
2025

CUSTOMER CHURN ANALYSIS

~ by Linh Nguyen



Table of Contents

- 01.** Introduction
- 02.** Executive Summary
- 03.** PHASE 1: Summarize Key Customer Insights
- 04.** PHASE 2: Build a churn prediction model to identify at-risk customers.
- 05.** Recommendations
- 06.** Conclusion

INTRODUCTION

Customer retention is one of the most critical challenges faced by telecom companies in today's competitive market. With numerous service providers offering comparable pricing and packages, customers are more empowered than ever to switch providers at the first sign of dissatisfaction. The telecom company at the focus of this project is currently experiencing a high churn rate, directly impacting its revenue and long-term sustainability.

To address this pressing issue, the Data & Analytics Consulting Division at PwC was engaged to conduct an in-depth analysis of customer churn patterns. This project aims to explore the key drivers behind customer churn by leveraging data-driven insights, enabling the client to make informed decisions and implement proactive strategies that improve customer loyalty and retention.

The analysis is divided into two main phases:

1. Exploratory Data Analysis (EDA) – Understanding the customer base through demographic segmentation, service usage patterns, billing behavior, and payment preferences.
2. Predictive Modeling – Developing machine learning models to predict churn, identify high-risk customer segments, and uncover the most significant factors contributing to customer attrition.

This report presents key findings from the analysis and offers strategic recommendations that the telecom company can adopt to mitigate churn and foster long-term customer relationships.

EXECUTIVE SUMMARY

This report presents a comprehensive analysis of customer churn for a leading telecom company facing rising attrition rates. Using data provided by the client, the project team at PwC conducted an Exploratory Data Analysis (EDA) followed by the development of a predictive churn model to uncover actionable insights.

Key Findings:

- **Churn Rate:** Approximately 26% of customers have churned, with the highest rates among those on month-to-month contracts and during the first five months of service.
- **Customer Demographics:** Higher churn is observed among younger customers, senior citizens without partners, and those without dependents, indicating that social factors may influence retention.
- **Service Usage:** Customers using fiber-optic internet exhibit the highest churn, while those without internet service have the lowest. Lack of add-on services like TechSupport or OnlineSecurity correlates with higher churn.
- **Billing and Payment:** Customers utilizing paperless billing and manual payment methods (e.g., electronic checks) are more prone to churn compared to those using automated methods (e.g., credit cards, bank transfers).
- **Contract Type:** Month-to-month contract holders are significantly more likely to churn than those on longer-term contracts.

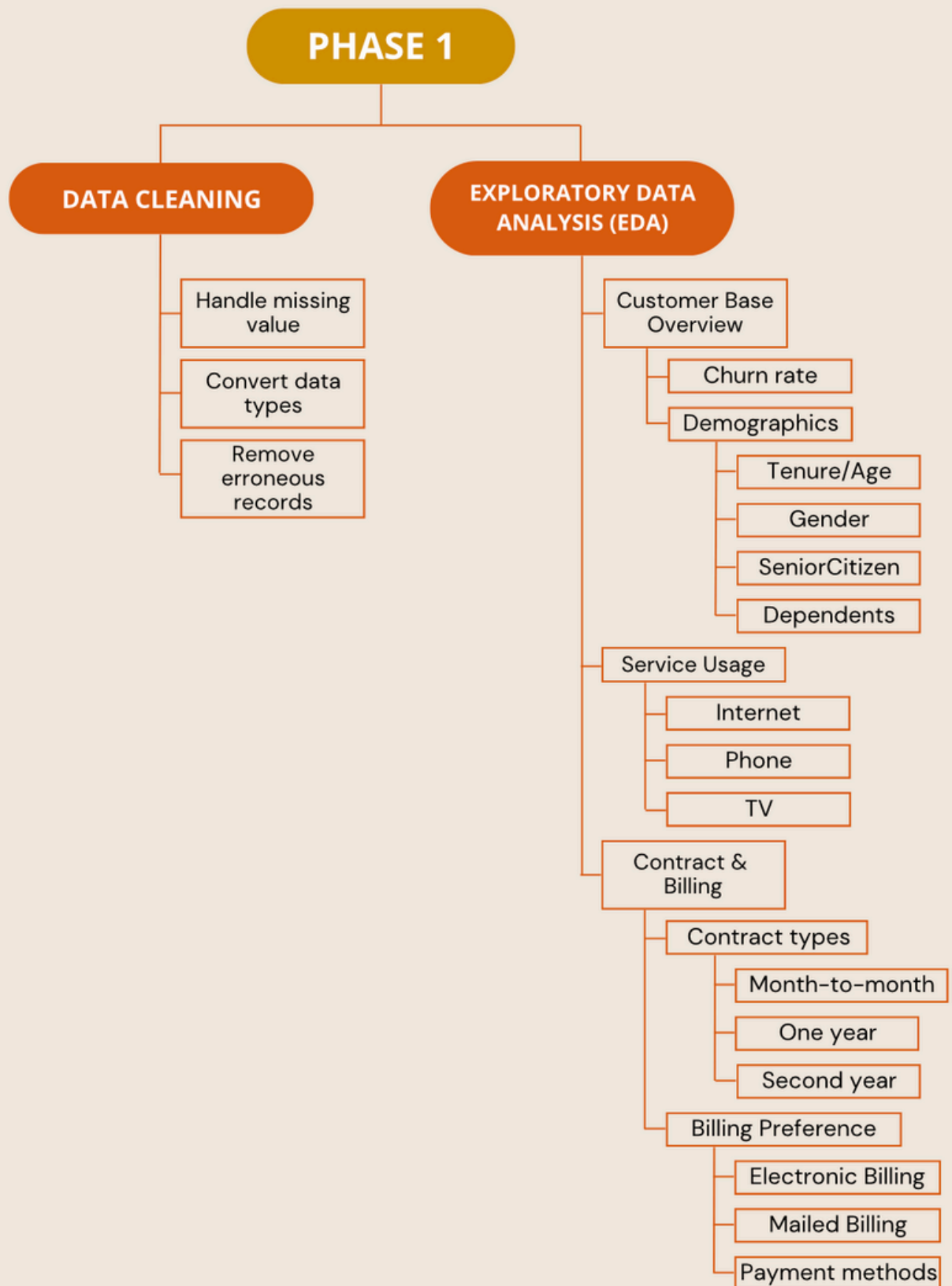
Model Performance:

Using machine learning models including Logistic Regression, Decision Trees, and XGBoost, the churn prediction model achieved an accuracy of **more than 80%**, with precision, recall, F1-score, and AUC-ROC metrics indicating robust predictive capabilities. Key predictive features included Contract Type (month-to-month) Number of Tech Support Tickets, Monthly Charges

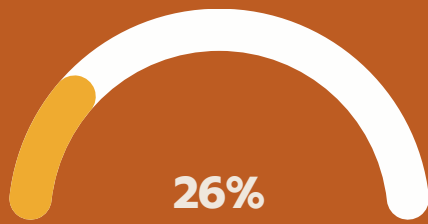
Strategic Recommendations:

- **Retention Programs:** Introduce loyalty rewards, discounts, or personalized plans for high-risk churn customers.
- **Flexible Billing Options:** Provide greater flexibility in billing cycles and payment methods to reduce dissatisfaction.
- **Improve Service Experience:** Focus on enhancing internet reliability and customer service touchpoints.
- **Proactive Engagement:** Use predictive insights to flag at-risk customers early and initiate outreach through customer support and marketing teams.

PHASE 1: Summarize key customer insights

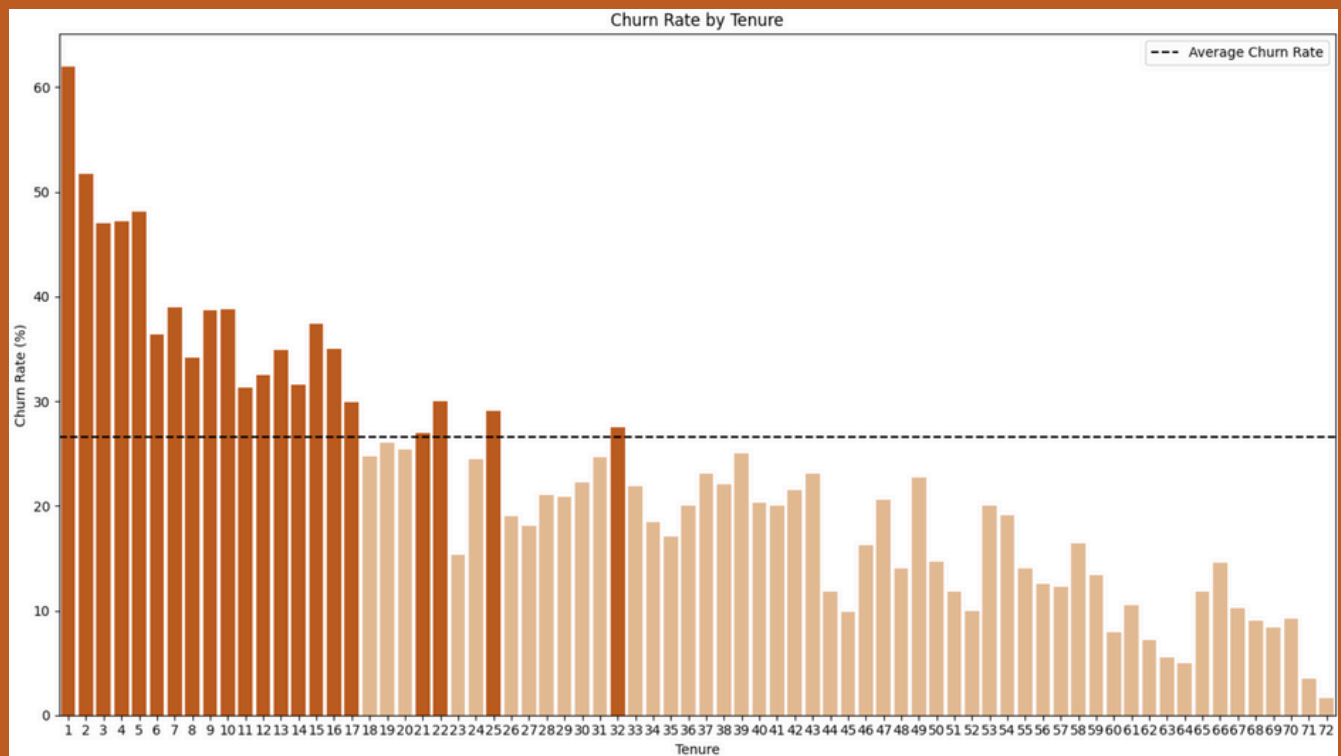


Churned Customers



→ Indicates more than 1 in 4 customers leave the provider

Do long-term customer churn less?



Churn Rate is **Highest** at the Start:

- Customers in their first months have a churn rate above average, peaking in the first 5 months. → This suggests that early retention is a critical challenge. New customers may not find value immediately or face onboarding issues.

Churn Rate **Decreases and Stabilizes** Over Time:

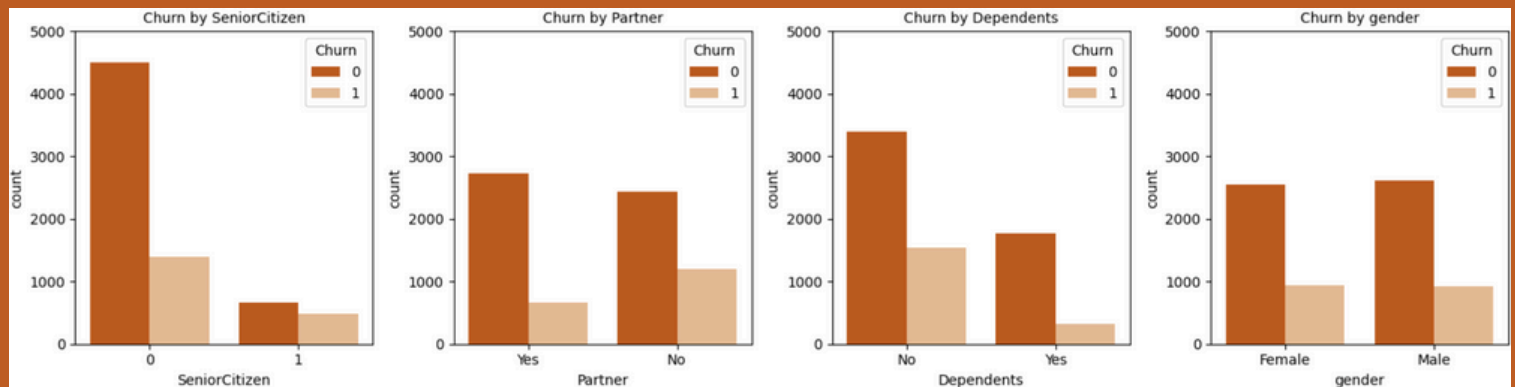
- After about month 15–20, churn drops below the average and becomes more stable, hovering mostly below. → This shows that once customers pass the early stage, they're more likely to stay longer (even if not dramatically loyal).

Spikes Occur Even in Later Tenure:

- There are occasional churn spikes (e.g., month 32, 49, 60), indicating that external events or contract cycles may influence churn. → These could correspond to end of contracts, price increases, or service changes.

“While long-term customers are more likely to stay, churn still occurs at later stages — suggesting loyalty is not guaranteed even after extended tenure.”

How Do Demographic Factors Affect Customer Churn?



Customers who are senior citizens without a partner have the highest churn rate, likely due to isolation or limited engagement with services. In contrast, non-senior customers with a partner show the lowest churn, benefiting from shared service usage and greater stability.



SeniorCitizen

- Observation: Most customers are not senior citizens (0). Among them, a significantly higher number do not churn compared to those who do.
- Effect on Churn: Senior citizens (1) show a slightly higher churn rate relative to their smaller population size. While fewer in number overall, the churn proportion is more balanced between stay and leave.



Dependents

- Observation: Customers with no dependents have a higher churn count, while those with dependents are more likely to stay.
- Effect on Churn: Having dependents correlates with lower churn, possibly due to the need for more stable services or long-term plans.



Partner

- Observation: Customers with partners are less likely to churn compared to those without partners.
- Effect on Churn: Among those with partners, churn numbers are low. In contrast, customers without partners have a higher churn rate.



Gender

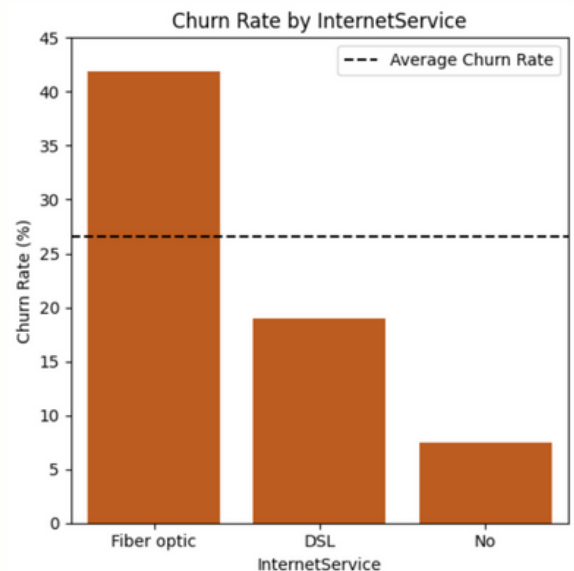
- Observation: The distribution of churn and non-churn is nearly identical between males and females.
- Effect on Churn: Gender does not seem to significantly influence churn behavior.
→ not a strong predictor

Why Do Customers With Services Churn More?

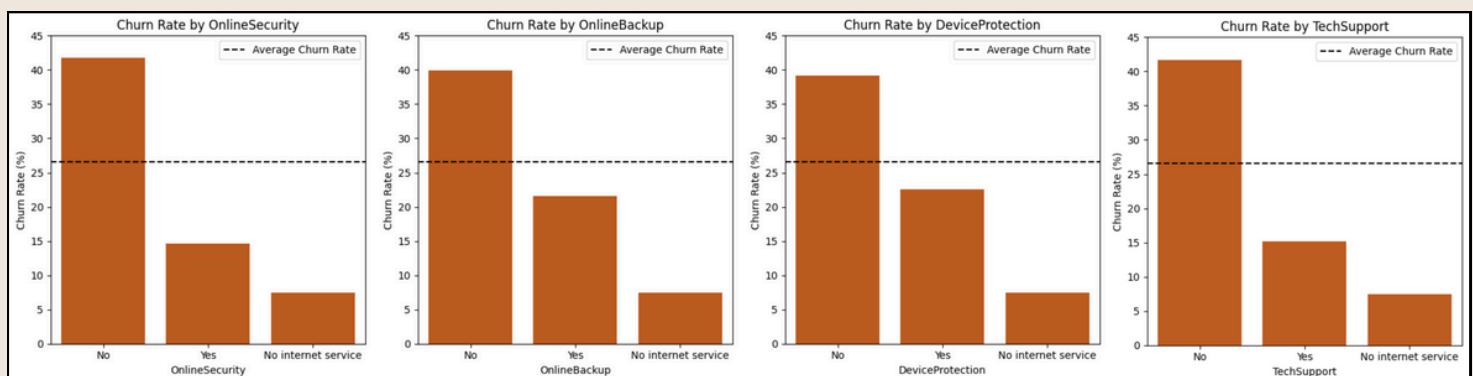
01 Fiber optic internet users have the highest churn rate (~42%)

→ Customers with more services have higher expectations, making them more prone to churn when disappointed

Customers who pay for premium services tend to expect high-quality performance and seamless access. When these expectations are not met, due to frequent outages or slow customer support—they are more likely to feel frustrated and consider switching providers.



02 Customers without TechSupport, OnlineSecurity, etc (churn around 40%) and customer with these services have churn rates as low as ~14-15% - showing a 28%+ difference

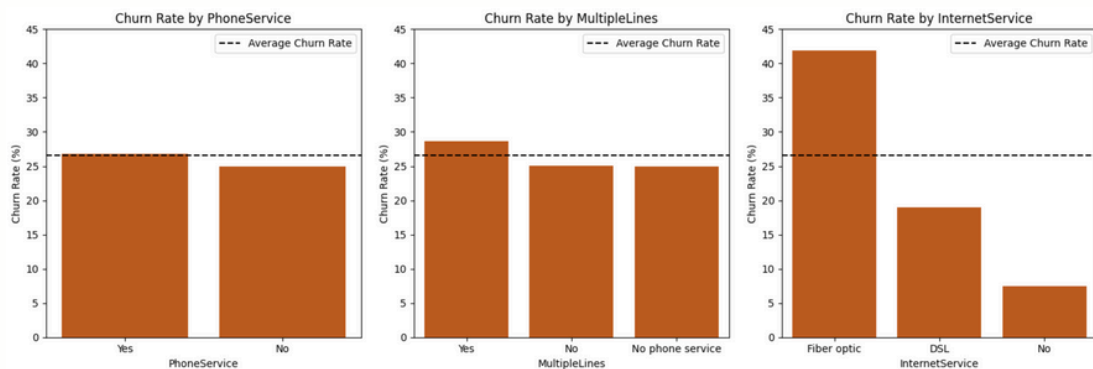


→ Lack of support services significantly increases the risk of churn

Churn is highest for customers who do not subscribe to add-on support services like TechSupport, OnlineSecurity, etc. While having internet or entertainment services is common, lacking the proper safety net (security or technical help) may leave customers vulnerable to issues that ultimately drive them away. Based on numTechTickets, technical issues are shown to be more frequent and escalate for some users, especially if they're using more services (some customers have up to **9 tickets**).

Why Do Customers With Services Churn More?

03 Higher engagement, higher churn rate (~27-42%)

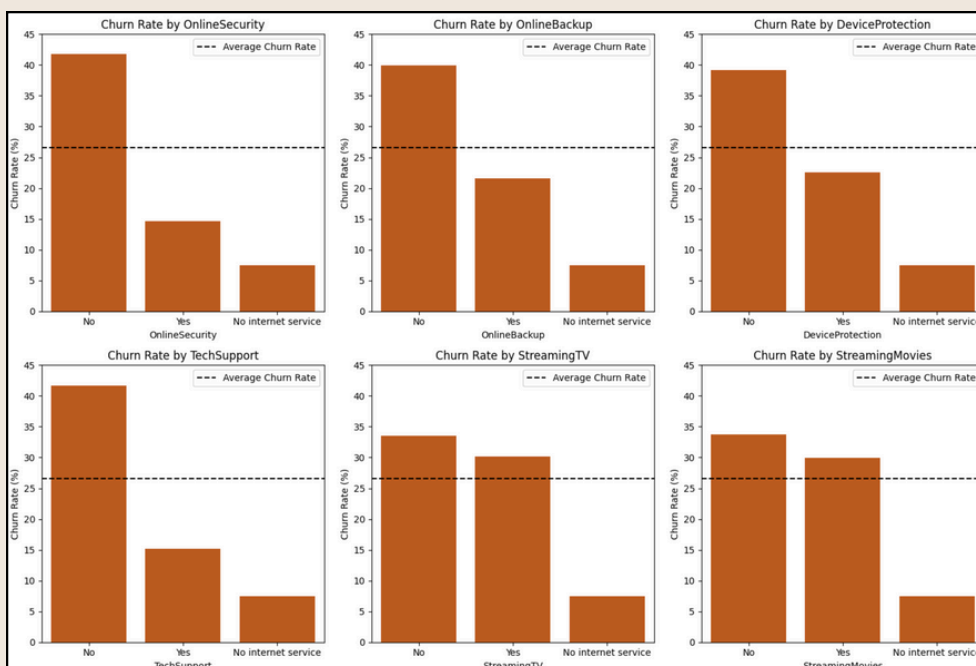


→ **Customers who are highly-engaged-but unsupported are most at risk**

Engaged users (those with multiple services like streaming, internet, and phone) have frequent interactions with the provider, which increases the likelihood of encountering issues. If these problems are not managed with adequate customer care, it leads to a higher chance of dissatisfaction and churn.

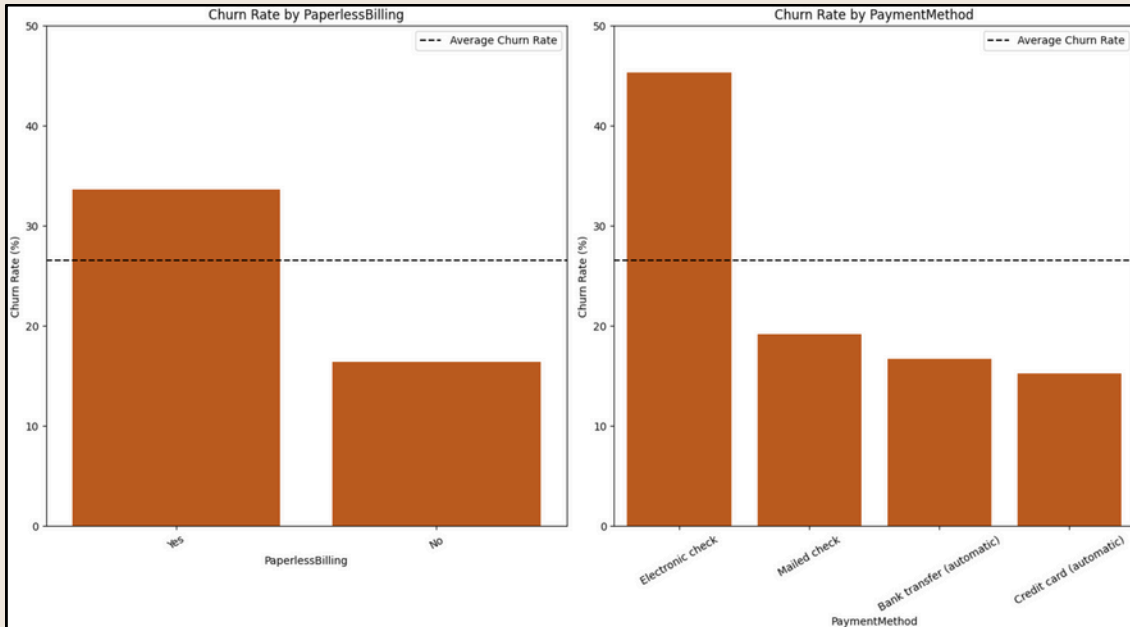
04 “No internet service” group has the lowest churn rate (~8%)

→ **Customers with no internet service or fewer services churn less due to limited expectations and engagement**



Churn is highest for customers who do not subscribe to add-on support services like TechSupport, OnlineSecurity, etc. While having internet or entertainment services is common, lacking the proper safety net (security or technical help) may leave customers vulnerable to issues that ultimately drive them away.

Which type of payment method has the highest customer churn rate?



~34%

Churned customers are more likely to use paperless billing

~45%

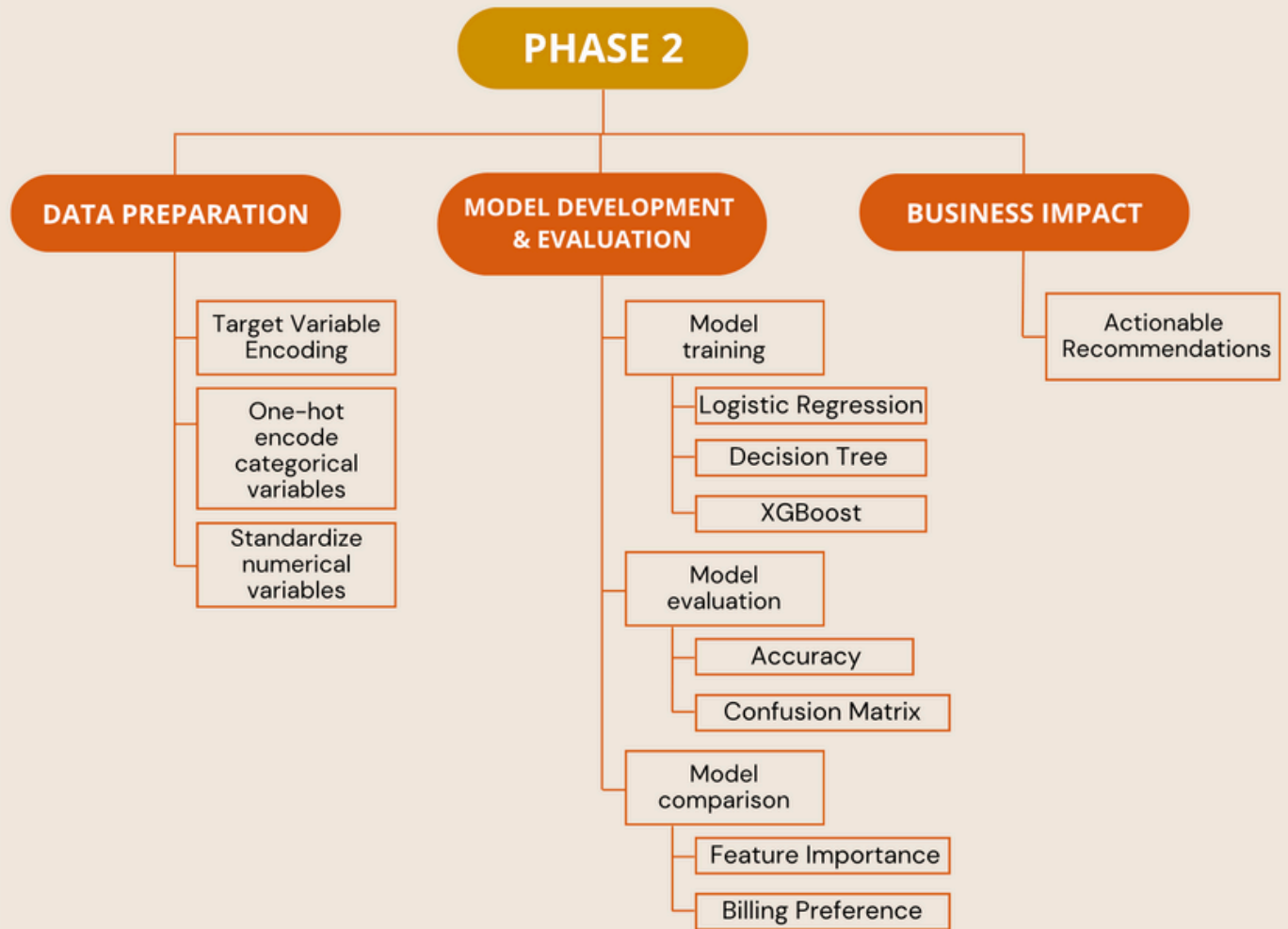
Churned customers tend to prefer manual methods like electronic checks more than automatic methods like credit cards or bank transfers.



Monthly contract customers churn the most!

- ! Offer more flexibility, so customers can leave anytime without penalties.
- ! Often used by newer or less committed customers who are testing the service.
- ! Less incentive to stay loyal compared to long-term contracts.

PHASE 2: Build a churn prediction model to identify at-risk customers.



Which model predicts customer churn most accurately?

Three machine learning models — Logistic Regression, Decision Tree, and XGBoost — were developed to predict customer churn. The dataset was split into 70% training and 30% testing using a fixed random state for consistency. For each model:

- The target variable was set as Churn, and all other columns were used as features.
- Each model was trained on the training set and evaluated on the testing set.
- Predictions were made, and performance was assessed using a confusion matrix and a classification report that included accuracy, precision, recall, and F1-score.
- Confusion matrices were visualized using heatmaps to clearly show true vs. predicted outcomes.

Given confusion matrix is structured and the formulas to calculate each metric from it:

	Predicted: No Churn (0)	Predicted: Churn (1)
Actual: No Churn (0)	True Negatives (TN)	False Positives (FP)
Actual: Churn (1)	False Negatives (FN)	True Positives (TP)

TN = correctly predicted no churn

FP = predicted churn but actually no churn

FN = predicted no churn but actually churn

TP = correctly predicted churn

Predicted Churn %:

$$\frac{TP}{TP + FP} \times 100$$

Predicted No Churn %:

$$\frac{TN}{TN + FN} \times 100$$

```

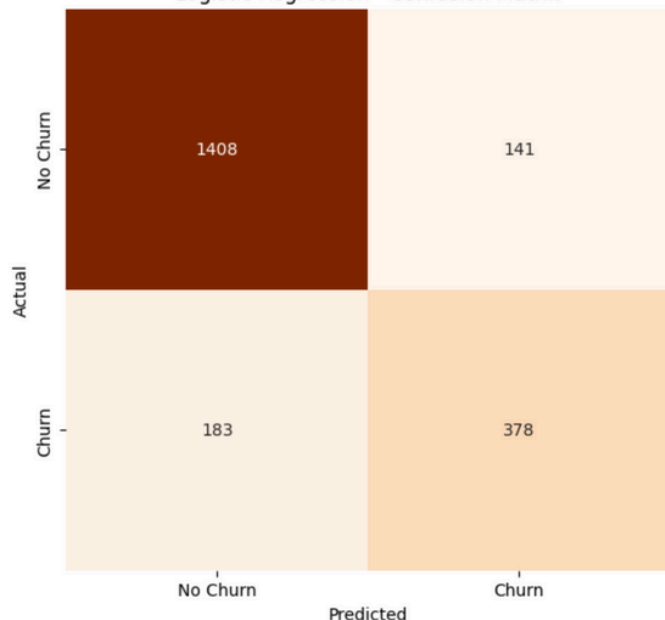
Classification Report:
              precision    recall  f1-score   support

     0       0.88        0.91        0.90        1549
     1       0.73        0.67        0.70         561

 accuracy          0.85        2110
 macro avg          0.81        0.79        0.80        2110
 weighted avg       0.84        0.85        0.84        2110

```

Logistic Regression - Confusion Matrix



Logistic Regression

```

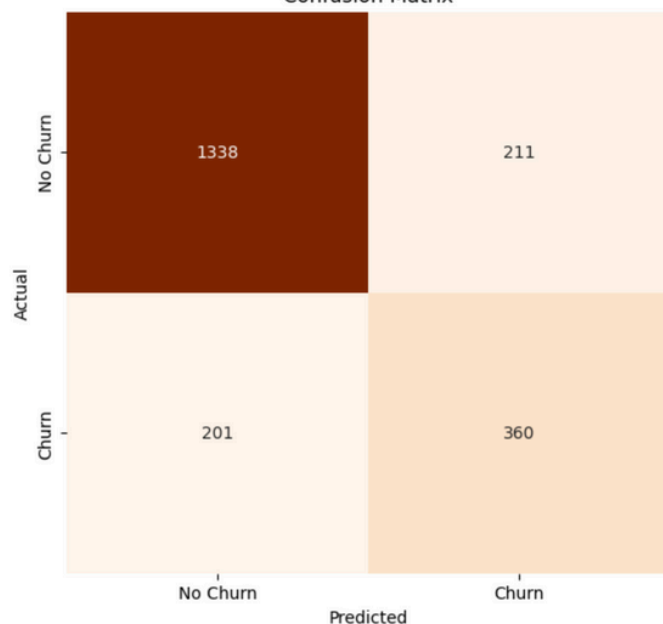
Decision Tree - Classification Report:
              precision    recall  f1-score   support

     0       0.87        0.86        0.87        1549
     1       0.63        0.64        0.64         561

 accuracy          0.80        2110
 macro avg          0.75        0.75        0.75        2110
 weighted avg       0.81        0.80        0.81        2110

```

Confusion Matrix



Decision Tree

```

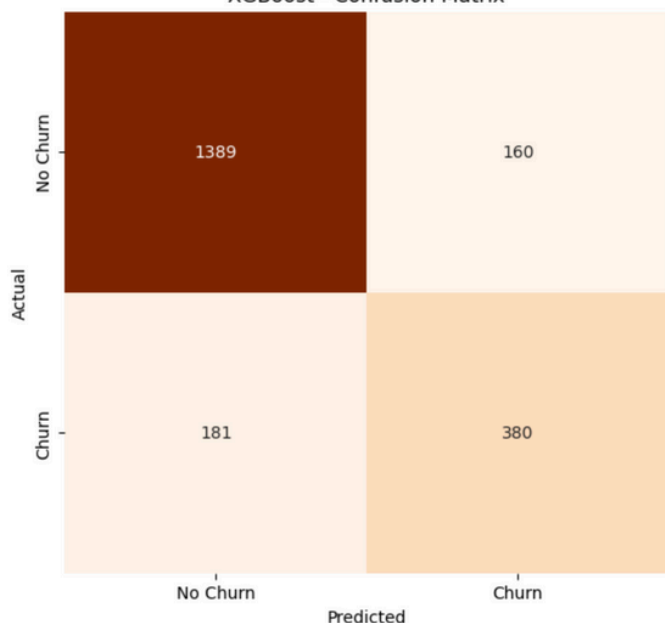
XGBoost - Classification Report:
              precision    recall  f1-score   support

     0       0.88        0.90        0.89        1549
     1       0.70        0.68        0.69         561

 accuracy          0.84        2110
 macro avg          0.79        0.79        0.79        2110
 weighted avg       0.84        0.84        0.84        2110

```

XGBoost - Confusion Matrix



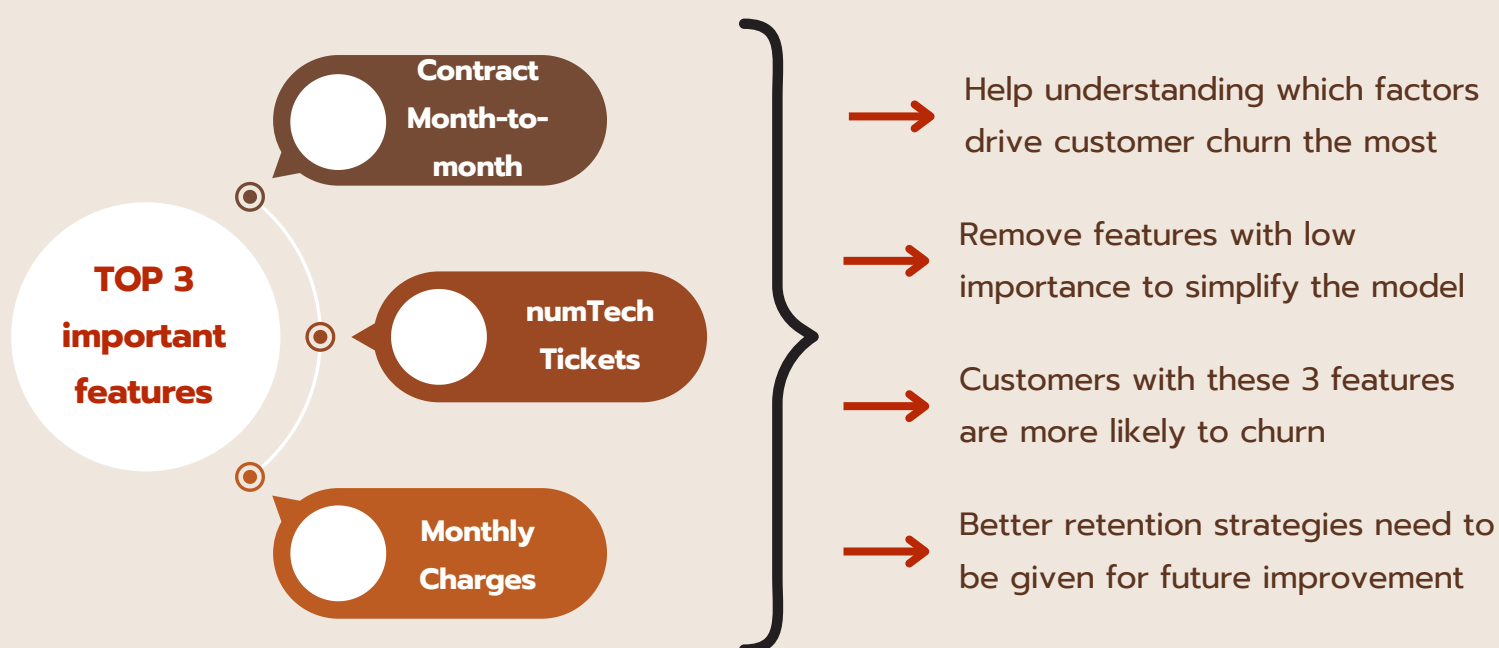
XGBoost

After careful calculation, the summary table is created as shown below:

Model	Accuracy	Precision	Recall	F1-score	Confusion Matrix	
					No Churn	Churn
Logistic Regression	85%	73%	67%	70%	88.5%	72.7%
Decision Tree	81%	64%	66%	65%	87.6%	64%
XGBoost	84%	70%	68%	69%	88.5%	70.4%

➔ **Logistic Regression is the best at predicting churned customers because:**

- It correctly identifies the highest percentage of churners (72.7%) .
- It has the highest accuracy (85%), precision (73%) and F1-score (70%) among the models.
- It's more balanced overall for churn prediction, making it more reliable in a real-world scenario where catching true churners is critical.





Retention Strategies



Targeted Loyalty Incentives for Predicted Churners

- Loyalty discounts to long-tenure customers showing churn risk.
- Exclusive bundle perks (e.g., TechSupport + Streaming add-ons) to boost engagement.



Flexible Payment Options for Financially Sensitive Customers

- For customers predicted to churn who have higher billing amounts, offer:
 - Split-payment plans to reduce monthly burden.
 - Promote stable payment methods (credit cards, bank transfers) to reduce churn from missed payments.



Service Reliability Focus for Technically Affected Users

- From churn model features (e.g., frequent tech issues), identify service-related churn drivers.
- For customers with repeated service tickets:
 - Proactively resolve issues using alerts from network analytics.
 - Prioritise them in technical support response queues.
 - Schedule preventative maintenance or audits, especially for fiber optic users.



Hyper-Personalised Outreach

- For churn-prone segments:
 - Launch personalised email/SMS campaigns with:
 - Targeted upgrade suggestions
 - Special renewal discounts
 - Surveys asking what might keep them
- Check in regularly with:
 - Month-to-month contract users
 - Recent complainants or downgraders



Monitoring & Iteration

- Set up monthly monitoring of churn model results → Track who accepted offers and who still churned.
- Feed this data back into model training to improve precision and recall over time.
- Use model to predict new customers whether they are likely to churn or not.

CONCLUSION

This analysis underscores the critical importance of early intervention and tailored retention strategies in mitigating customer churn within the telecom sector. By identifying key risk factors—such as month-to-month contracts, lack of support services, and specific demographic profiles—companies can proactively address customer needs and enhance satisfaction. The predictive models developed, particularly the Logistic Regression model with an accuracy of 85%, provide a robust framework for forecasting churn and informing strategic decisions. Implementing targeted retention programs, offering flexible billing options, and improving service experiences are essential steps toward reducing churn rates and fostering long-term customer loyalty. Continuous monitoring and refinement of these strategies will be vital in adapting to evolving customer behaviors and market dynamics.