Customer Churn Prediction for SyriaTel

Business understanding

- SyriaTel, like many telecom providers, operates in a highly competitive market where customer loyalty is crucial. Retaining existing subscribers is significantly more cost-effective than acquiring new ones—making churn a serious business concern.

- Churn, or the loss of customers, directly reduces revenue and threatens long-term profitability. However, churn rarely happens at random; it's often triggered by issues like poor service quality, pricing dissatisfaction, inadequate customer support, or more attractive competitor offers.

- By predicting which customers are most likely to leave, SyriaTel can take proactive, data-driven steps—such as personalized offers or improved service—to reduce churn and strengthen customer retention.

Business Goal

i) **Build a predictive model** to identify customers likely to churn

ii) **Gain insights** into key factors driving churn

iii) **Provide strategic recommendations** to reduce churn and improve retention

Data Understanding

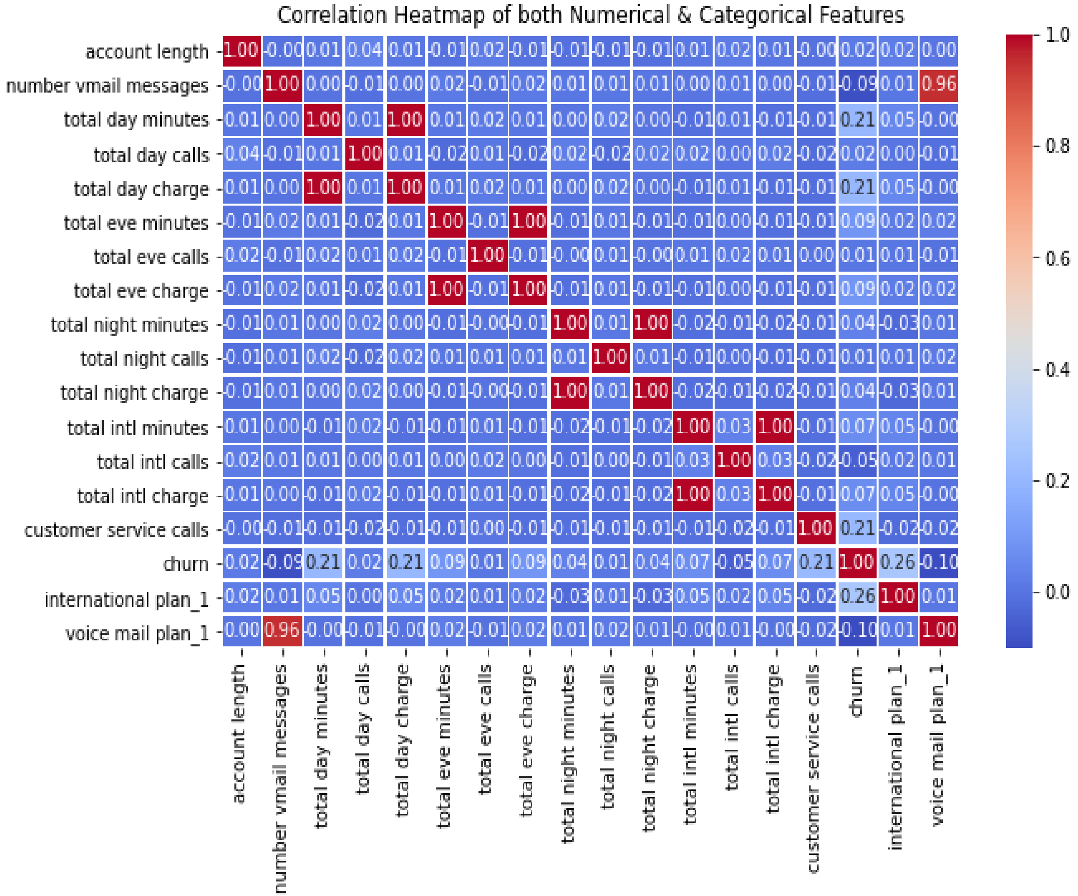
- The project used the "Churn in Telecoms" dataset from Kaggle.
- Dataset contains 3,333 entries and 21 columns.
- There were no missing values hence no need of further cleaning.
- Dataset included both categorical and numerical variables.
- Key categorical features: state, international plan, voice mail plan, churn.
- Key numerical features: total day minutes, customer service calls, total day charge etc

Steps followed in Exploratory Data Analysis

- Steps followed in exploratory data analysis
- Dropped low-value columns like phone number.
- Performed descriptive analysis on numerical features.
- Checked for class imbalance in churn variable.
- Applied one-hot encoding to categorical variables international plan &voice mail plan.
- Converted all categorical data to numeric format.
- Conducted correlation analysis to explore relationships and multicollinearity.

Correlation matrix

- **From the heatmap, here are the key findings:**
- **International_plan_Yes** has the highest positive correlation with churn (0.26), suggesting those on the plan are more likely to churn (though still a weak correlation).
- **Customer service calls**, **total day charge**, and **total day minutes** follow with ~0.21 correlation.
- All other features have very weak correlations (-0.02 to 0.09).
- This indicates **no strong linear relationships** and **low risk of multicollinearity**.

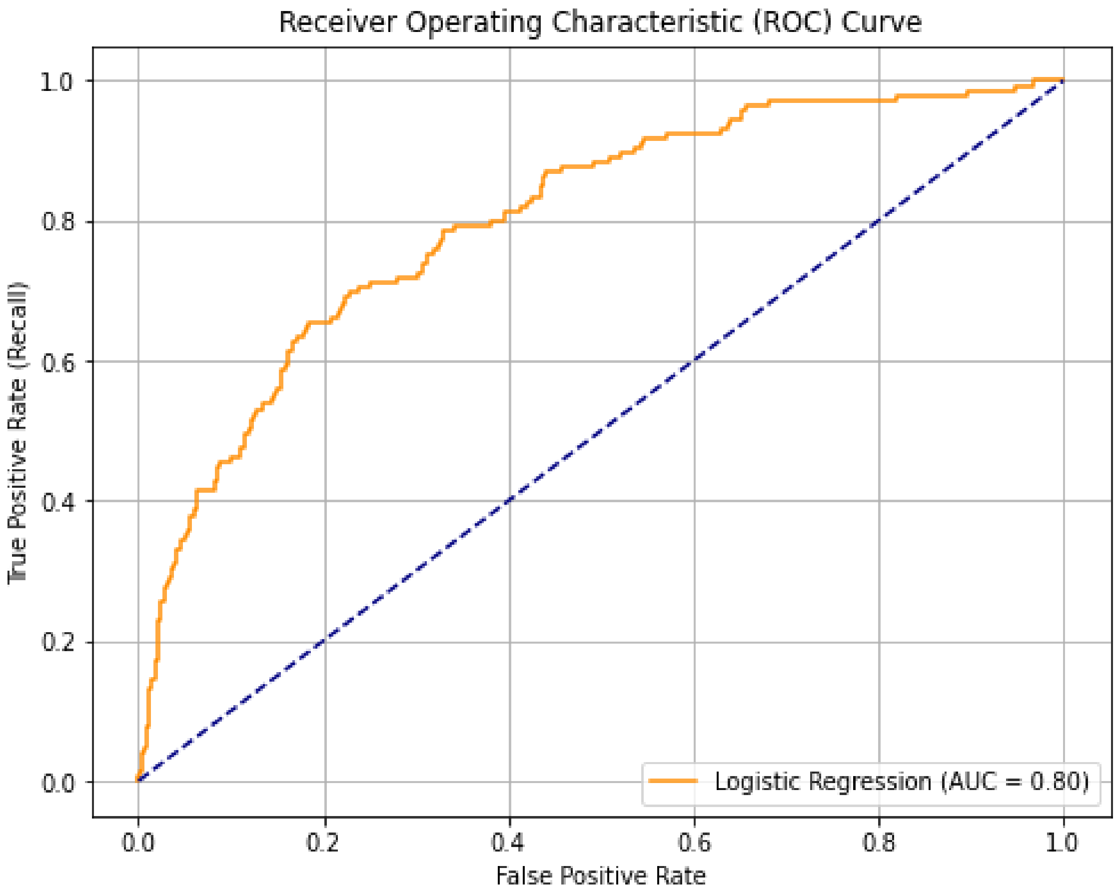


Modelling

- **Train-test split** used to separate data for learning and performance evaluation.
- **Standard scaling** applied to numerical features in the training set.
- **SMOTE** used to balance class distribution (50% churn / 50% no churn).
- **Logistic Regression** trained on resampled data and evaluated using:
  - Accuracy, Precision, Recall, Confusion Matrix, ROC Curve.
- **Random Forest** and **Decision Tree** models also trained and evaluated similarly.
- **Hyperparameter tuning** applied to RF and DT to improve performance.

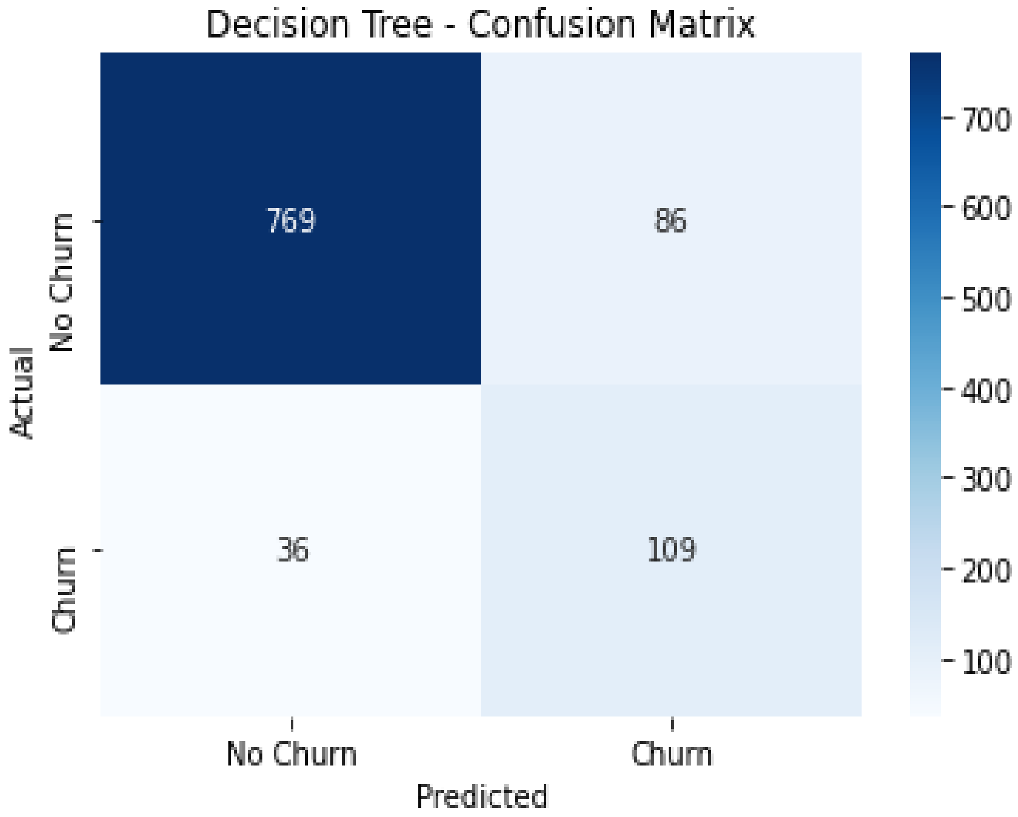
Evaluation-Logistic Model

- The Logistic Regression model achieved an accuracy of 0.72 with a precision of 0.30, recall of 0.71, and F1 score of 0.42.
- The confusion matrix revealed 103 true positives, 42 false negatives, 239 false positives, and 616 true negatives.
- In terms of cross-validation, the model achieved an average accuracy of 75% across 5 folds, indicating a reasonably good ability to distinguish between churned and non-churned customers.
- The AUC score of 0.8015 suggests that the model has an 80.15% chance of correctly ranking a randomly chosen churned customer above a non-churned one, highlighting decent discriminative power despite its lower precision.



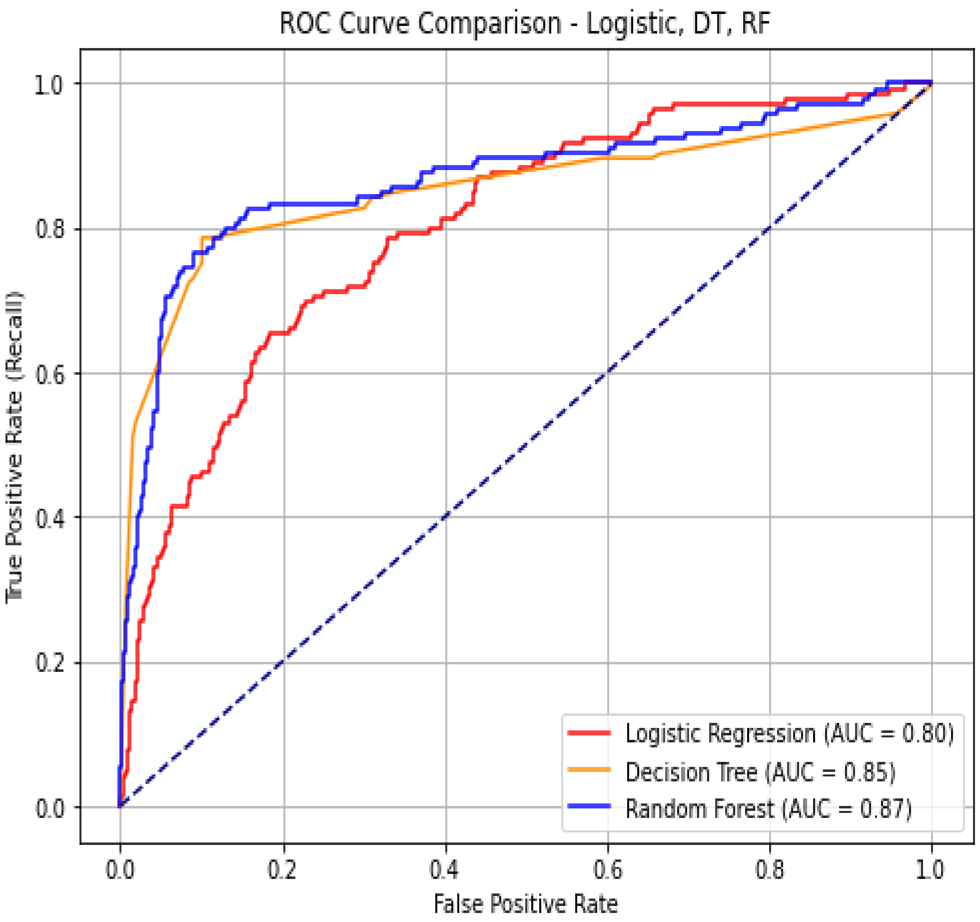
Evaluation – Decision Trees

- The **Decision Tree** model achieved a strong accuracy of 0.88, indicating it correctly classified 88% of the customers.
- It recorded a **precision of 0.56** and a **recall of 0.75**, showing it was fairly effective at identifying churned customers while maintaining a moderate rate of false positives.
- The **confusion matrix** revealed 769 true negatives, 86 false positives, 36 false negatives, and 109 true positives, demonstrating the model's strength in correctly identifying both churned and non-churned customers.
- With a **cross-validation accuracy of 0.86,** the model showed consistent performance across different data folds, reinforcing its reliability.
- Overall, the Decision Tree offered balanced performance with better recall and accuracy than the logistic model, making it a strong candidate for churn prediction.



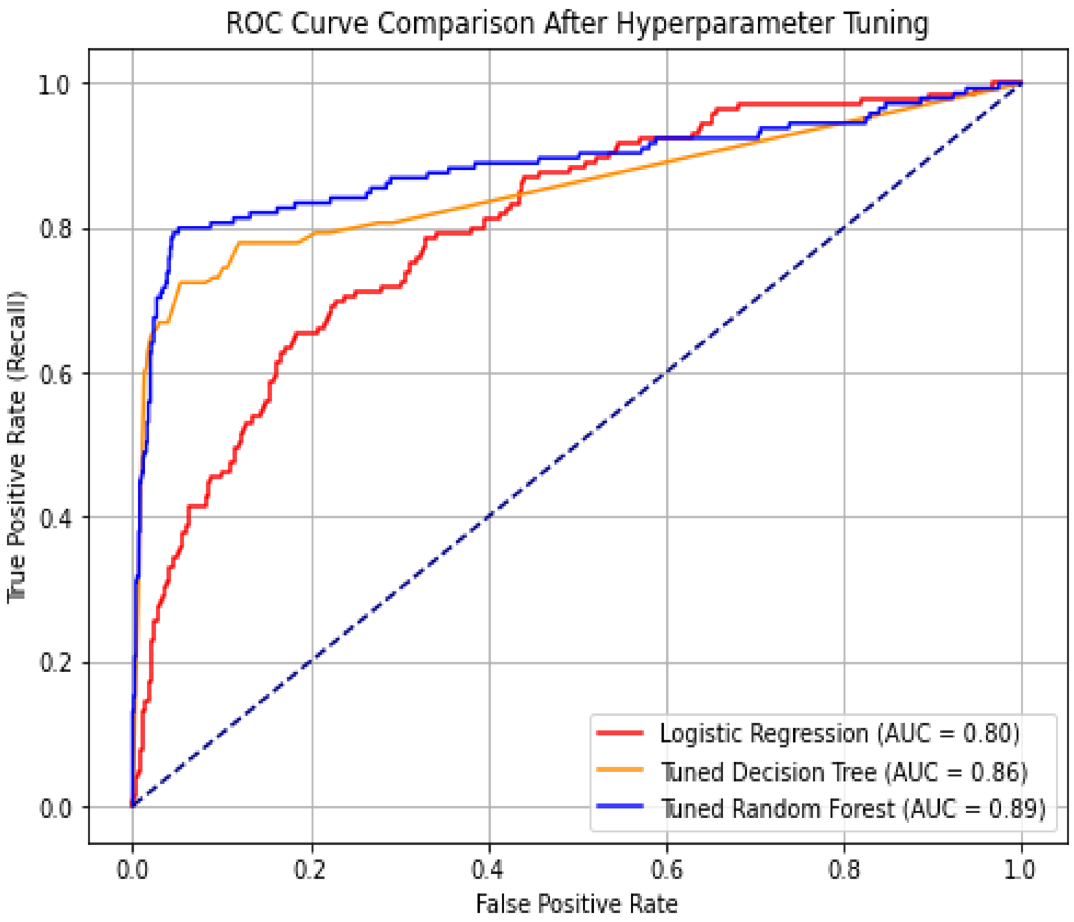
Evaluation- Random Forest

- The **Random Forest** model delivered the best overall performance, achieving an **accuracy of 0.90**, with **precision of 0.64** and **recall of 0.73**.
- It correctly identified most non-churned customers with **795 true negatives** and detected **106 true churn cases**, while keeping **false positives (60)** and **false negatives (39)** relatively low.
- The model demonstrated strong generalization, with a **cross-validation accuracy of 0.87**, consistently classifying 87% of customers correctly across different splits.
- This makes Random Forest the most reliable and balanced model for predicting churn in this study.



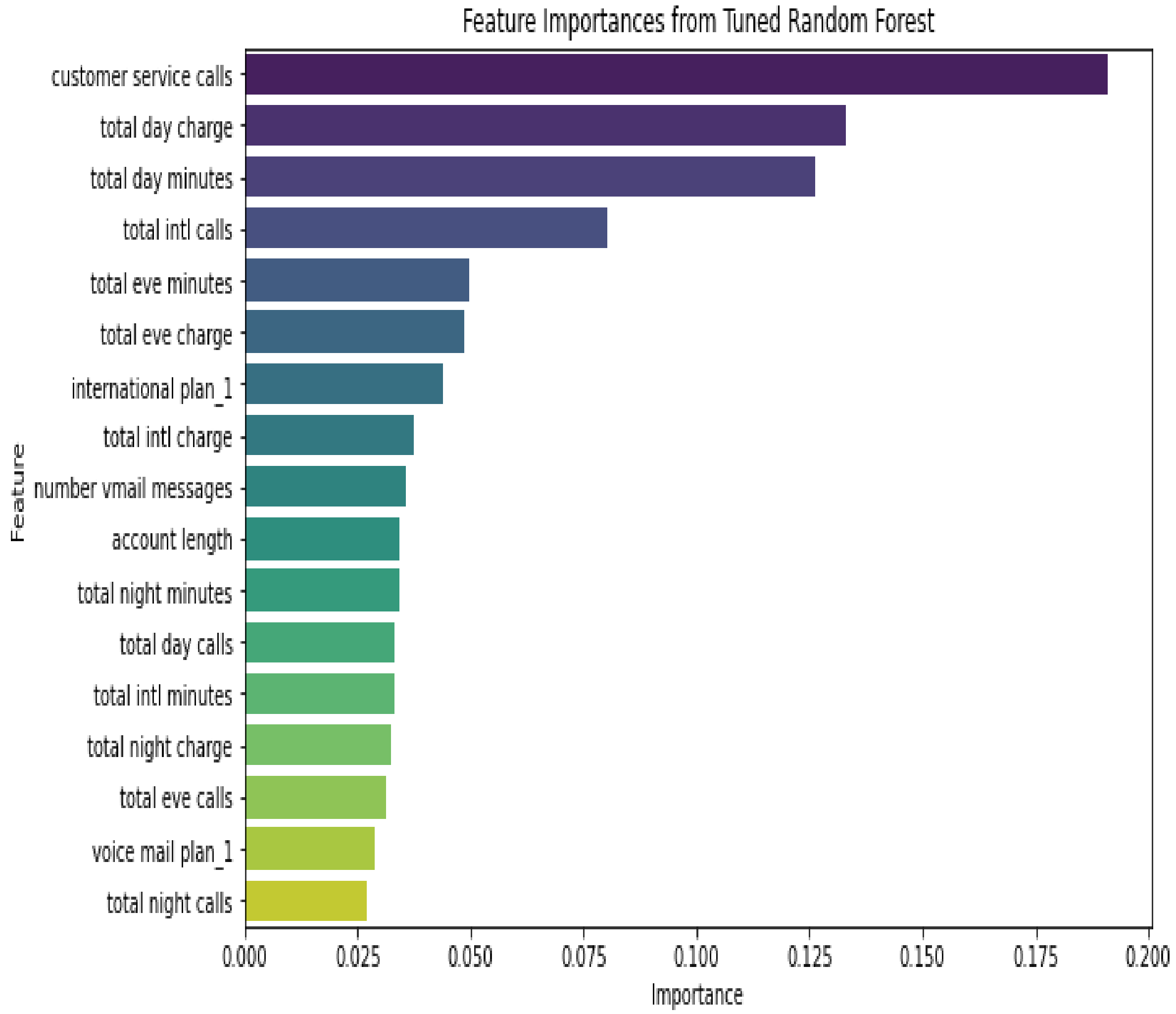
Hyperparameter Tuning

- **After hyperparameter tuning**, both models showed notable improvement. The **Decision Tree** reached an **accuracy of 90%**, up from ~84%, with more consistent results across folds (±0.01 std). However, it remains somewhat prone to overfitting on complex patterns.
- The **Random Forest** model achieved the **highest accuracy of 95%**, with excellent stability (±0.01 std). Tuning significantly enhanced its generalization and reduced overfitting, thanks to the ensemble approach.
- In terms of **ROC scores**, the **tuned Random Forest** led with an **AUC of 0.89**, followed by the **tuned Decision Tree** at **0.86**. **Logistic Regression** remained a solid baseline with an **AUC of 0.80**, though it lagged behind the other models



Feature Selection

- **Feature selection** was performed using the best-performing model — Random Forest — to identify the key drivers of customer churn. This approach leveraged the model's ability to rank features based on their importance in predicting churn, ensuring more reliable insights.
- **Customer service calls** emerged as the most important feature for predicting churn, suggesting that frequent contact with support may indicate dissatisfaction or unresolved issues.
- This is closely followed by **total day charge** and **total day minutes**, implying that higher daytime usage and related costs could also signal a higher likelihood of churn.



Recommendations & Next Steps

- **Enhance Customer Support:** Service calls are a top churn driver—improve satisfaction through feedback surveys, sentiment analysis, and agent training.
- **Engage High-Usage Customers:** Customers with high daytime usage and charges are at higher risk. Offer personalized plans, loyalty rewards, and proactive retention strategies.
- **Embed Insights into Strategy:** Incorporate churn drivers into regular business reviews and continuously retrain models to adapt to evolving customer behavior.
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- **Next Steps**
- **Model Deployment:** Integrate the Random Forest model into SyriaTel's customer management system for real-time churn prediction.
- **Monitor Model Performance:** Track prediction accuracy and update the model regularly with new data to maintain relevance.
- **Operationalize Interventions:** Develop automated workflows for retention offers, triggered by churn risk scores.
- **Cross-Functional Collaboration:** Work with customer service, marketing, and product teams to act on churn insights.

THANK YOU