCRIPTION OF CLEANED DATA**

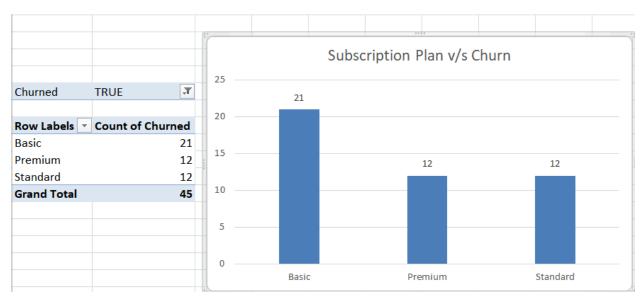
```
df.info()
✓ 0.3s
                                                                      Python
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250 entries, 0 to 249
Data columns (total 11 columns):
    Column
                      Non-Null Count Dtype
0
   CustomerID
                    250 non-null object
1 Date
                     250 non-null object
2
   SubscriptionPlan 250 non-null object
3 AgeGroup
                    250 non-null object
4 Login_x
                    250 non-null int64
5 WatchTimeMinutes x 250 non-null int64
6
   ContentPreference 250 non-null object
                    250 non-null bool
7 Churned
                    45 non-null
8
   ChurnDate
                                   object
9 TotalLogin
                    250 non-null int64
10 TotalWatchTime 250 non-null
                                    int64
dtypes: bool(1), int64(4), object(6)
memory usage: 19.9+ KB
```

| <b>df.</b><br>✓ 0.1s | describe() |                    |            |                |
|----------------------|------------|--------------------|------------|----------------|
|                      | Login_x    | WatchTimeMinutes_x | TotalLogin | TotalWatchTime |
| count                | 250.000000 | 250.000000         | 250.000000 | 250.000000     |
| mean                 | 0.636000   | 44.748000          | 51.708000  | 3702.952000    |
| std                  | 0.482114   | 47.974522          | 14.148337  | 2300.822414    |
| min                  | 0.000000   | 0.000000           | 10.000000  | 340.000000     |
| 25%                  | 0.000000   | 0.000000           | 45.000000  | 1608.250000    |
| 50%                  | 1.000000   | 35.000000          | 55.000000  | 3934.500000    |
| 75%                  | 1.000000   | 77.500000          | 63.000000  | 5065.750000    |
| max                  | 1.000000   | 180.000000         | 71.000000  | 8716.000000    |
|                      |            |                    |            |                |

| df.nunique()  √ 0.0s |     |
|----------------------|-----|
| CustomerID           | 250 |
| Date                 | 37  |
| SubscriptionPlan     | 3   |
| AgeGroup             | 4   |
| Login_x              | 2   |
| WatchTimeMinutes_x   | 92  |
| ContentPreference    | 4   |
| Churned              | 2   |
| ChurnDate            | 36  |
| TotalLogin           | 54  |
| TotalWatchTime       | 242 |
| dtype: int64         |     |

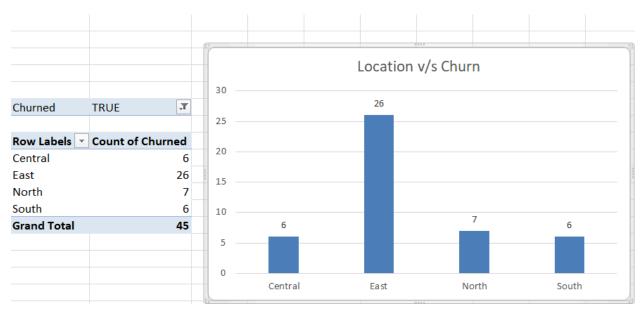


#### **UNIVARIATE ANALYSIS**



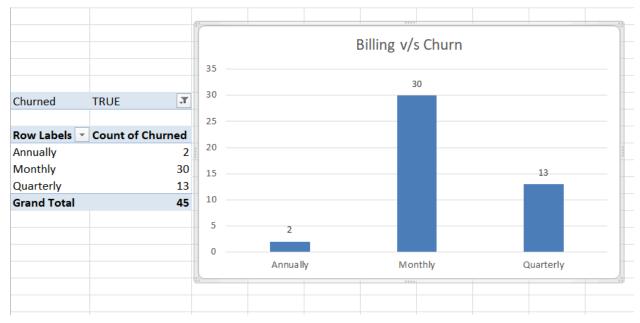
Customers on the Basic plan show the highest churn (21) compared to Premium and Standard plans (12 each).

This indicates that users with lower-tier subscriptions are more likely to discontinue the service.



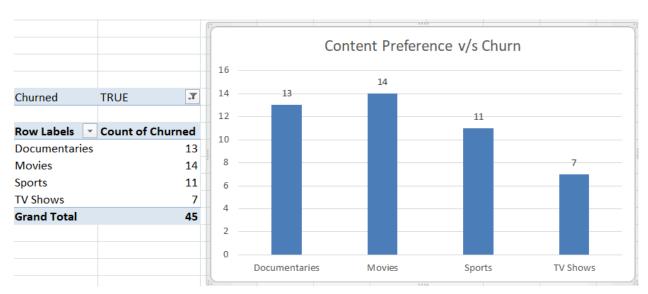
The East region records the highest churn (26 customers), which is significantly larger than other regions.

This suggests that geographic location may play a key role in customer retention, with the East requiring focused interventions.



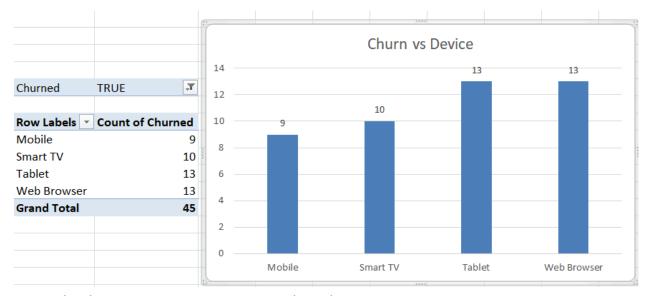
The monthly billing cycle shows the highest churn (30 customers), far exceeding quarterly (13) and annual (2).

This indicates that shorter billing cycles may increase churn risk, as customers find it easier to discontinue.



Customers preferring Movies (14) and Documentaries (13) have the highest churn, followed by Sports (11).

TV Shows have the lowest churn (7), indicating stronger retention among this group.

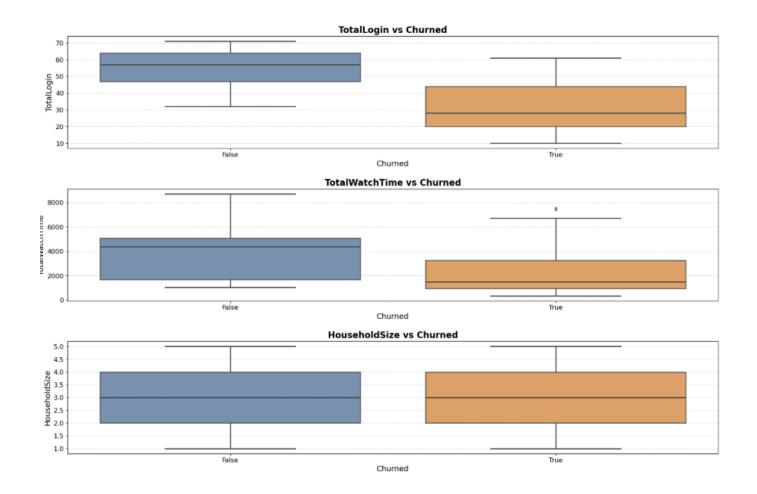


Churn is highest among users accessing via Tablet (13) and Web Browser (13). Mobile (9) and Smart TV (10) users show relatively lower churn, suggesting stronger engagement on these devices.

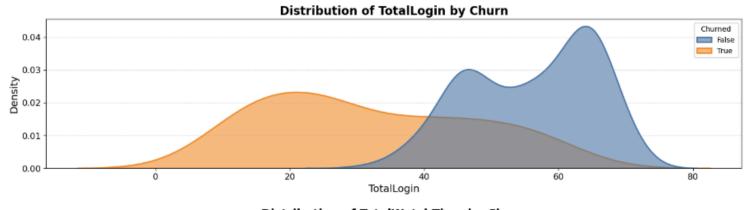


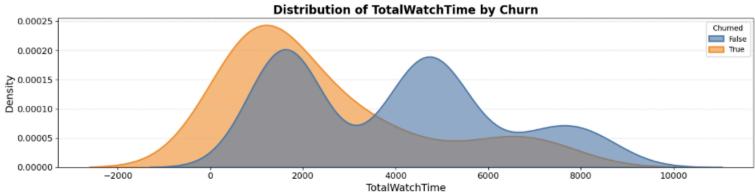
Churn is highest in families with 3 members (15), followed by 4 members (12). Very small (1–2) and very large (5) families show lower churn, suggesting mid-sized families are more prone to leaving.

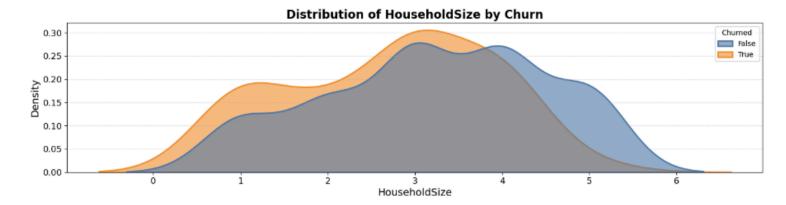
### **BIVARIATE ANALYSIS**



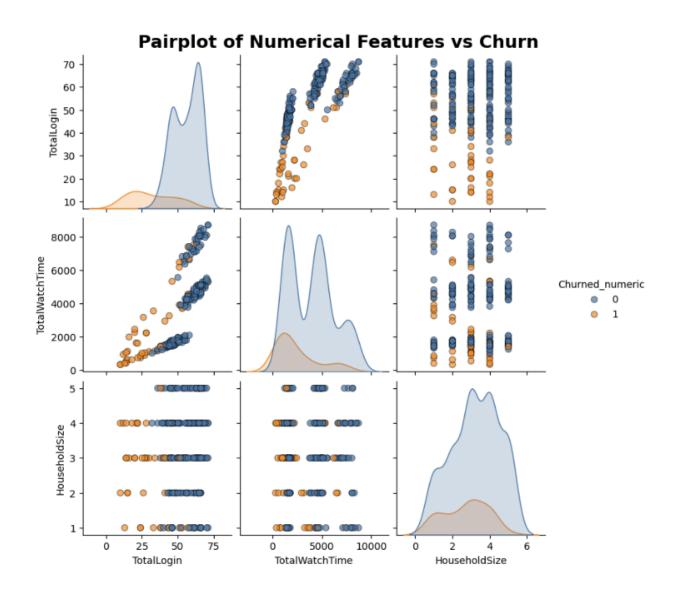
Lower engagement (logins) strongly correlates with churn.
Engagement in watch time is a key predictor of churn.
Household size is less influential than activity metrics.
This means behavioral factors (logins & watch time) are much stronger indicators of churn than demographics (like household size).







## **MULTIVARIATE ANALYSIS**



The correlation heatmap shows that TotalLogin and TotalWatchTime are strongly correlated (0.75), indicating similar usage patterns, while churn is negatively correlated with TotalLogin (-0.66), suggesting higher engagement reduces churn likelihood. HouseholdSize shows little correlation with churn.

# Correlation Heatmap (Numerical Features & Churn)

