Introduction

Business problem: SyriaTel Churn Prediction

Presenter: Joanne Kariuki

Stakeholder: SyriaTel Shareholders and Business Team

Project Goals

- **Examined** Customer behavior and service usage patterns from the dataset to understand key indicators of churn.
- **Identified** The most influential features contributing to customer churn, such as frequent customer service interactions.
- **Recommended** Strategic actions to proactively retain high-risk customers.

Data Understanding

The data source for this analysis was gotten from 'bigml_59c28831336c6604c800002a.csv' We will:

- Import the relevant libraries
- Load the data into a dataframe
- Explore and extract data for my analysis
- Data Visualization interpretation
- Provide Recommendations

Import libraries

In [32]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder, StandardScaler

from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, roc_
auc_score, roc_curve
```

Load Data

In [9]:

```
data = pd.read_csv('C:/Projects/Phase3_churn_prediction/bigml_59c28831336c6604c800002a.cs
v', index_col=0)
data.head()
```

Out[9]:

	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total eve charge	total night minutes	total night calls
state														
KS	128	415	382-4657	no	yes	25	265.1	110	45.07	197.4	99	16.78	244.7	91

state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total eve charge	total night minutes	total night calls
OH	107	415	371-7191	no	yes	26	161.6	123	27.47	195.5	103	16.62	254.4	103
NJ	137	415	358-1921	no	no	0	243.4	114	41.38	121.2	110	10.30	162.6	104
OH	84	408	375-9999	yes	no	0	299.4	71	50.90	61.9	88	5.26	196.9	89
OK	75	415	330-6626	yes	no	0	166.7	113	28.34	148.3	122	12.61	186.9	121

Data Understanding

In [10]:

```
data.shape
```

Out[10]:

```
(3333, 20)
```

In [11]:

```
print(data.info())
print(data.describe())
print(data['churn'].value_counts(normalize=True))
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3333 entries, KS to TN
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   account length          3333 non-null   int64
 1   area code               3333 non-null   int64
 2   phone number            3333 non-null   object
 3   international plan      3333 non-null   object
 4   voice mail plan         3333 non-null   object
 5   number vmail messages   3333 non-null   int64
 6   total day minutes       3333 non-null   float64
 7   total day calls         3333 non-null   int64
 8   total day charge        3333 non-null   float64
 9   total eve minutes       3333 non-null   float64
 10  total eve calls         3333 non-null   int64
 11  total eve charge        3333 non-null   float64
 12  total night minutes     3333 non-null   float64
 13  total night calls       3333 non-null   int64
 14  total night charge      3333 non-null   float64
 15  total intl minutes      3333 non-null   float64
 16  total intl calls        3333 non-null   int64
 17  total intl charge       3333 non-null   float64
 18  customer service calls  3333 non-null   int64
 19  churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(3)
memory usage: 524.0+ KB
None
       account length    area code  number vmail messages  total day minutes  \
count     3333.000000  3333.000000            3333.000000        3333.000000
mean       101.064806   437.182418               8.099010         179.775098
std         39.822106    42.371290              13.688365          54.467389
min          1.000000   408.000000               0.000000           0.000000
25%         74.000000   408.000000               0.000000         143.700000
50%        101.000000   415.000000               0.000000         179.400000
75%        127.000000   510.000000              20.000000         216.400000
max        243.000000   510.000000              51.000000         350.800000

       total day calls  total day charge  total eve minutes  total eve calls  \
count      3333.000000       3333.000000        3333.000000      3333.000000
mean        100.435644         30.562307         200.980348       100.114311
std          20.069084          9.259435          50.713844        19.922625
min           0.000000          0.000000           0.000000         0.000000
25%          87.000000         24.430000         166.600000        87.000000
```

```
50%         101.000000          30.500000          201.400000        100.000000
75%         114.000000          36.790000          235.300000        114.000000
max         165.000000          59.640000          363.700000        170.000000

       total eve charge  total night minutes  total night calls  \
count       3333.000000          3333.000000        3333.000000
mean          17.083540           200.872037         100.107711
std            4.310668            50.573847          19.568609
min            0.000000            23.200000          33.000000
25%           14.160000           167.000000          87.000000
50%           17.120000           201.200000         100.000000
75%           20.000000           235.300000         113.000000
max           30.910000           395.000000         175.000000

       total night charge  total intl minutes  total intl calls  \
count         3333.000000         3333.000000       3333.000000
mean             9.039325           10.237294          4.479448
std              2.275873            2.791840          2.461214
min              1.040000            0.000000          0.000000
25%              7.520000            8.500000          3.000000
50%              9.050000           10.300000          4.000000
75%             10.590000           12.100000          6.000000
max             17.770000           20.000000         20.000000

       total intl charge  customer service calls
count        3333.000000             3333.000000
mean            2.764581                1.562856
std             0.753773                1.315491
min             0.000000                0.000000
25%             2.300000                1.000000
50%             2.780000                1.000000
75%             3.270000                2.000000
max             5.400000                9.000000
churn
False    0.855086
True     0.144914
Name: proportion, dtype: float64
```

Data Cleaning

In [15]:

```python
# check for missing values
print(data.isnull().sum())
```

```
account length            0
area code                 0
phone number              0
international plan        0
voice mail plan           0
number vmail messages     0
total day minutes         0
total day calls           0
total day charge          0
total eve minutes         0
total eve calls           0
total eve charge          0
total night minutes       0
total night calls         0
total night charge        0
total intl minutes        0
total intl calls          0
total intl charge         0
customer service calls    0
churn                     0
dtype: int64
```

In [17]:

```python
# Drop irrelevant columns
```

```
data_clean = data.drop(columns=['phone number'])

# Label encode binary features
le_international = LabelEncoder()
le_voicemail = LabelEncoder()
data_clean['international plan'] = le_international.fit_transform(data_clean['internation
al plan'])
data_clean['voice mail plan'] = le_voicemail.fit_transform(data_clean['voice mail plan']
)

# Split features and target
X = data_clean.drop(columns=['churn'])
y = data_clean['churn']

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
)

# Scale numerical features
scaler = StandardScaler()
num_cols = ['total day minutes', 'account length']  # Add all numerical columns
X_train[num_cols] = scaler.fit_transform(X_train[num_cols])
X_test[num_cols] = scaler.transform(X_test[num_cols])

print("Preprocessing complete!")
print(f"Training set: {X_train.shape}, Test set: {X_test.shape}")
```

```
Preprocessing complete!
Training set: (2666, 18), Test set: (667, 18)
```

In [20]:

```
data_clean
```

Out[20]:

state	account length	area code	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total eve charge	total night minutes	total night calls	total night charge
KS	128	415	0	1	25	265.1	110	45.07	197.4	99	16.78	244.7	91	11.01
OH	107	415	0	1	26	161.6	123	27.47	195.5	103	16.62	254.4	103	11.45
NJ	137	415	0	0	0	243.4	114	41.38	121.2	110	10.30	162.6	104	7.32
OH	84	408	1	0	0	299.4	71	50.90	61.9	88	5.26	196.9	89	8.86
OK	75	415	1	0	0	166.7	113	28.34	148.3	122	12.61	186.9	121	8.41
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
AZ	192	415	0	1	36	156.2	77	26.55	215.5	126	18.32	279.1	83	12.56
WV	68	415	0	0	0	231.1	57	39.29	153.4	55	13.04	191.3	123	8.61
RI	28	510	0	0	0	180.8	109	30.74	288.8	58	24.55	191.9	91	8.64
CT	184	510	1	0	0	213.8	105	36.35	159.6	84	13.57	139.2	137	6.26
TN	74	415	0	1	25	234.4	113	39.85	265.9	82	22.60	241.4	77	10.86

3333 rows × 19 columns

Modelling

Logistic Regression: Baseline Model

In [37]:

```
baseline_model = LogisticRegression(max_iter=1000)
baseline_model.fit(X_train, y_train)
y_pred_log = baseline_model.predict(X_test)

print("\n--- Logistic Regression Evaluation ---")
print(confusion_matrix(y_test, y_pred_log))
print(classification_report(y_test, y_pred_log))
```

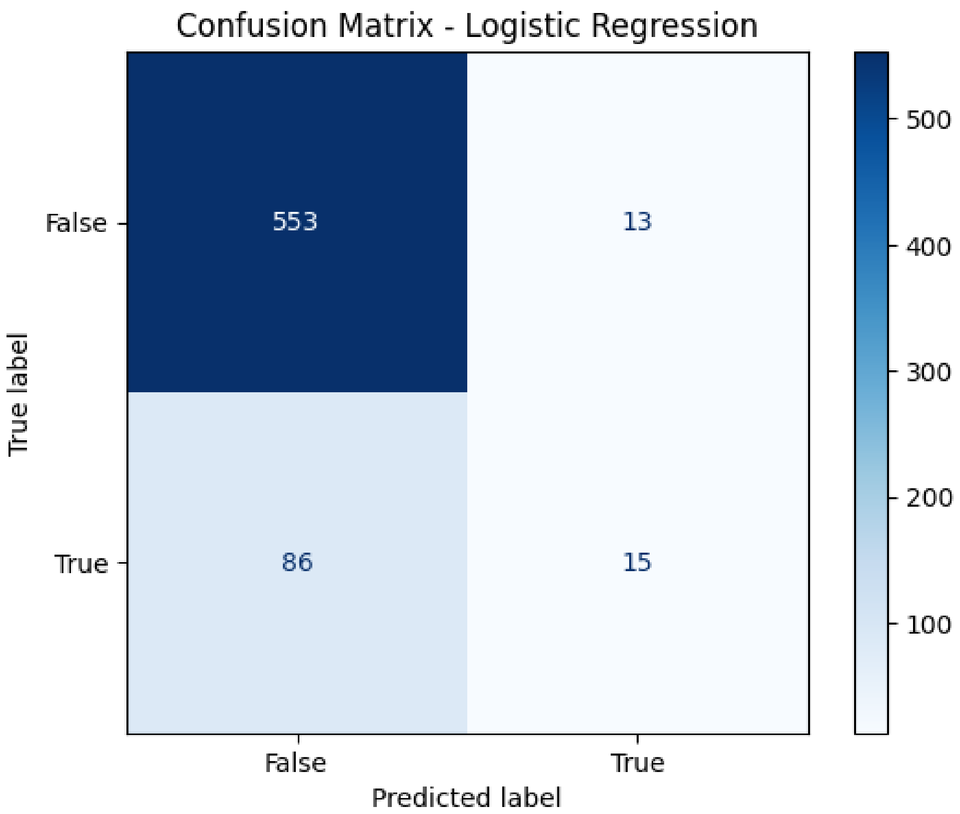
```
--- Logistic Regression Evaluation ---
[[553  13]
 [ 86  15]]
              precision    recall  f1-score   support

       False       0.87      0.98      0.92       566
        True       0.54      0.15      0.23       101

    accuracy                           0.85       667
   macro avg       0.70      0.56      0.58       667
weighted avg       0.82      0.85      0.81       667
```

```
c:\Projects\myenv\Lib\site-packages\sklearn\linear_model\_logistic.py:465: ConvergenceWar
ning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Visualisation - Confusion Matrix for Logistic Regression

In [ ]:

```
from sklearn.metrics import ConfusionMatrixDisplay

# Logistic Regression
ConfusionMatrixDisplay.from_estimator(baseline_model, X_test, y_test, cmap='Blues')
plt.title("Confusion Matrix - Logistic Regression")
plt.show()
```



Decision Tree Classifier: Comparison Model

In [19]:

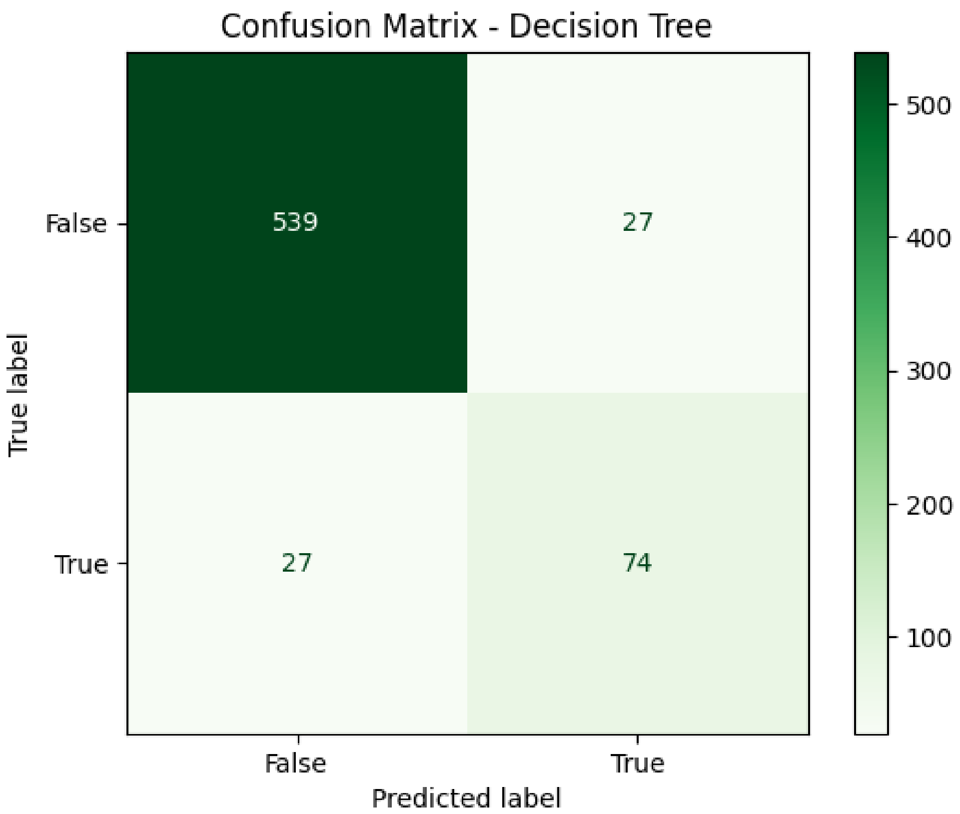
```
dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)

print("\n--- Decision Tree Evaluation ---")
print(confusion_matrix(y_test, y_pred_dt))
print(classification_report(y_test, y_pred_dt))
```

```
--- Decision Tree Evaluation ---
[[539  27]
 [ 27  74]]
              precision    recall  f1-score   support

       False       0.95      0.95      0.95       566
        True       0.73      0.73      0.73       101

    accuracy                           0.92       667
   macro avg       0.84      0.84      0.84       667
weighted avg       0.92      0.92      0.92       667
```

Visualisation - Confusion Matrix for Decision Tree

In [26]:

```
ConfusionMatrixDisplay.from_estimator(dt, X_test, y_test, cmap='Greens')
plt.title("Confusion Matrix - Decision Tree")
plt.show()
```



Decision Tree with hyperparameters

In [21]:

```
params = {'max_depth': [3, 5, 10], 'min_samples_split': [2, 10, 20]}
grid_dt = GridSearchCV(DecisionTreeClassifier(random_state=42), param_grid=params, cv=5)
grid_dt.fit(X_train, y_train)
y_pred_tuned = grid_dt.predict(X_test)
```

```
print("\n--- Tuned Decision Tree Evaluation ---")
print(confusion_matrix(y_test, y_pred_tuned))
print(classification_report(y_test, y_pred_tuned))
```

```
--- Tuned Decision Tree Evaluation ---
[[557   9]
 [ 33  68]]
              precision    recall  f1-score   support

       False       0.94      0.98      0.96       566
        True       0.88      0.67      0.76       101

    accuracy                           0.94       667
   macro avg       0.91      0.83      0.86       667
weighted avg       0.93      0.94      0.93       667
```

Interpretation

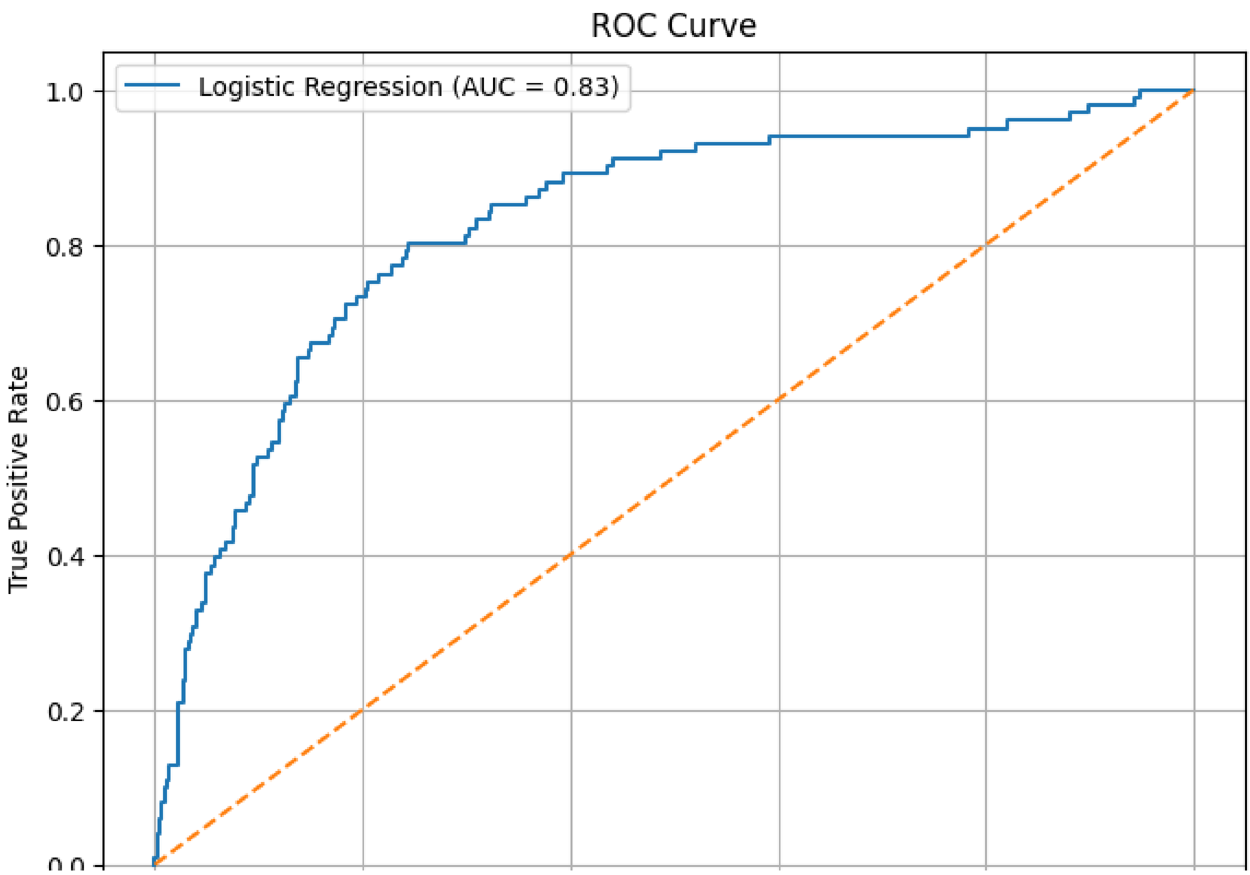
Decision Tree is Clearly Superior for Churn Detection

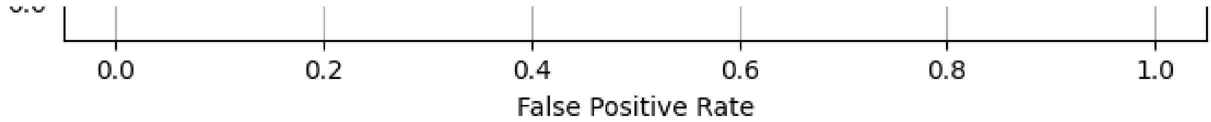
- **73% recall vs logistic's 15% - Identifies more actual churners**
- **Maintains reasonable 73% precision (only 27% false alarms)**

ROC Curve__

In [22]:

```
y_probs = baseline_model.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_probs)
plt.figure(figsize=(8,6))
plt.plot(fpr, tpr, label=f'Logistic Regression (AUC = {roc_auc_score(y_test, y_probs):.2f
})')
plt.plot([0,1],[0,1],'--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.grid()
plt.show()
```





Interpretation

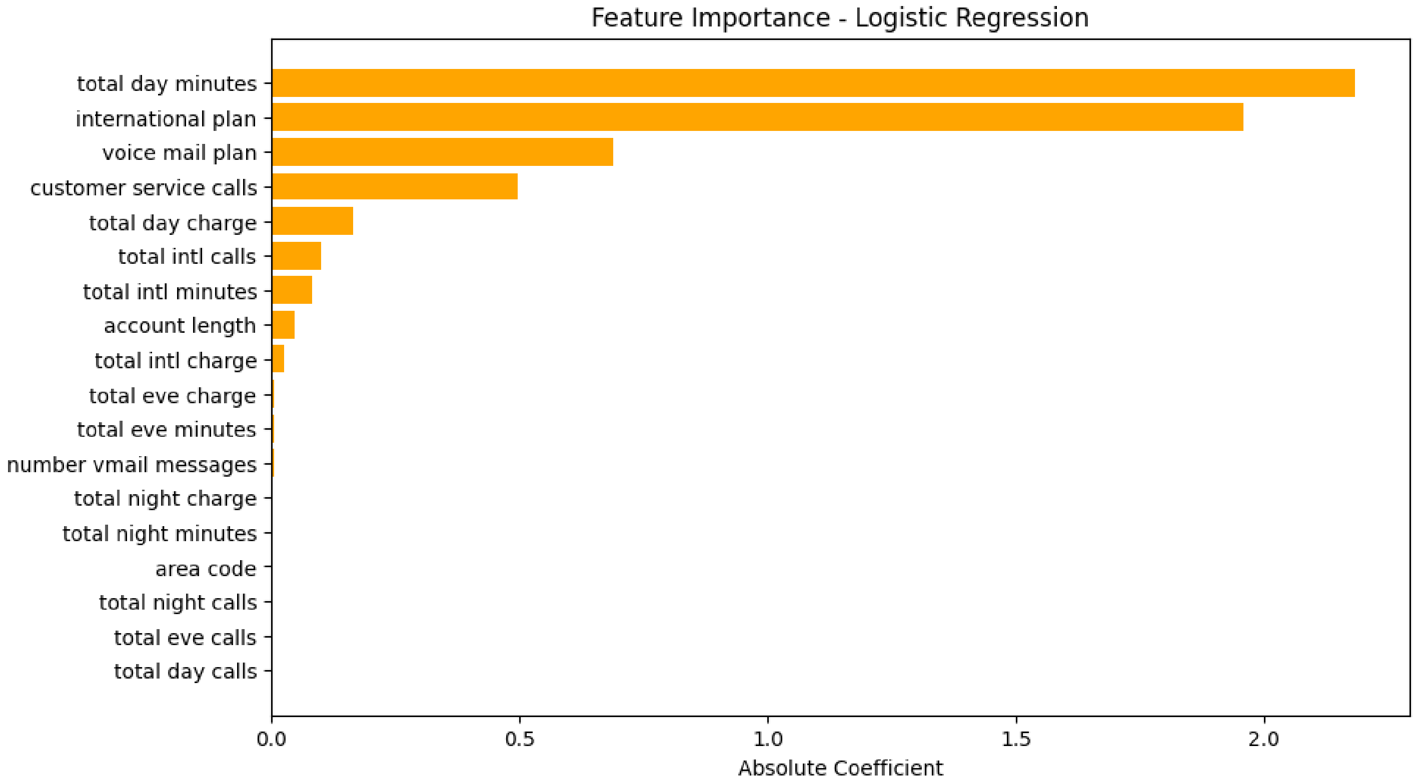
- **The closer the curve is to the top-left corner, the better the model is at distinguishing churners.This means there's an 83% chance the model ranks a random churner higher than a random non-churner.**
- **A diagonal line means random guessing (AUC = 0.5).**
- **Our Logistic Regression AUC = 0.83, indicating strong model performance.**

Feature importance & Evaluation

Logistic Regression

In [30]:

```
# Get feature importance (absolute value of coefficients)
coefs = baseline_model.coef_[0]
features = X_train.columns
coef_df = pd.DataFrame({
    'Feature': features,
    'Coefficient': coefs,
    'AbsCoefficient': np.abs(coefs)
}).sort_values('AbsCoefficient', ascending=False)

# Plot
plt.figure(figsize=(10, 6))
plt.barh(coef_df['Feature'], coef_df['AbsCoefficient'], color='orange')
plt.xlabel("Absolute Coefficient")
plt.title("Feature Importance - Logistic Regression")
plt.gca().invert_yaxis()
plt.show()
```

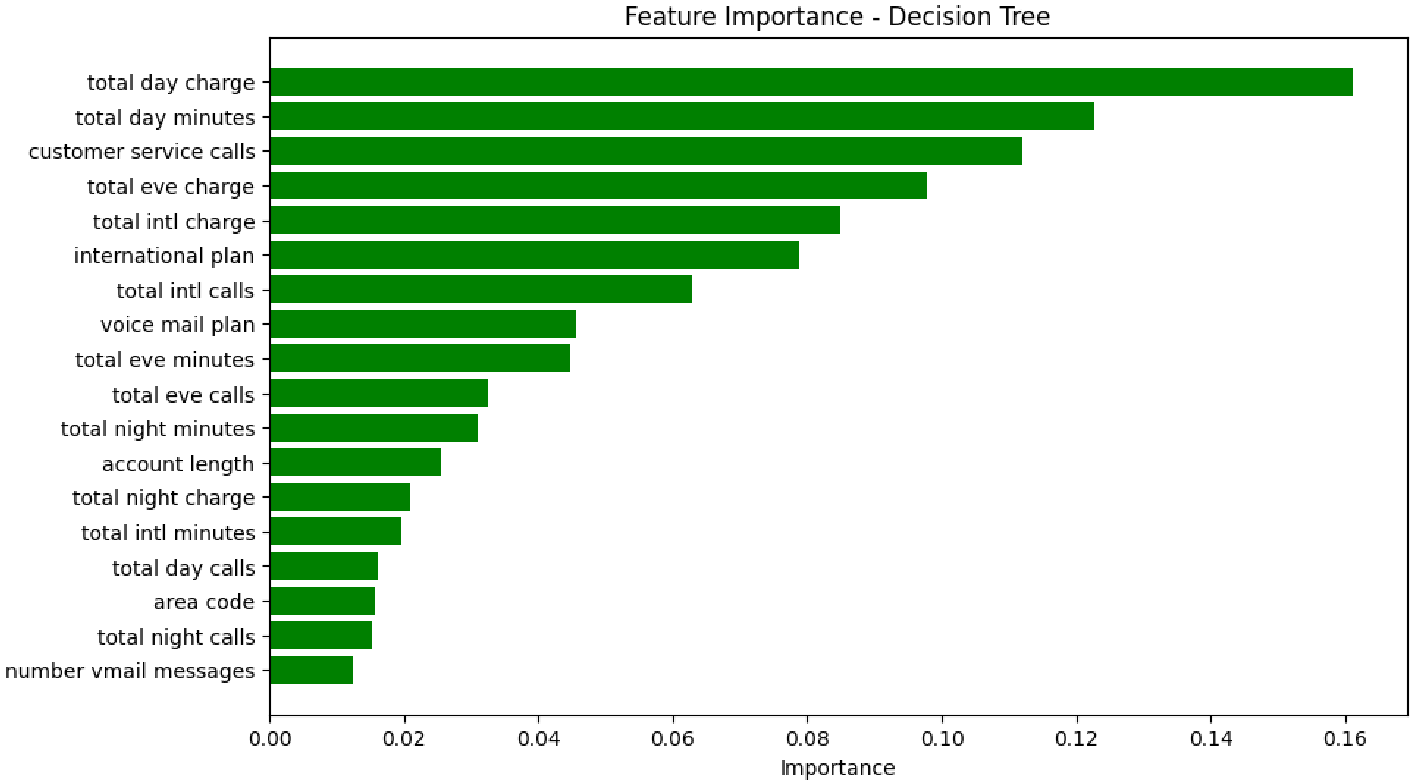


Decision Tree

In [31]:

```
importances = dt.feature_importances_
```

```python
feature_names = X_train.columns
indices = np.argsort(importances)[::-1]

# Plot
plt.figure(figsize=(10, 6))
plt.title("Feature Importance - Decision Tree")
plt.barh(range(len(importances)), importances[indices], align="center", color='green')
plt.yticks(range(len(importances)), [feature_names[i] for i in indices])
plt.xlabel("Importance")
plt.gca().invert_yaxis()
plt.show()
```



Interpretation: Both models consistently highlight call duration metrics (particularly daytime usage) as the strongest predictors of churn, with total day minutes ranking #1 in logistic regression and total day charge being the most important feature in the decision tree.

Other top predictors of churn: Customer Service Calls International Plans

Conclusion

Following my analysis:

- **The tuned deision tree model works best as it catches 67% of churners(vs 15% with logistic regression)**
- **The tuned decision tree model is also 88% accurate when predicting churn and makes only 9 false alarms per 566 customers**
- **The key warning signs for customers likely to churn are:**
  - **High daytime call usage**
  - **Many customer service calls**
  - **Cutomers that have an international plan**