Telecom Churn Analysis

1. **Project Overview**
   a. **Objective / Problem Statement**
   The objective of this analysis is to evaluate the current performance metrics, such as Churn Rate, ARPU, and other key KPIs, while identifying and analyzing the primary factors driving customer churn. The goal is to understand not only which variables have the most significant impact, but also the direction of their effect, in order to inform targeted retention strategies and improve overall customer lifetime value.

   b. **Project Scope**
      i. The project focuses on analyzing customer churn for a telecom company.
      ii. It covers customer demographics, services used, and other factors like tenure. Payment mode and Contract duration.
      iii. It utilises a predictive model (logistic regression) to identify top factors contributing to churn and the direction.
      iv. It includes building an interactive Power BI dashboard for executives.
      v. It does **not** include real-time streaming data or predicting Churn using the model (out of scope).

   c. **Key Stakeholders / Audience**
      i. **Executive Leadership:** For strategic decision-making and business impact assessment.

      ii. **Customer Experience Team:** To design and implement initiatives that enhance customer satisfaction and retention.

      iii. **Marketing Team:** To develop targeted campaigns aimed at reducing churn and increasing customer engagement.

iv. **Sales Team:** To tailor offerings, strengthen customer relationships, and support long-term contract adoption.

2. Data / Requirements

a. Data Sources

The dataset for this project is derived from a CSV flat file containing customer churn information along with associated variables that may influence churn behavior. This dataset serves as the foundation for analyzing churn patterns, identifying key contributing factors, and developing actionable retention strategies.

b. Data Description

Column	Description
customerID	Unique ID for each customer
gender	Gender of the customer (Male/Female)
SeniorCitizen	Indicates if the customer is a senior citizen (1 = Yes, 0 = No)
Partner	Whether the customer has a partner (Yes/No)
Dependents	Whether the customer has dependents (Yes/No)
tenure	Number of months the customer has stayed with the company (0–72)
PhoneService	Whether the customer has a phone service (Yes/No)
MultipleLines	Customer has multiple phone lines (Yes/No/No phone service)
InternetService	Internet provider (DSL, Fiber optic, No)
OnlineSecurity	Whether the customer has online security addon (Yes/No/No internet service)
OnlineBackup	Whether the customer has online backup addon (Yes/No/No internet service)
DeviceProtection	Device protection plan (Yes/No/No internet service)
TechSupport	Tech support addon (Yes/No/No internet service)

StreamingTV	Streaming TV service (Yes/No/No internet service)
StreamingMovies	Streaming movies service (Yes/No/No internet service)
Contract	Contract type (Month-to-month, One year, Two year)
PaperlessBilling	Paperless billing option (Yes/No)
PaymentMethod	Payment method (Electronic check, Mailed check, Bank transfer, Credit card)
MonthlyCharges	Amount charged per month (float)
TotalCharges	Total amount charged (should be numeric but currently stored as object)
Churn	Whether the customer churned (Yes/No)

c. Tools & Technologies Used

Power BI, in combination with Power Query, was utilized for data preparation and analysis. R integration within Power BI was employed to enhance the analytical capabilities, with R Visuals specifically used to build and implement a logistic regression model. This model enabled the identification of the top factors contributing to customer churn, providing deeper insights to support data-driven decision-making.

3. Methodology / Approach

a. Data Preparation

i. **File Loading:** The dataset was imported into Power Query for preprocessing. Query names were standardized and made user-friendly for easier navigation and interpretation.

ii. **Handling Missing Values:** The *Total Cost* column contained approximately 1% invalid values. These were attributed to new subscribers who had recently joined and had not yet been billed. Since the analysis focused on historical data and missing values could negatively impact the logistic regression model, these observations were removed.

iii. **Resolving Inconsistencies:** Several categorical columns (*MultipleLines, OnlineSecurity, OnlineBackup, DeviceProtection, TechSupport, StreamingTV, StreamingMovies*) contained inconsistent values such as “No internet service” or “No phone service” instead of a simple “No.” These values were standardized to ensure consistency across the dataset.

iv. **Improving Data Intuitiveness:** The *SeniorCitizen* column originally used binary values (1/0). These were replaced with “Yes/No” to improve clarity and readability.

b. Data Modeling / Calculations

i. The analysis was conducted using a single consolidated table to ensure simplicity and clarity in modeling. Multiple DAX measures were created to facilitate detailed insights and support key calculations throughout the analysis.

ii. Some of the key DAX measures included:

1. Churn Percentage

```
Churn Rate % =

    VAR churned_count = CALCULATE(COUNTROWS('Telecom
Dataset'),'Telecom Dataset'[Churn] = "Yes")

    VAR Total_cust = CALCULATE(COUNTROWS('Telecom
Dataset'),ALLSELECTED('Telecom Dataset'))



    RETURN DIVIDE(churned_count,Total_cust,"No Data")
```

2. ARPU

```
ARPU = DIVIDE(Sum('Telecom Dataset'[MonthlyCharges]),
COUNTROWS(FILTER('Telecom Dataset', 'Telecom Dataset'[Churn] =
"No")), Blank())
```

3. Average Revenue

```
AvgMonthlyRevenue = AVERAGEX('Telecom Dataset','Telecom
Dataset'[MonthlyCharges])
```

4. Average Tenure

```
AvgTenureMonths = AVERAGEX(FILTER('Telecom Dataset','Telecom
Dataset'[Churn] = "Yes"),'Telecom Dataset'[tenure])
```

5. CLV

```
CLV = [AvgMonthlyRevenue]*[AvgTenureMonths]
```

6. Revenue Impact

```
Revenue Impact % = DIVIDE([Churned Revenue],CALCULATE(SUM('Telecom
Dataset'[MonthlyCharges]), ALLSELECTED('Telecom Dataset')),
Blank())
```

iii. Predictive Modeling for Churn Analysis

A predictive model was developed to identify the key factors contributing to customer churn.

1. **Modeling Approach**
    a. A **logistic regression model** was chosen to analyze the factors contributing to customer churn, as it is well-suited for predicting binary outcomes. The model was implemented using **R Visuals** within Power BI, allowing seamless integration of statistical modeling with interactive dashboards.
    b. The analysis identified the **top 10 factors** driving churn based on their statistical significance, determined by the lowest p-values. These insights provided a clear understanding of the key variables influencing customer attrition, enabling targeted strategies to improve retention.

	Factor_influencing_churn	Impact
tenure	tenure	Negatively affect churn
MonthlyCharges	MonthlyCharges	Positively affect churn
PhoneService	PhoneService	Negatively affect churn
TotalCharges	TotalCharges	Positively affect churn
ContractTwo year	ContractTwo year	Negatively affect churn
ContractOne year	ContractOne year	Negatively affect churn
OnlineSecurity	OnlineSecurity	Negatively affect churn
TechSupport	TechSupport	Negatively affect churn
InternetServiceNo	InternetServiceNo	Positively affect churn
InternetServiceFiber optic	InternetServiceFiber optic	Positively affect churn

c. The **sign of each coefficient** in the logistic regression model was used to determine the direction of its effect on churn. For example, a positive coefficient for *MonthlyCharges* indicates that an increase in monthly charges is associated with a higher likelihood of a customer churning, while a negative coefficient suggests a protective effect against churn.

d. The model performance metrics (as shown below) indicate that the logistic regression provides a reasonable predictive capability for churn. However, detailed model evaluation and predictive application are beyond the scope of this project and are not covered in this analysis.

	Metric	Value
1	Accuracy	0.737
2	Sensitivity (Recall)	0.707
3	Specificity	0.748
4	AUC	0.808

c. Visualization / Design Principles

i. Report Structure

1. Executive Summary

The dashboard was designed to provide a comprehensive view of customer churn and key performance indicators (KPIs) for quick insights:

a. **KPI Overview:** Card visuals were used to display key metrics at a glance, including Churn Rate, Monthly Recurring Revenue (MRR), Customer Lifetime Value (CLV), and Average Revenue Per User (ARPU).

b. **Predictive Modeling:** An R script visual was employed to develop a logistic regression model, identifying the top 10 factors contributing to churn. A table visual was used to present these variables along with their respective impact—positive or negative—on churn probability.

c. **Churn Distribution Analysis:** Bar and column charts were created to examine churn rates across different tenure groups and payment modes, providing insight into patterns of customer attrition.

d. **Contract Type Analysis:** A pie chart was used to evaluate which contract categories (month-to-month, one-year, or two-year) contributed most to the overall churn rate, highlighting areas for potential retention initiatives.

These visualizations collectively enable stakeholders to quickly understand churn drivers, monitor key metrics, and support data-driven decision-making for customer retention strategies.

2. Services

Bar and pie charts were utilized to analyze **churn percentage** and **revenue impact percentage** across various customer service categories. This enabled a clear understanding of how different service options influence both customer attrition and financial outcomes.

To enhance user experience, **bookmarks** were implemented to create an app-like, interactive interface. Users can click on buttons corresponding to specific factors or variables, dynamically updating the visuals to display data relevant to the selected category. This approach allows stakeholders to explore the data intuitively and gain actionable insights quickly.

3. Demographics

Bar and pie charts were used to analyze **churn percentage** and **revenue impact percentage** across various **customer demographic categories**, providing insights into how different demographic factors influence churn and financial outcomes.

To enhance usability, **bookmarks** were implemented, creating an app-like interactive experience. Users can click on buttons corresponding to specific demographic factors or variables, dynamically updating the visuals to display the relevant data.

Additionally, a dedicated page was included for users who wish to review the **model performance metrics**, ensuring transparency and accessibility for stakeholders interested in the predictive analysis.

4. Analysis & Findings

a. Key Metrics Defined

i. **Churn Rate (%):** The percentage of customers who discontinue their subscription within a given period. This metric highlights customer retention performance and helps identify segments at higher risk of leaving.

ii. **Average Revenue Per User (ARPU):** The average monthly revenue generated per subscriber. ARPU provides insights into revenue efficiency and helps evaluate the financial impact of pricing strategies and upsell opportunities.

iii. **Customer Lifetime Value (CLV):** The projected total revenue a business can expect from a customer over the entire duration of their relationship. CLV is critical for assessing the long-term value of retaining customers versus acquiring new ones.

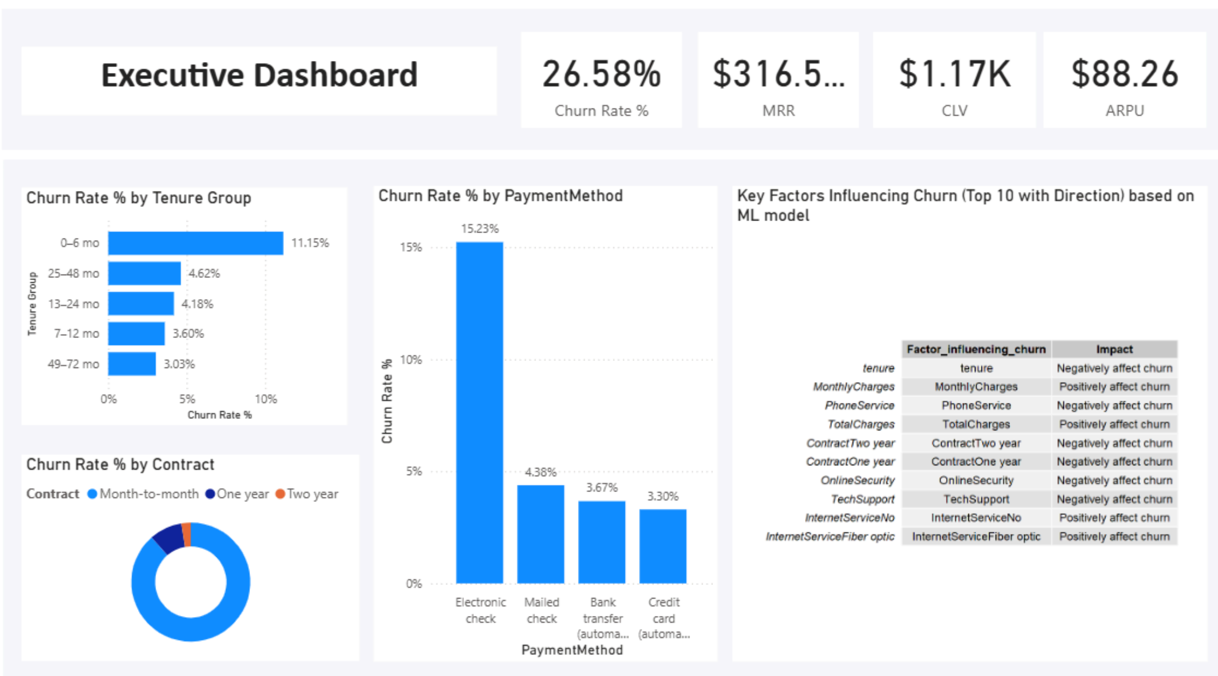
iv. **Monthly Recurring Revenue (MRR):** The predictable revenue earned each month from active subscriptions. MRR is a key financial metric for subscription-based businesses, offering visibility into revenue stability and growth.

v. **Revenue Impact:** The total financial effect of churn on the business, calculated by quantifying lost revenue due to customer attrition. This metric underscores the importance of effective retention strategies to safeguard profitability.

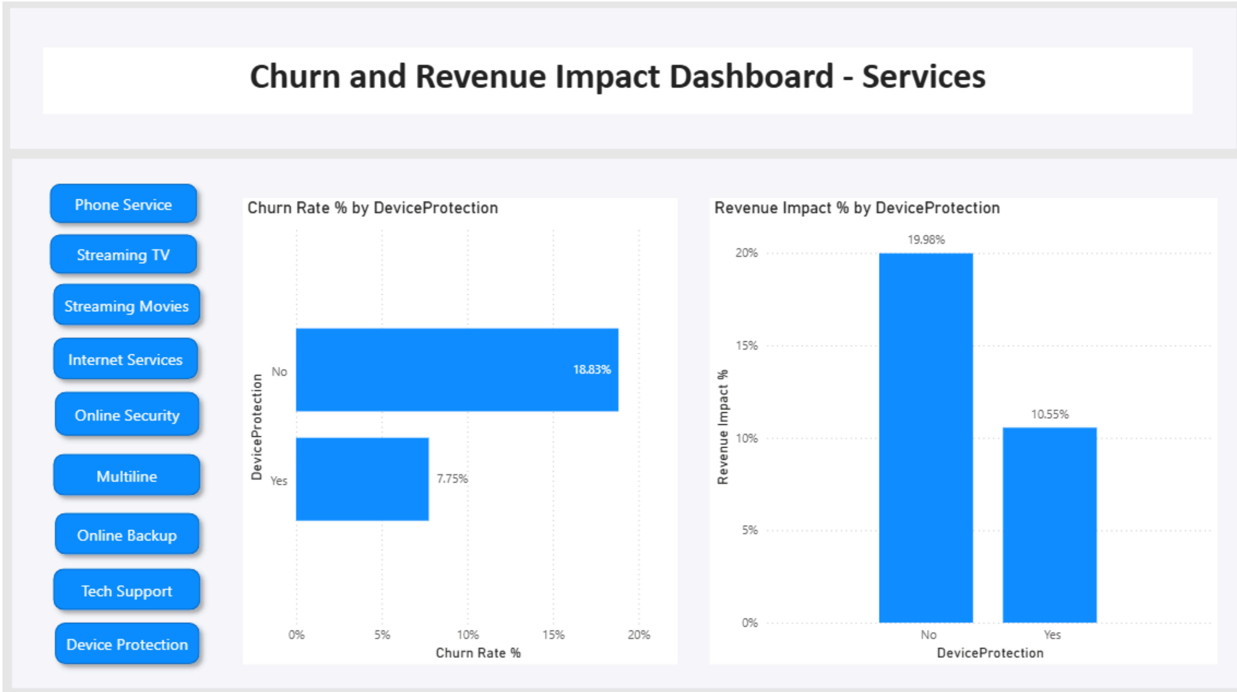
b. Final Dashboard / Prototype Overview

The attached screenshots present a detailed view of the dashboard, highlighting the key insights derived from the churn analysis. The visualizations are designed to provide a clear understanding of the factors influencing customer churn and to guide data-driven retention strategies.

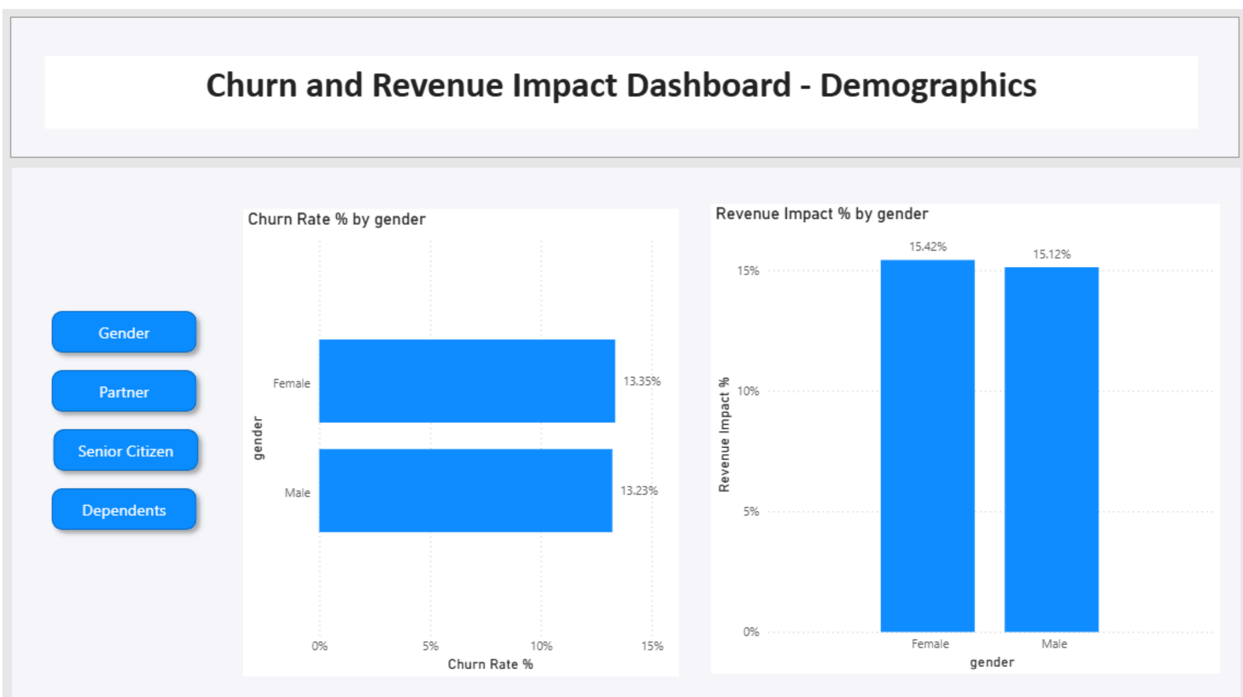
Executive Summary



Services



Demographics



c. Features & Functionality

The executive dashboard provides a **quick snapshot of the current status of key KPIs**, enabling stakeholders to monitor overall performance at a glance.

Subsequent pages, focusing on **service** and **demographics**, offer a more detailed, factor-level breakdown of **churn percentage** and **revenue impact**, allowing for deeper insights into the drivers of customer attrition.

Both the service and demographics pages leverage the **bookmark feature** to create an app-like interactive experience. Users can toggle between different variables with a single click, making the dashboard intuitive and easy to navigate.

5. **Results / Impact** - **Key Insights and recommendations**

- Tenure is the strongest contributor to churn. Customers with higher tenure show a much lower likelihood of leaving, while those in the early stages of their relationship with the company—particularly within the first 0–6 months—exhibit the highest churn rates. Therefore, retention campaigns should focus on customers with low tenure. Additionally, offering reduced rates or exclusive benefits to long-term customers after they reach a certain tenure milestone can both strengthen loyalty among existing users and encourage new customers to stay longer.
- Monthly charges are the second most influential factor in churn. To address this, the company can consider lowering prices, providing bundled offerings (e.g., internet + phone + TV at a discounted rate compared to purchasing separately), or enhancing perceived value by including perks such as free streaming subscriptions, additional data, or priority customer support. These measures will help customers feel they are receiving a fair deal.
- Contract type also plays a critical role. Subscribers with one- or two-year contracts exhibit significantly lower churn rates compared to those on month-to-month plans. To leverage this, the company could offer discounted monthly rates for 12- or 24-month commitments, or include added incentives such as free extra data or streaming subscriptions. This aligns with another key observation: subscribers who opt for streaming add-ons are less likely to churn.

7. Conclusion

The analysis provides a thorough understanding of customer churn and the key factors influencing it. **Tenure** emerged as the most significant contributor, with customers in the first 0–6 months exhibiting the highest likelihood of churn. This highlights the importance of targeted retention strategies for new customers, while long-term customers can be incentivized with reduced rates or added benefits to strengthen loyalty.

Monthly charges and **contract type** were identified as other critical drivers of churn. Customers with higher monthly charges or on month-to-month plans are more prone to leaving, suggesting that bundling services, offering value-added perks, or promoting longer-term contracts can effectively reduce attrition. Additionally, subscribers who utilize streaming or other add-on services demonstrate lower churn rates, underscoring the potential of cross-selling and service enhancement strategies.

The predictive **logistic regression model** further validated these insights, identifying the top factors contributing to churn and quantifying their directional impact. The interactive dashboard, featuring KPI cards, charts, and bookmarks, provides stakeholders with both a high-level overview and detailed factor-level breakdowns, enabling data-driven decisions for retention initiatives.

Overall, this analysis equips the organization with actionable insights to **proactively reduce churn, optimize revenue, and improve customer lifetime value** through targeted interventions, informed pricing strategies, and enhanced customer engagement.