Summary

Objective:

The primary objective of this analysis is to **understand customer churn behavior** using the **Telco-Customer-Churn** dataset. By examining customer demographics, tenure, and subscription characteristics, we aim to identify **factors leading to customer attrition** and recommend actionable insights for improving customer retention.

Dataset Overview:

- File: Telco-Customer-Churn.csv
- Total Records: ~7,043 customers
- Key Features:
 - o Demographic: gender, SeniorCitizen, Partner, Dependents
 - Account Info: tenure, MonthlyCharges, TotalCharges
 - Service Info: InternetService, OnlineSecurity, TechSupport, etc.
 - Target Variable: Churn (Yes/No)

Data Cleaning & Preprocessing Highlights:

- 1. **TotalCharges** had some empty string entries (likely customers with 0 tenure). These were:
 - Replaced with 0 (0.11% of data)
 - Converted to float for analysis
- SeniorCitizen column was encoded from numeric (0/1) to categorical (Yes, No) for better readability.
- 3. Verified:

- No missing values
- No duplicate customerID
- Balanced categorical types

III Churn Distribution:

- Churned Customers: 1,869 out of 7,043 → 26.54%
- Non-Churned Customers: 5,174 → 73.46%
- Insight: Roughly 1 in 4 customers is churning, which is a significant metric for business losses.
 - ✓ This sets the foundation for understanding **why** this group is leaving.

Visual Insights & Key Findings:

★ 1. Churn by Gender

- Males: 50.5% of customers | Churn Rate: ~26.6%
- Females: 49.5% of customers | Churn Rate: ~26.4%

Conclusion: Gender **does not significantly impact churn**. Both genders behave similarly.

📌 2. Churn by Senior Citizen Status

- Senior Citizens (Yes): 16.2% of customers
 - Churned: ~42.2%
- Non-Seniors (No): 83.8% of customers
 - o Churned: ~23.1%

Conclusion: Senior citizens are ~1.8 times more likely to churn than non-senior customers. This could be due to affordability, tech adoption, or support.

♣ 3. Tenure vs Churn

- Customers with **tenure < 10 months** had the **highest churn rate**.
- Churn steadily decreases as tenure increases.

Conclusion: Retaining users in the **first year** is crucial. Long-term customers are **much more loyal**.

Potential Areas to Explore Further:

- Contract type, paperless billing, monthly charges, and other service-specific attributes may show strong churn patterns.
- Use clustering or predictive modeling (logistic regression, random forest) to build a churn prediction model.

X Tools & Libraries Used:

- Language: Python
- Libraries: pandas, seaborn, matplotlib, numpy
- Techniques: Data cleaning, grouped bar plots, pie charts, stacked bar charts, histograms

Final Notes:

This EDA has provided **actionable insights** into customer churn. Notably:

- Churn is a serious issue affecting over 26% of the customer base.
- Senior citizens and new users (low tenure) are high-risk segments.

• Gender is not a discriminatory factor.

The analysis creates a solid foundation for:

- Building a predictive churn model
- Designing targeted retention strategies