Netflix Customer Churn & Engagement Analysis

1 – Introduction

1.1 Background

Customer churn is a critical challenge for subscription-based platforms such as Netflix. Churn refers to customers who discontinue their subscription, directly impacting revenue and long-term growth. Understanding customer behavior, engagement patterns, and inactivity helps businesses design better retention strategies.

This report presents an end-to-end data analytics case study that analyzes customer churn and engagement using exploratory data analysis (EDA) and an interactive Power BI dashboard.

1.2 Objectives

- Analyze customer churn patterns
- Study engagement and inactivity behavior
- Identify high-risk customer segments
- Visualize insights using Power BI
- Provide actionable business recommendations

2 – Dataset Overview & Methodology

2.1 Dataset Description

Each row in the dataset represents a unique customer. The dataset includes subscription details, engagement behavior, device usage, and churn status.

Key fields used:

```
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   customer_id            5000 non-null   object
 1   age                    5000 non-null   int64
 2   gender                 5000 non-null   object
 3   subscription_type      5000 non-null   object
 4   watch_hours            5000 non-null   float64
 5   last_login_days        5000 non-null   int64
 6   region                 5000 non-null   object
 7   device                 5000 non-null   object
 8   monthly_fee            5000 non-null   float64
 9   churned                5000 non-null   int64
 10  payment_method         5000 non-null   object
 11  number_of_profiles     5000 non-null   int64
 12  avg_watch_time_per_day 5000 non-null   float64
 13  favorite_genre         5000 non-null   object
 14  engagement_level       5000 non-null   object
 15  inactive_user          5000 non-null   bool
dtypes: bool(1), float64(3), int64(4), object(8)
```

2.2 Data Quality & Preparation

The dataset was checked for missing values, duplicates, and inconsistencies. No major data quality issues were found. All aggregations were performed directly during analysis and visualization.

Null Values :

```
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   customer_id            5000 non-null   object
 1   age                    5000 non-null   int64
 2   gender                 5000 non-null   object
 3   subscription_type      5000 non-null   object
 4   watch_hours            5000 non-null   float64
 5   last_login_days        5000 non-null   int64
 6   region                 5000 non-null   object
 7   device                 5000 non-null   object
 8   monthly_fee            5000 non-null   float64
 9   churned                5000 non-null   int64
 10  payment_method         5000 non-null   object
 11  number_of_profiles     5000 non-null   int64
 12  avg_watch_time_per_day 5000 non-null   float64
 13  favorite_genre         5000 non-null   object
 14  engagement_level       5000 non-null   object
 15  inactive_user          5000 non-null   bool
dtypes: bool(1), float64(3), int64(4), object(8)
```

Duplicated values:

```
df.duplicated().sum()

[20] 21ms
np.int64(0)
```

3 – Exploratory Data Analysis (EDA)

EDA was conducted using Python to understand distributions and behavioral relationships between churn and engagement.

Churned vs Active Customers

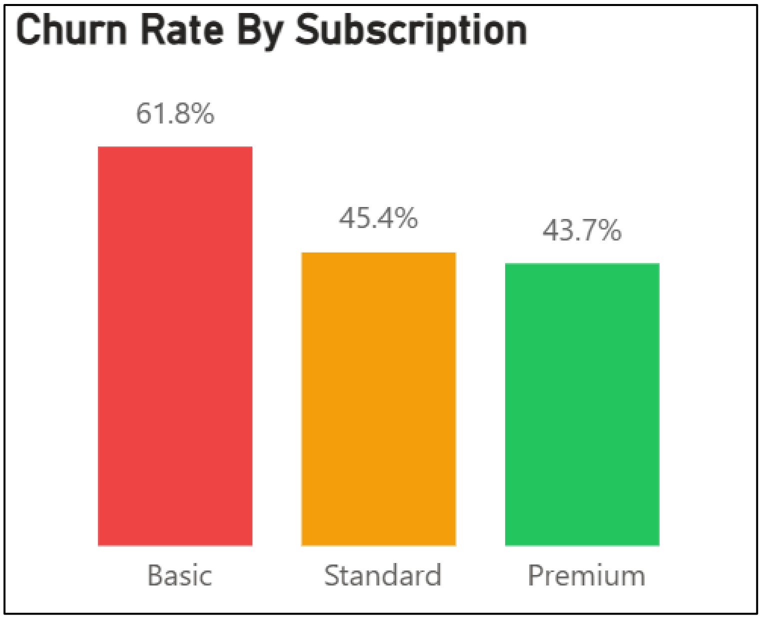
This visualization highlights the proportion of churned customers compared to active users, establishing churn as a significant business concern.

Inactivity vs Watch Hours

The scatter plot shows that churned users typically have higher inactivity and lower watch hours, while active users show consistent engagement.

4 – Subscription & Plan-Based Analysis

Churn Rate by Subscription Type

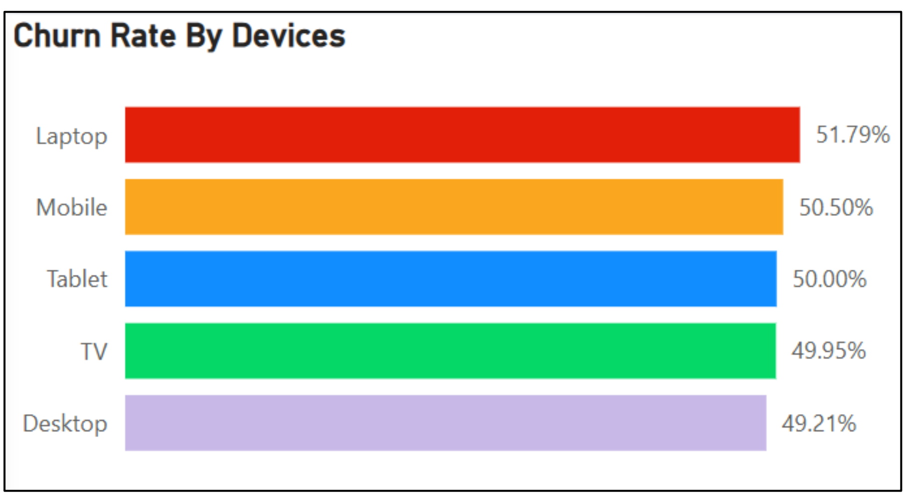


Lower-tier subscription plans demonstrate higher churn rates, suggesting that perceived value and pricing influence retention.

Dashboard KPIs Overview

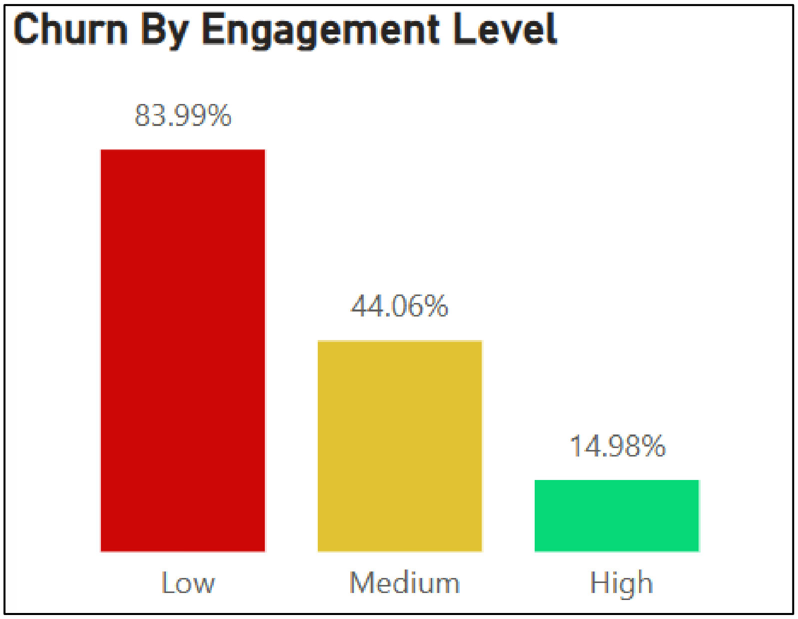
The Power BI dashboard includes key metrics such as total customers, churned customers, and average watch hours, providing a high-level summary of platform performance.

Churn Rate by Device



Device-based analysis shows that users accessing the platform through certain devices exhibit higher churn, highlighting the importance of cross-device user experience.

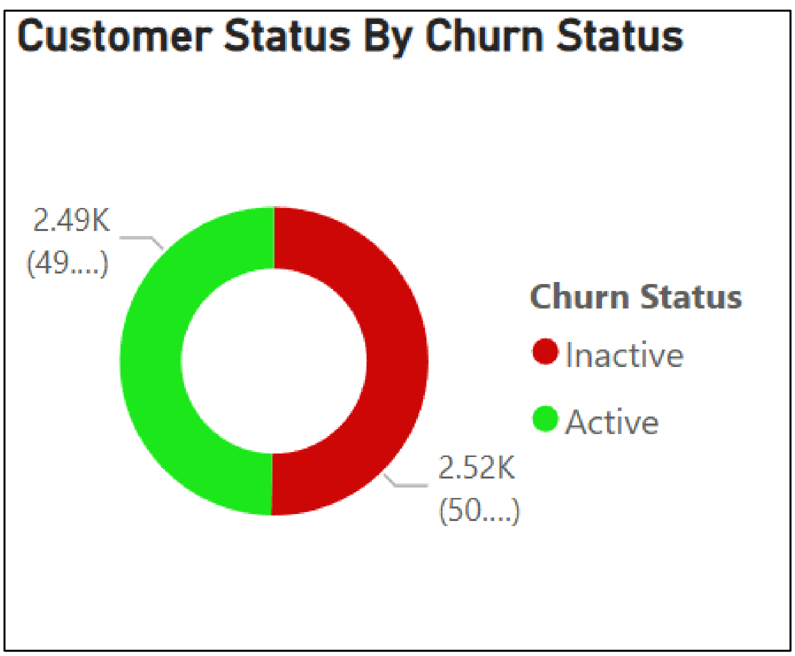
Churn by Engagement Level



Customers with low engagement levels have significantly higher churn rates, making engagement the strongest predictor of churn.

6 – Conclusions & Recommendations

Average Watch Hours by Churn Status



This visual reinforces the relationship between low watch hours and churn behavior.

Key Findings

- Engagement level strongly influences churn
- Inactivity is an early warning signal
- Lower subscription tiers experience higher churn
- Device experience affects retention

Recommendations

- Target low-engagement users with personalized campaigns
- Improve value propositions for basic subscription plans
- Monitor inactivity thresholds proactively
- Enhance device-specific user experience

Conclusion

This project demonstrates a complete analytics workflow combining EDA, dashboarding, and business interpretation. The insights derived can help subscription platforms reduce churn and improve customer retention.