2491 lines (2491 loc) · 558 KB

Final Project Submission

Please fill out:

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- Student pace: part time
- Scheduled project review date/time:
- Instructor name: BRIAN CHACHA
- Blog post URL:

In [1]:

```
# Your code here - remember to use markdown cells for comments as well!
```

Business Understanding

Telecom Customer Churn Prediction for Executive Leadership Team at SyriaTel Telecommunications Company

Stakeholder

Executive Leadership Team at SyriaTel Telecommunications Company

Business Problem

Customer churn is a critical challenge in the telecommunications industry. Acquiring new customers costs 5-25 times more than retaining existing ones. Our telecom company is experiencing customer attrition and needs to:

1. **Identify customers at high risk of churning** before they leave
2. **Understand key factors** that contribute to customer churn
3. **Develop targeted retention strategies** to reduce churn rate

Success Criteria

- Build a predictive model with **high recall** (we want to catch most customers who will churn, even if we have some false positives).
- **Recall is prioritized** because the cost of losing a customer is much higher than the cost of offering retention incentives to someone who might not churn.
- Identify actionable features that the business can influence.
- Target: Achieve recall of at least 70% on the test set

Key Questions

1. Can we predict which customers will churn?
2. What are the strongest predictors of churn?
3. Which customer segments are at highest risk?
4. What interventions might reduce churn?

In [5]:

```
# Import necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (classification_report, confusion_matrix, accuracy_score, precision_score, recall_s
```

```
import warnings
warnings.filterwarnings('ignore')

# Set style for better visualization
sns.set_style('whitegrid')
plt.rcParams['figure.figsize'] = (12, 6)
```

Data Understanding

In [6]:

```
# Load the dataset
df = pd.read_csv("SyriaTelCustomerChurn.csv")

# Display the shape of the dataset
print("Dataset Shape:", df.shape)
```

```
Dataset Shape: (3333, 21)
```

In [7]:

```
# Display first few rows
df.head()
```

Out[7]:

	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 calls	total eve charge	total night minutes	tota nigh call
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78	244.7	9
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62	254.4	10
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30	162.6	10
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26	196.9	8
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61	186.9	12

5 rows × 21 columns

In [8]:

```
# Dataset info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   state                   3333 non-null   object 
 1   account length          3333 non-null   int64  
 2   area code               3333 non-null   int64  
 3   phone number            3333 non-null   object 
 4   international plan      3333 non-null   object 
 5   voice mail plan         3333 non-null   object 
 6   number vmail messages   3333 non-null   int64  
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64  
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64  
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64  
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64  
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64  
```

```
 20  churn                  3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

Data Dictionary

Understanding our features:

Target Variable:

- `churn` : Whether the customer left (True/False)

Customer Demographics:

- `state` : US State (2-letter code)
- `area code` : Area code of phone number
- `phone number` : Customer's phone number
- `account length` : Number of days the account has been active

Service Plans:

- `international plan` : Whether customer has international plan (yes/no)
- `voice mail plan` : Whether customer has voicemail plan (yes/no)
- `number vmail messages` : Number of voicemail messages

Usage Patterns (Day/Evening/Night/International):

- `total X minutes` : Total minutes used
- `total X calls` : Total number of calls
- `total X charge` : Total charges

Customer Service:

- `customer service calls` : Number of calls to customer service

In [9]:

```python
# Statistical summary
df.describe()
```

Out[9]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total ev charg
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.00000
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.980348	100.114311	17.08354
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.713844	19.922625	4.31066
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00000
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.600000	87.000000	14.16000
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.400000	100.000000	17.12000
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.300000	114.000000	20.00000
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.700000	170.000000	30.91000

Check for Missing Values

In [11]:

```python
# Missing values
missing = df.isnull().sum()
missing_pct = 100 * missing / len(df)
missing_df = pd.DataFrame({'Missing_Count': missing, 'Percentage': missing_pct})
missing_df = missing_df[missing_df['Missing_Count'] > 0].sort_values('Missing_Count', ascending=False)
if missing_df.empty:
    print("No missing values in the dataset.")
```

```
No missing values in the dataset.
```

Target Variable Analysis

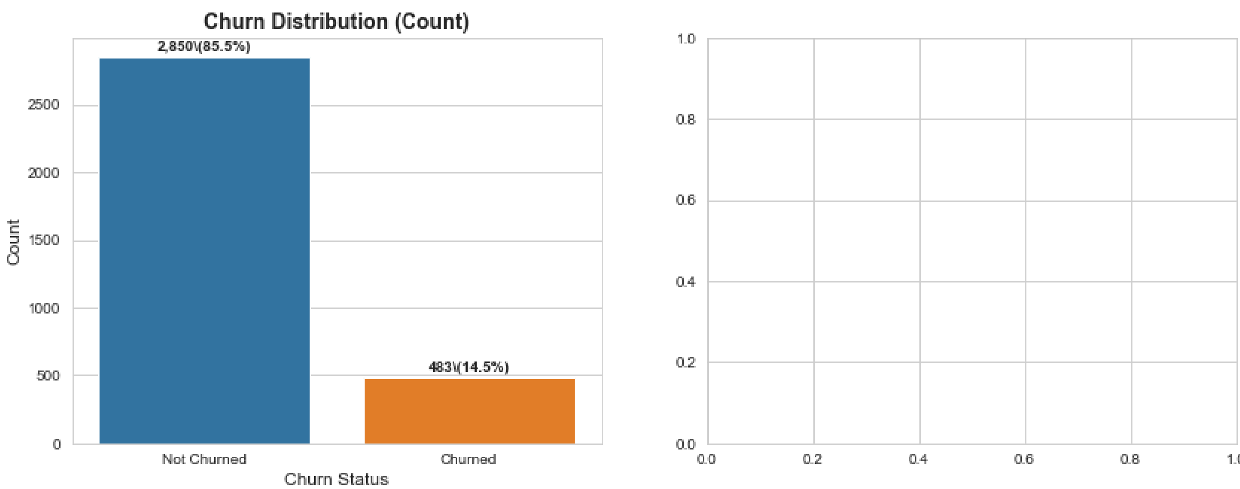
In [12]:

```
# Churn distribution
churn_counts = df['churn'].value_counts()
churn_pct = 100 * df['churn'].value_counts(normalize=True)
print ("Churn Distribution:", churn_counts)
print ("Churn Percentage:", churn_pct)
print(f"Not Churned (False): {churn_counts[False]:,} ({churn_pct[False]:.2f}%)")
print(f"Churned (True): {churn_counts[True]:,} ({churn_pct[True]:.2f}%)")
```

```
Churn Distribution: False    2850
True      483
Name: churn, dtype: int64
Churn Percentage: False    85.508551
True     14.491449
Name: churn, dtype: float64
Not Churned (False): 2,850 (85.51%)
Churned (True): 483 (14.49%)
```

In [13]:

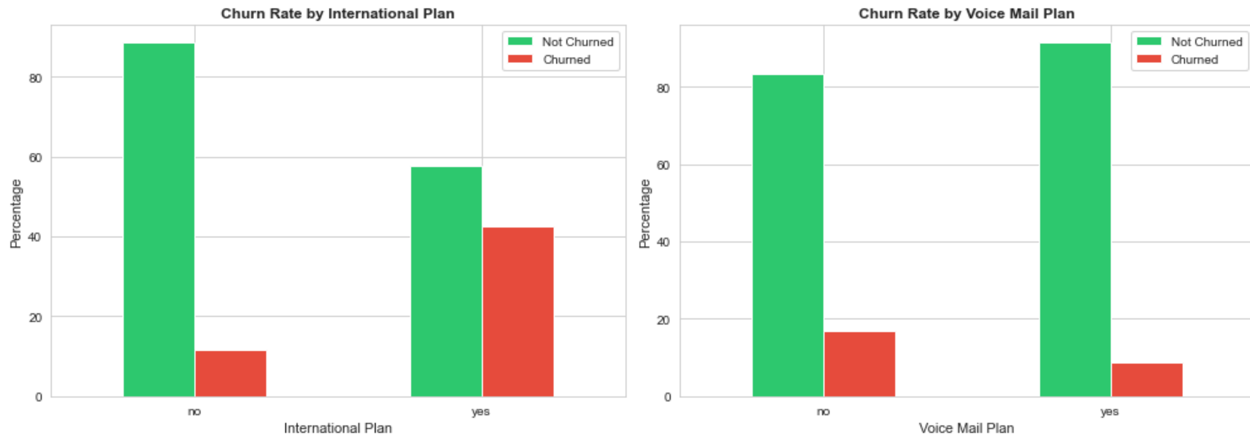
```
# Visualization
fig, axes = plt.subplots(1, 2, figsize=(14, 5))
# Count plot
sns.countplot(data=df, x='churn', ax=axes[0])
axes[0].set_title('Churn Distribution (Count)', fontsize=14, fontweight='bold')
axes[0].set_xlabel('Churn Status', fontsize=12)
axes[0].set_ylabel('Count', fontsize=12)
axes[0].set_xticklabels(['Not Churned', 'Churned'])
# Add value labels
for i, v in enumerate(churn_counts):
    axes[0].text(i, v + 50, f'{v:,}\({churn_pct[i]:.1f}%)', ha='center', fontsize=10, fontweight='bold')
```



Exploratory Data Analysis

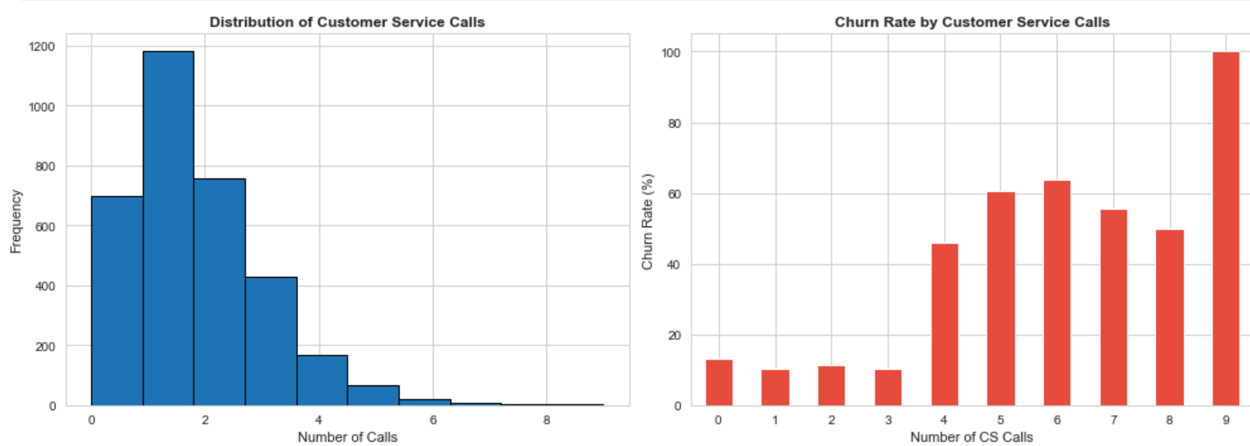
In [18]:

```
# Convert churn to binary for analysis
df['churn_binary'] = df['churn'].astype(int)
# Analyze categorical features
categorical_features = ['international plan', 'voice mail plan']
fig, axes = plt.subplots(1, 2, figsize=(14, 5))
for idx, feature in enumerate(categorical_features):
     # Calculate churn rate by feature
    churn_by_feature = df.groupby(feature)['churn'].value_counts(normalize=True).unstack()
    churn_by_feature = churn_by_feature * 100
    churn_by_feature.plot(kind='bar', ax=axes[idx], color=['#2ecc71', '#e74c3c'])
    axes[idx].set_title(f'Churn Rate by {feature.title()}', fontsize=12, fontweight='bold')
    axes[idx].set_xlabel(feature.title(), fontsize=11)
    axes[idx].set_ylabel('Percentage', fontsize=11)
    axes[idx].legend(['Not Churned', 'Churned'])
    axes[idx].set_xticklabels(axes[idx].get_xticklabels(), rotation=0)
plt.tight_layout()
plt.show()
```



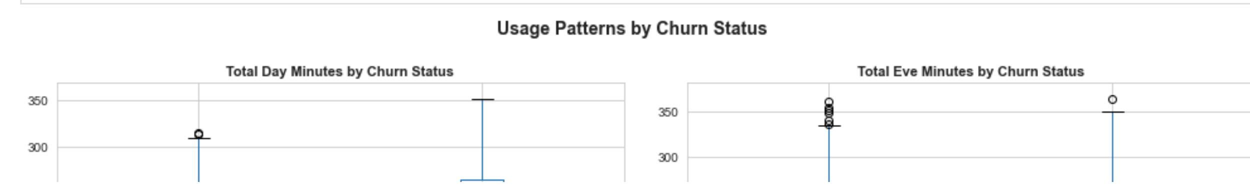
In [20]:

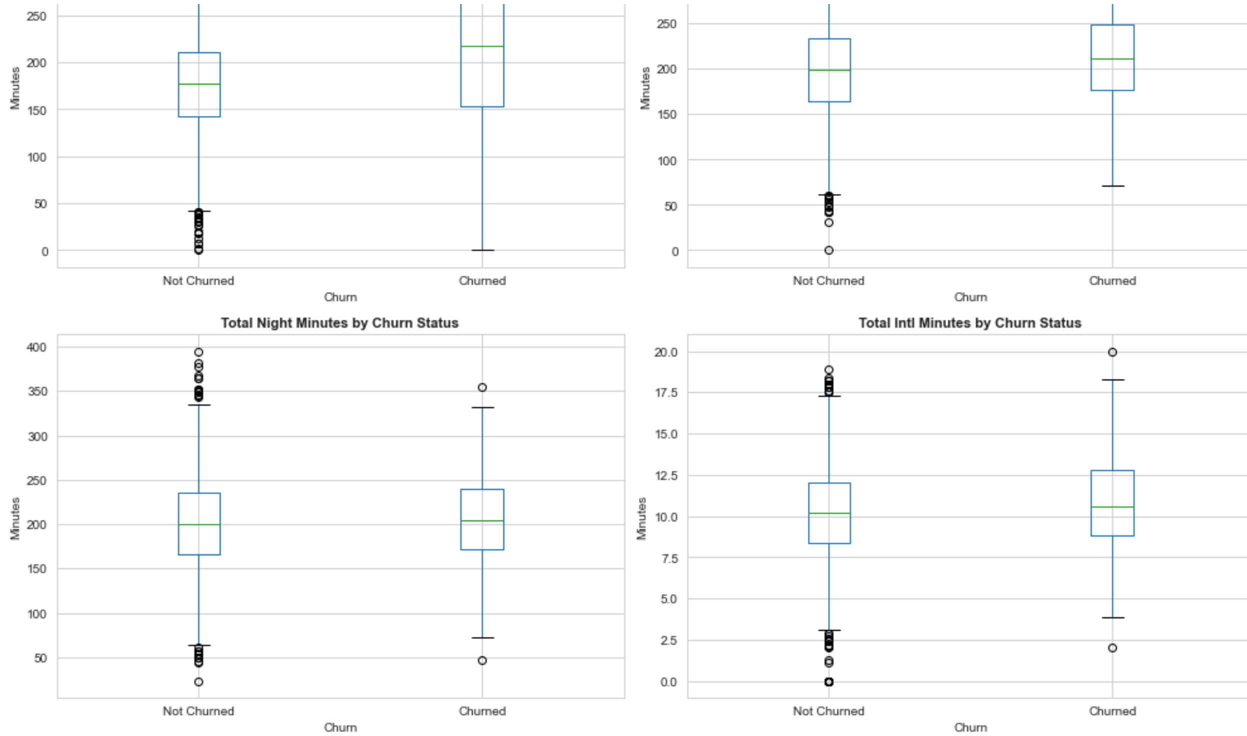
```
# Analyze customer service calls
fig, axes = plt.subplots(1, 2, figsize=(14, 5))
# Distribution of customer service calls
df['customer service calls'].hist(bins=10, ax=axes[0], edgecolor='black')
axes[0].set_title('Distribution of Customer Service Calls', fontsize=12, fontweight='bold')
axes[0].set_xlabel('Number of Calls', fontsize=11)
axes[0].set_ylabel('Frequency', fontsize=11)
# Churn rate by customer service calls
churn_by_cs_calls = df.groupby('customer service calls')['churn'].mean() * 100
churn_by_cs_calls.plot(kind='bar', ax=axes[1], color='#e74c3c')
axes[1].set_title('Churn Rate by Customer Service Calls', fontsize=12, fontweight='bold')
axes[1].set_xlabel('Number of CS Calls', fontsize=11)
axes[1].set_ylabel('Churn Rate (%)', fontsize=11)
axes[1].set_xticklabels(axes[1].get_xticklabels(), rotation=0)
plt.tight_layout()
plt.show()
```



In [21]:

```
# Analyze usage patterns
usage_features = ['total day minutes', 'total eve minutes', 'total night minutes', 'total intl minutes']
fig, axes = plt.subplots(2, 2, figsize=(14, 10))
axes = axes.ravel()
for idx, feature in enumerate(usage_features):
    df.boxplot(column=feature, by='churn', ax=axes[idx])
    axes[idx].set_title(f'{feature.title()} by Churn Status', fontsize=11, fontweight='bold')
    axes[idx].set_xlabel('Churn', fontsize=10)
    axes[idx].set_ylabel('Minutes', fontsize=10)
    plt.sca(axes[idx])
    plt.xticks([1, 2], ['Not Churned', 'Churned'])
plt.suptitle('Usage Patterns by Churn Status', fontsize=14, fontweight='bold', y=1.00)
plt.tight_layout()
plt.show()
```

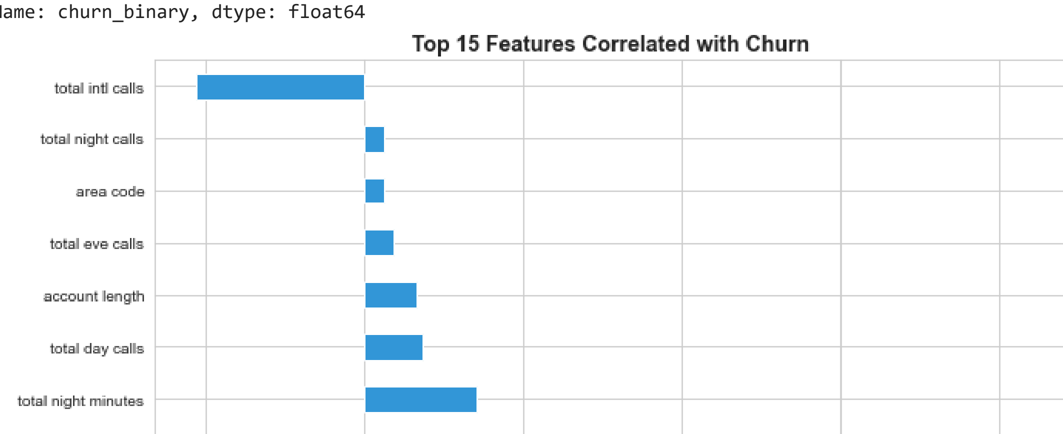


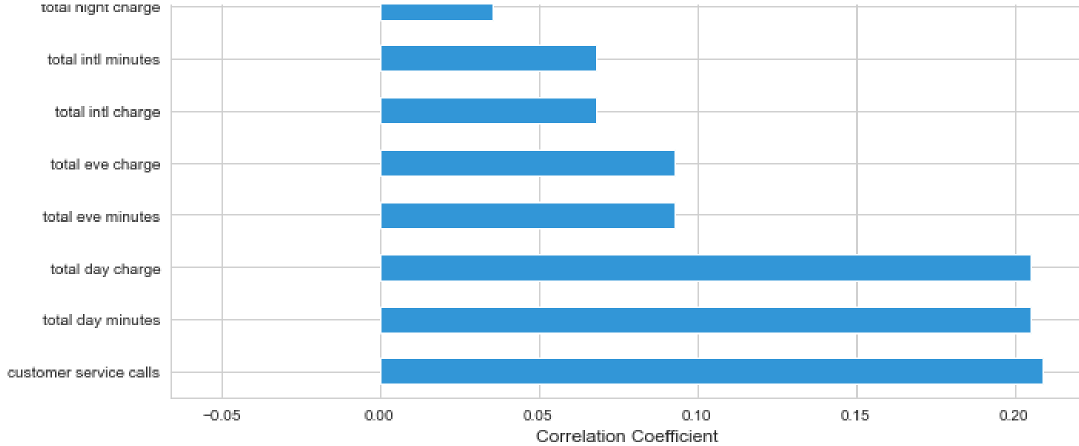


In [22]:

```python
# Correlation analysis
# Select numeric features
numeric_features = df.select_dtypes(include=[np.number]).columns.tolist()
numeric_features.remove('churn_binary')  # We'll add it back later for correlation
# Calculate correlation with churn
correlations = df[numeric_features + ['churn_binary']].corr()['churn_binary'].sort_values(ascending=False)
correlations = correlations.drop('churn_binary')
print("Top 10 Features Correlated with Churn:")
print(correlations.head(10))
# Visualize
fig, ax = plt.subplots(figsize=(10, 8))
top_corr = correlations.head(15)
top_corr.plot(kind='barh', ax=ax, color='#3498db')
ax.set_title('Top 15 Features Correlated with Churn', fontsize=14, fontweight='bold')
ax.set_xlabel('Correlation Coefficient', fontsize=12)
plt.tight_layout()
plt.show()
```

```
Top 10 Features Correlated with Churn:
customer service calls    0.208750
total day minutes         0.205151
total day charge          0.205151
total eve minutes         0.092796
total eve charge          0.092786
total intl charge         0.068259
total intl minutes        0.068239
total night charge        0.035496
total night minutes       0.035493
total day calls           0.018459
Name: churn_binary, dtype: float64
```





Key Findings from EDA

1. **Class Imbalance**: ~14.5% churn rate (typical for telecom)
2. **Customer Service Calls**: Strong predictor - customers with 4+ calls have much higher churn
3. **International Plan**: Customers with international plans show higher churn rates
4. **Voice Mail Plan**: Customers with voice mail plans show lower churn rates
5. **Usage Patterns**: International usage shows correlation with churn
6. **Account Length**: Weaker correlation suggests tenure alone isn't protective

Data Preparation

Feature Engineering

In [25]:

```
# Create a copy for modeling
df_model = df.copy()
# Drop unnecessary columns
columns_to_drop = ['phone number', 'churn_binary']  # Phone number is identifier, churn_binary is duplicate
df_model = df_model.drop(columns=columns_to_drop)
# Feature Engineering
# 1. Total usage across all time periods
df_model['total_minutes'] = (df_model['total day minutes'] +
                             df_model['total eve minutes'] +
                             df_model['total night minutes'] +
                             df_model['total intl minutes'])
df_model['total_calls'] = (df_model['total day calls'] +
                           df_model['total eve calls'] +
                           df_model['total night calls'] +
                           df_model['total intl calls'])
df_model['total_charge'] = (df_model['total day charge'] +
                            df_model['total eve charge'] +
                            df_model['total night charge'] +
                            df_model['total intl charge'])
# 2. Average call duration
df_model['avg_call_duration'] = df_model['total_minutes'] / (df_model['total_calls'] + 1)  # +1 to avoid divisi
# 3. International usage ratio
df_model['intl_usage_ratio'] = df_model['total intl minutes'] / (df_model['total_minutes'] + 1)  # +1 to avoid
# 4. Customer service calls flag (high risk: 4+)
df_model['high_cs_calls'] = (df_model['customer service calls'] >= 4).astype(int)
# 5. Revenue per day
df_model['revenue_per_day'] = df_model['total_charge'] / (df_model['account length'] + 1) # +1 to avoid divisio


print(f"New dataset shape: {df_model.shape}")
print(f"New features created:")
print(["total_minutes", "total_calls", "total_charge", "avg_call_duration",
       "intl_usage_ratio", "high_cs_calls", "revenue_per_day"])
```

```
New dataset shape: (3333, 27)
New features created:
['total_minutes', 'total_calls', 'total_charge', 'avg_call_duration', 'intl_usage_ratio', 'high_cs_calls', 'reven
ue_per_day']
```

Encode Categorical Variables

In [26]:
```
# Binary encoding for yes/no features
binary_features = ['international plan', 'voice mail plan']
for feature in binary_features:
    df_model[feature] = (df_model[feature] == 'yes').astype(int)
# One-hot encoding for state
# Note: We'll use get_dummies for state, but be cautious as it has many categories
# For production, we might want to group low-frequency states
df_model = pd.get_dummies(df_model, columns=['state'], drop_first=True, prefix='state')
# For area code, we'll keep it as numeric (it's already encoded)
# But we could also one-hot encode it
df_model = pd.get_dummies(df_model, columns=['area code'], drop_first=True, prefix='area')

print(" Categorical encoding complete!")
print(f"Final dataset shape: {df_model.shape}")
```

```
 Categorical encoding complete!
Final dataset shape: (3333, 77)
```

Train-Test Split

In [36]:
```
# Separate features and target
X = df_model.drop('churn', axis=1)
y = df_model['churn'].astype(int)  # Convert True/False to 1/0
# Train-test split (80/20),
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, stratify=y)
print(f"Training set size: {X_train.shape[0]:,} samples")

print(f"Test set size: {X_test.shape[0]:,} samples")

print(f"Feature count: {X_train.shape[1]}")

print(f"Class distribution in training set:")

print(y_train.value_counts(normalize=True))

print(f"Class distribution in test set:")

print(y_test.value_counts(normalize=True))
```

```
Training set size: 2,666 samples
Test set size: 667 samples
Feature count: 76
Class distribution in training set:
0    0.855214
1    0.144786
Name: churn, dtype: float64
Class distribution in test set:
0    0.854573
1    0.145427
Name: churn, dtype: float64
```

Feature Scaling

In [38]:
```
# Standardize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Convert back to DataFrame for easier handling
X_train_scaled = pd.DataFrame(X_train_scaled, columns=X_train.columns, index=X_train.index)
X_test_scaled = pd.DataFrame(X_test_scaled, columns=X_test.columns, index=X_test.index)

print("Scaled features sample:")
print(X_train_scaled.head())
```

```
Scaled features sample:
      account length  international plan  voice mail plan  \
3286        0.125737           -0.325216         1.625447
86         -0.175309           -0.325216        -0.615216
1349       -0.752313           -0.325216         1.625447
1649        0.727828           -0.325216        -0.615216
```

```
3000       -0.350919           -0.325216        -0.615216

      number vmail messages  total day minutes  total day calls  \
3286               1.606822           0.743376         0.225611
86                -0.588791          -0.401294         0.225611
1349               1.021325          -0.704945         0.325566
1649              -0.588791          -2.048368        -0.723960
3000              -0.588791           0.800425         0.425520

      total day charge  total eve minutes  total eve calls  total eve charge  \
3286          0.743639           0.426270         0.445403          0.426916
86           -0.401678          -0.904961         0.045354         -0.903861
1349         -0.704787          -0.746481         0.245378         -0.745379
1649         -2.048208          -0.146239         0.495409         -0.146413
3000          0.799931          -1.449735        -0.704736         -1.449223

      ...  state_TX  state_UT  state_VA  state_VT  state_WA  state_WI  \
3286  ... -0.147809 -0.150437 -0.149128 -0.145137 -0.136835 -0.159326
86    ... -0.147809 -0.150437 -0.149128 -0.145137 -0.136835 -0.159326
1349  ... -0.147809 -0.150437 -0.149128 -0.145137 -0.136835 -0.159326
1649  ... -0.147809 -0.150437 -0.149128 -0.145137 -0.136835 -0.159326
3000  ... -0.147809 -0.150437 -0.149128 -0.145137 -0.136835 -0.159326

      state_WV  state_WY  area_415  area_510
3286 -0.185839 -0.151736  0.997752 -0.570131
86   -0.185839 -0.151736 -1.002253 -0.570131
1349 -0.185839 -0.151736 -1.002253  1.753982
1649 -0.185839 -0.151736 -1.002253 -0.570131
3000 -0.185839 -0.151736 -1.002253  1.753982

[5 rows x 76 columns]
```

Modeling

Model Evaluation Function

We'll create a function to consistently evaluate all our models.

In [44]:

```python
# Function to evaluate model
def evaluate_model(model, X_train, X_test, y_train, y_test, model_name):
    """
    Evaluate model performance and display metrics
    """
    print(f"{'='*60}")
    print(f"{model_name}")
    print(f"{'='*60}")

    # Predictions
    y_train_pred = model.predict(X_train)
    y_test_pred = model.predict(X_test)

    # Probabilities for ROC-AUC
    y_train_proba = model.predict_proba(X_train)[:, 1]
    y_test_proba = model.predict_proba(X_test)[:, 1]

    # Calculate metrics
    metrics = {
        'Train Accuracy': accuracy_score(y_train, y_train_pred),
        'Test Accuracy': accuracy_score(y_test, y_test_pred),
        'Train Precision': precision_score(y_train, y_train_pred),
        'Test Precision': precision_score(y_test, y_test_pred),
        'Train Recall': recall_score(y_train, y_train_pred),
        'Test Recall': recall_score(y_test, y_test_pred),
        'Train F1-Score': f1_score(y_train, y_train_pred),
        'Test F1-Score': f1_score(y_test, y_test_pred),
        'Train ROC-AUC': roc_auc_score(y_train, y_train_proba),
        'Test ROC-AUC': roc_auc_score(y_test, y_test_proba)
    }

    # Display metrics
    print("Performance Metrics:")
    print("-" * 60)
    for metric, value in metrics.items():
        print(f"{metric:20s}: {value:.4f}")
```

```
    # Confusion Matrix
    print("Confusion Matrix (Test Set):")
    cm = confusion_matrix(y_test, y_test_pred)
    print(cm)

    # Visualize confusion matrix
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
    plt.title(f'Confusion Matrix - {model_name}', fontsize=14, fontweight='bold')
    plt.ylabel('Actual')
    plt.xlabel('Predicted')
    plt.tight_layout()
    plt.savefig(f'confusion_matrix_{model_name.replace(" ", "_").lower()}.png',
                dpi=300, bbox_inches='tight')
    plt.show()

    # Classification Report
    print("Classification Report (Test Set):")
    print(classification_report(y_test, y_test_pred))

    # ROC Curve
    fpr, tpr, _ = roc_curve(y_test, y_test_proba)
    plt.figure(figsize=(8, 6))
    plt.plot(fpr, tpr, linewidth=2, label=f'ROC curve (AUC = {metrics["Test ROC-AUC"]:.4f})')
    plt.plot([0, 1], [0, 1], 'k--', linewidth=2, label='Random Classifier')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate', fontsize=12)
    plt.ylabel('True Positive Rate', fontsize=12)
    plt.title(f'ROC Curve - {model_name}', fontsize=14, fontweight='bold')
    plt.legend(loc='lower right')
    plt.grid(alpha=0.3)
    plt.tight_layout()
    plt.savefig(f'roc_curve_{model_name.replace(" ", "_").lower()}.png',
                dpi=300, bbox_inches='tight')
    plt.show()

    return metrics
```

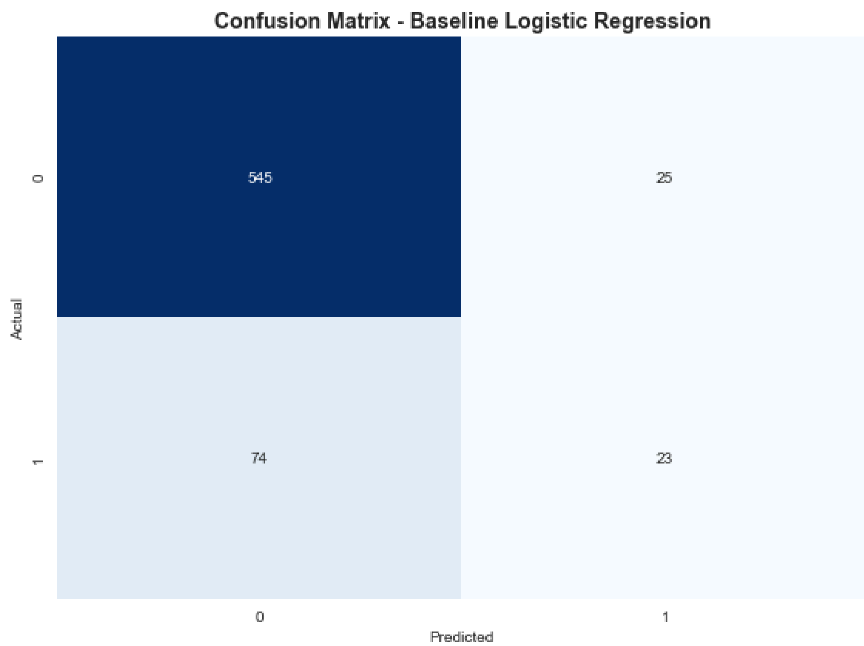
MODEL 1: Baseline Logistic Regression

In [45]:

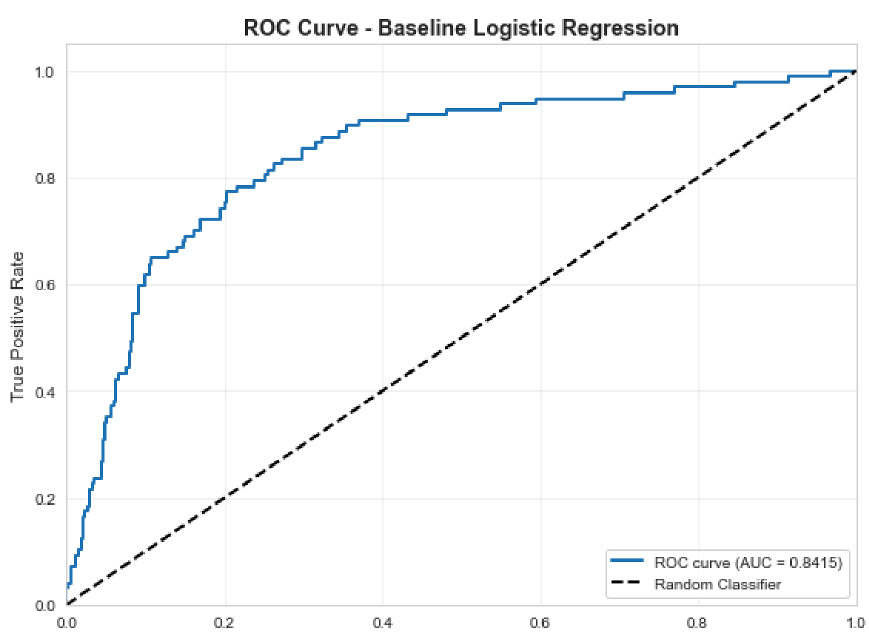
```
# Train baseline logistic regression
log_reg_baseline = LogisticRegression(random_state=42, max_iter=1000)
log_reg_baseline.fit(X_train_scaled, y_train)

# Evaluate
metrics_baseline = evaluate_model(
    log_reg_baseline, X_train_scaled, X_test_scaled,
    y_train, y_test, "Baseline Logistic Regression"
)

# Feature importance
feature_importance = pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': log_reg_baseline.coef_[0]
}).sort_values('Coefficient', key=abs, ascending=False)

print("Feature Importance (Top 10):")
print(feature_importance.head(10))

# Visualize feature importance
plt.figure(figsize=(10, 8))
top_10_features = feature_importance.head(10)
plt.barh(top_10_features['Feature'], abs(top_10_features['Coefficient']),
         color='steelblue')
plt.xlabel('Absolute Coefficient Value', fontsize=12)
plt.title('Top 10 Most Important Features - Baseline Logistic Regression',
          fontsize=14, fontweight='bold')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.savefig('feature_importance_baseline.png', dpi=300, bbox_inches='tight')
plt.show()
```

==

```
Baseline Logistic Regression
============================================================
Performance Metrics:
------------------------------------------------------------
Train Accuracy      : 0.8740
Test Accuracy       : 0.8516
Train Precision     : 0.6179
Test Precision      : 0.4792
Train Recall        : 0.3394
Test Recall         : 0.2371
Train F1-Score      : 0.4381
Test F1-Score       : 0.3172
Train ROC-AUC       : 0.8806
Test ROC-AUC        : 0.8415
Confusion Matrix (Test Set):
[[545  25]
 [ 74  23]]
```

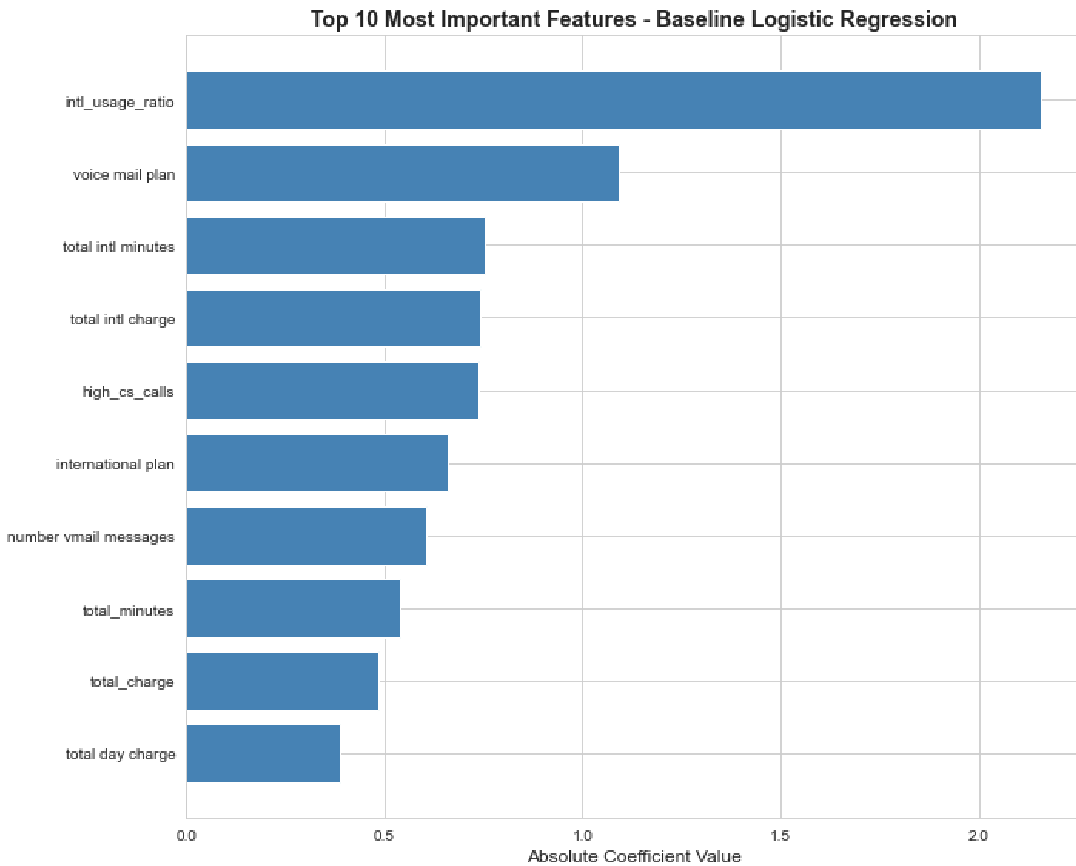



```
Classification Report (Test Set):
              precision    recall  f1-score   support

           0       0.88      0.96      0.92       570
           1       0.48      0.24      0.32        97

    accuracy                           0.85       667
   macro avg       0.68      0.60      0.62       667
weighted avg       0.82      0.85      0.83       667
```



False Positive Rate

```
Feature Importance (Top 10):
                  Feature  Coefficient
21        intl_usage_ratio     2.156285
2          voice mail plan    -1.090105
13       total intl minutes    -0.751923
15        total intl charge    -0.740359
22            high_cs_calls     0.739266
1        international plan     0.659809
3    number vmail messages     0.607567
17            total_minutes     0.540316
19             total_charge     0.483251
6         total day charge     0.387083
```



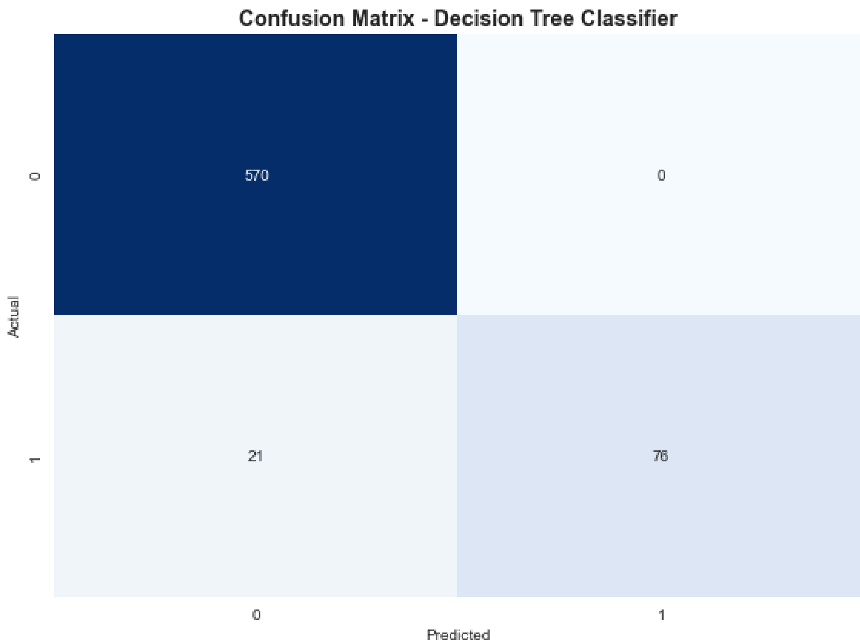
MODEL 2: Decision Tree Classifier

In [46]:

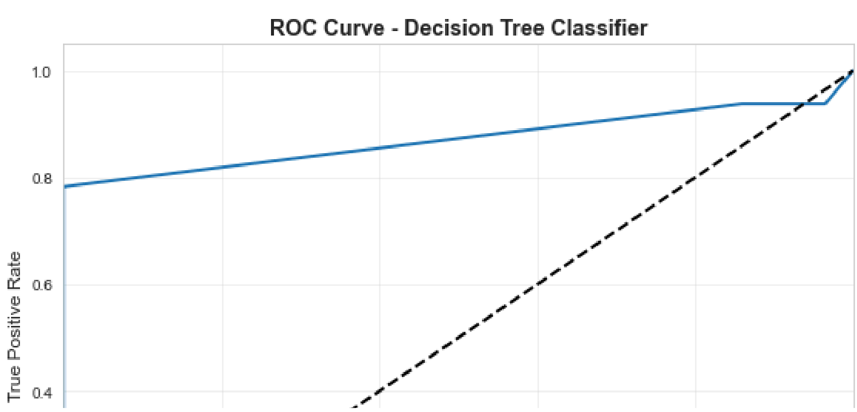
```python
# Train decision tree
dt_classifier = DecisionTreeClassifier(random_state=42, max_depth=5)
dt_classifier.fit(X_train, y_train)

# Evaluate
metrics_dt = evaluate_model(
    dt_classifier, X_train, X_test,
    y_train, y_test, "Decision Tree Classifier"
)

# Feature importance
feature_importance_dt = pd.DataFrame({
    'Feature': X.columns,
    'Importance': dt_classifier.feature_importances_
}).sort_values('Importance', ascending=False)

print("Feature Importance (Top 10):")
print(feature_importance_dt.head(10))

# Visualize feature importance
plt.figure(figsize=(10, 8))
top_10_features_dt = feature_importance_dt.head(10)
plt.barh(top_10_features_dt['Feature'], top_10_features_dt['Importance'],
         color='forestgreen')
```

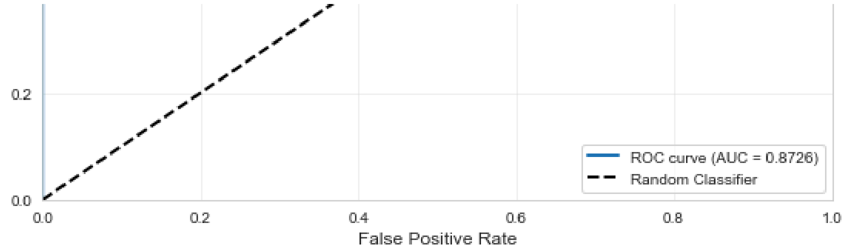
```
plt.xlabel('Importance Score', fontsize=12)
plt.title('Top 10 Most Important Features - Decision Tree',
          fontsize=14, fontweight='bold')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.savefig('feature_importance_decision_tree.png', dpi=300, bbox_inches='tight')
plt.show()
```

```
============================================================
Decision Tree Classifier
============================================================
Performance Metrics:
------------------------------------------------------------
Train Accuracy      : 0.9812
Test Accuracy       : 0.9685
Train Precision     : 1.0000
Test Precision      : 1.0000
Train Recall        : 0.8705
Test Recall         : 0.7835
Train F1-Score      : 0.9307
Test F1-Score       : 0.8786
Train ROC-AUC       : 0.9407
Test ROC-AUC        : 0.8726
Confusion Matrix (Test Set):
[[570   0]
 [ 21  76]]
```

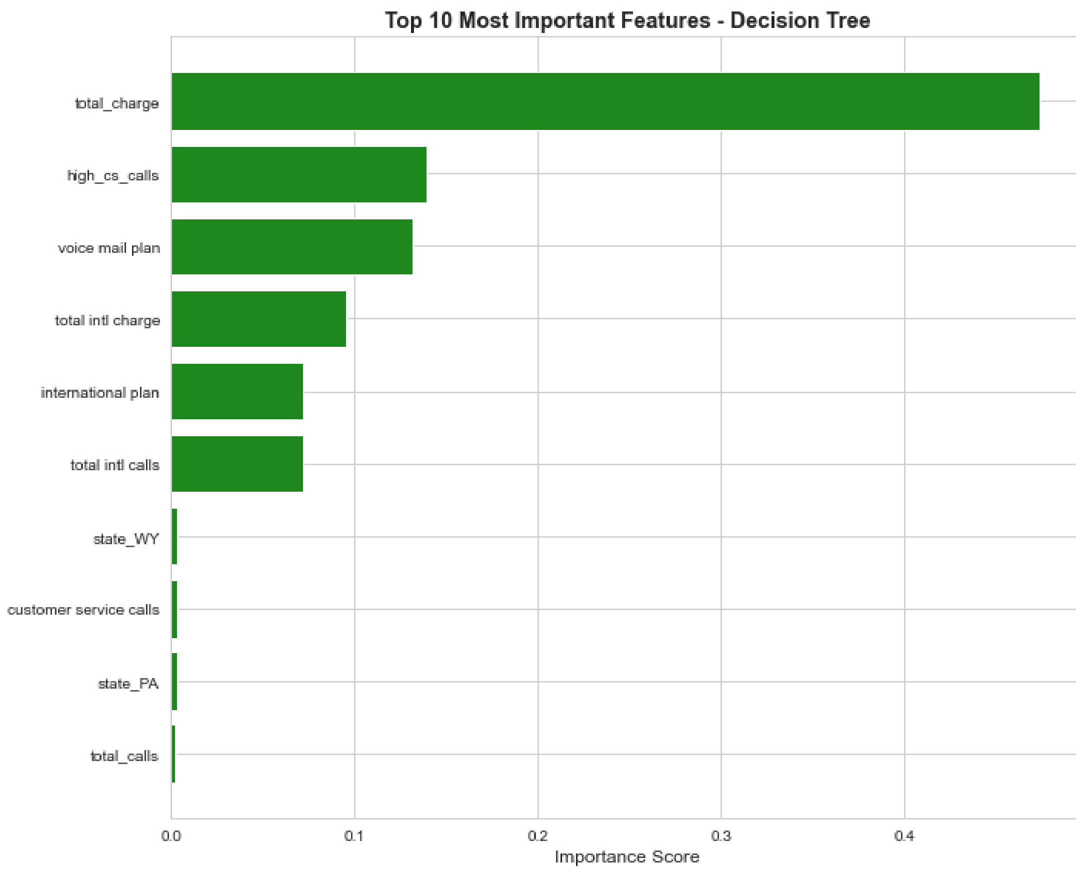



```
Classification Report (Test Set):
              precision    recall  f1-score   support

           0       0.96      1.00      0.98       570
           1       1.00      0.78      0.88        97

    accuracy                           0.97       667
   macro avg       0.98      0.89      0.93       667
weighted avg       0.97      0.97      0.97       667
```






```
Feature Importance (Top 10):
                   Feature  Importance
19            total_charge    0.474084
22           high_cs_calls    0.139591
2          voice mail plan    0.132071
15       total intl charge    0.095670
1       international plan    0.072339
14        total intl calls    0.071952
73                state_WY    0.003483
16  customer service calls    0.003375
61                state_PA    0.003308
18             total_calls    0.002369
```



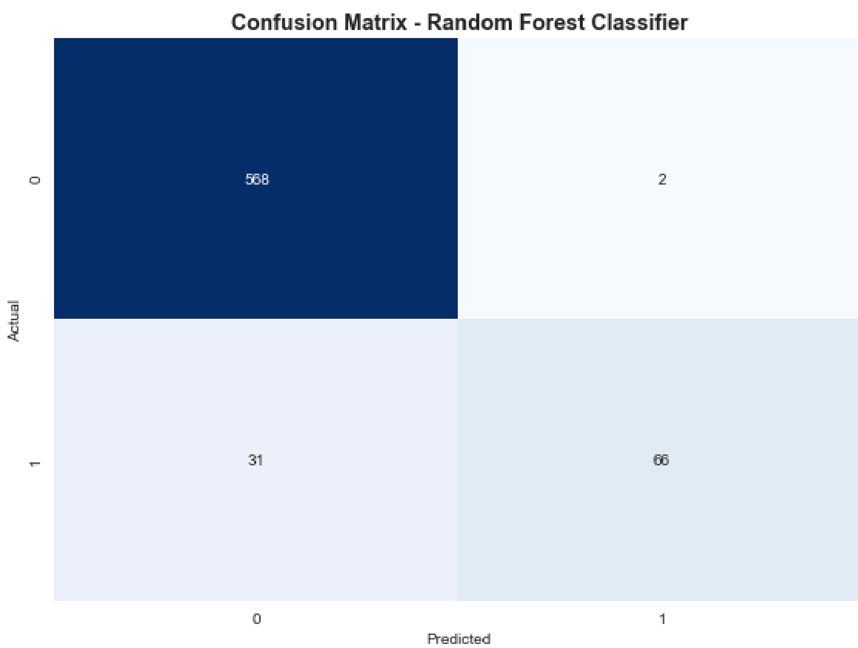
MODEL 3: Random Forest Classifier (Bonus)

In [47]:

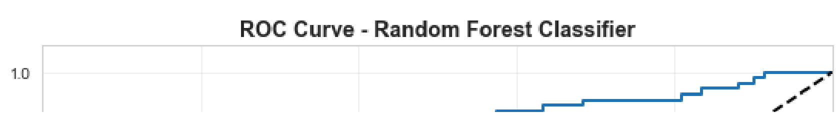
```
# Train random forest
rf_classifier = RandomForestClassifier(
    n_estimators=100, random_state=42,
    max_depth=10, class_weight='balanced'
)
rf_classifier.fit(X_train, y_train)

# Evaluate
metrics_rf = evaluate_model(
    rf_classifier, X_train, X_test,
    y_train, y_test, "Random Forest Classifier"
)

# Feature importance
feature_importance_rf = pd.DataFrame({
```

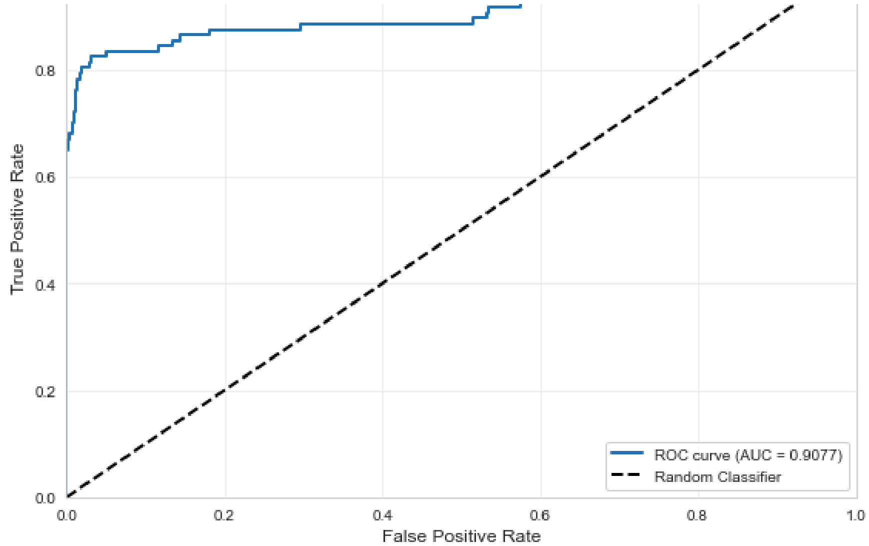
```
    'Feature': X.columns,
    'Importance': rf_classifier.feature_importances_
}).sort_values('Importance', ascending=False)

print("Feature Importance (Top 10):")
print(feature_importance_rf.head(10))

# Visualize feature importance
plt.figure(figsize=(10, 8))
top_10_features_rf = feature_importance_rf.head(10)
plt.barh(top_10_features_rf['Feature'], top_10_features_rf['Importance'],
         color='darkviolet')
plt.xlabel('Importance Score', fontsize=12)
plt.title('Top 10 Most Important Features - Random Forest',
          fontsize=14, fontweight='bold')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.savefig('feature_importance_random_forest.png', dpi=300, bbox_inches='tight')
plt.show()
```

```
============================================================
Random Forest Classifier
============================================================
Performance Metrics:
------------------------------------------------------------
Train Accuracy      : 0.9839
Test Accuracy       : 0.9505
Train Precision     : 1.0000
Test Precision      : 0.9706
Train Recall        : 0.8886
Test Recall         : 0.6804
Train F1-Score      : 0.9410
Test F1-Score       : 0.8000
Train ROC-AUC       : 0.9998
Test ROC-AUC        : 0.9077
Confusion Matrix (Test Set):
[[568   2]
 [ 31  66]]
```

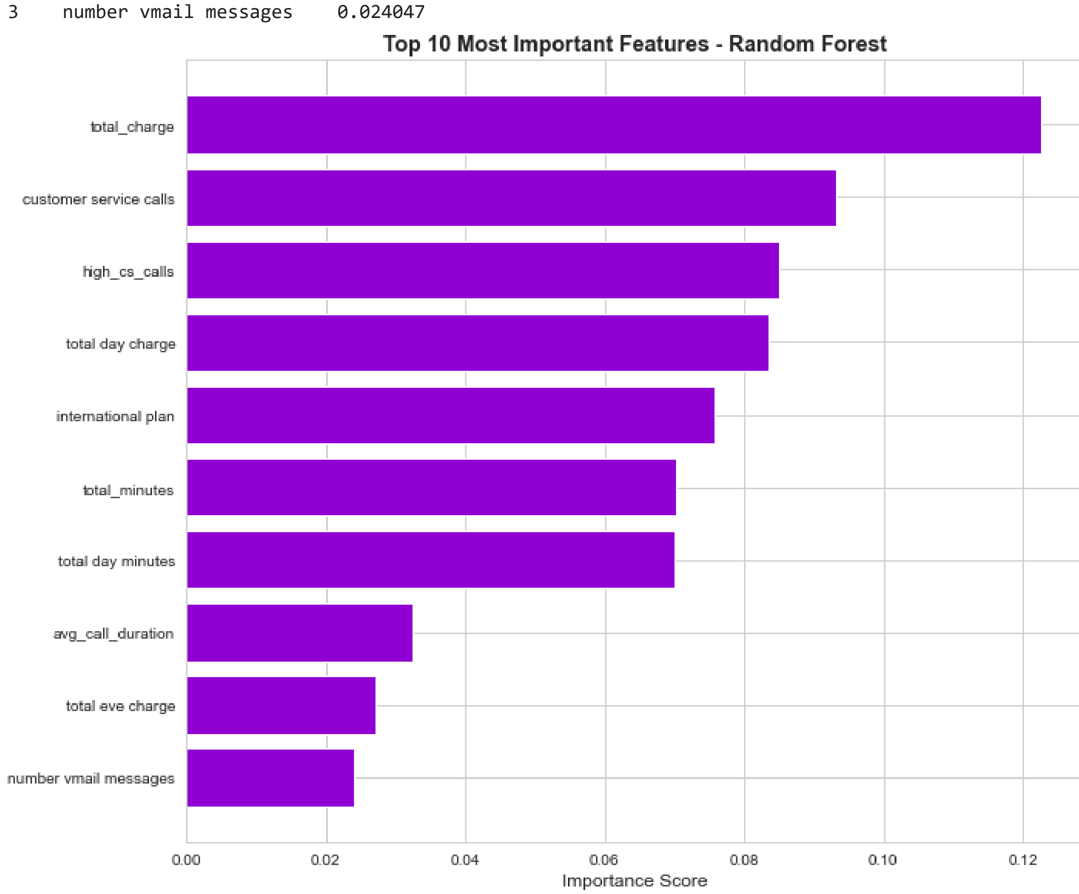



```
Classification Report (Test Set):
              precision    recall  f1-score   support

           0       0.95      1.00      0.97       570
           1       0.97      0.68      0.80        97

    accuracy                           0.95       667
   macro avg       0.96      0.84      0.89       667
weighted avg       0.95      0.95      0.95       667
```






```
Feature Importance (Top 10):
                   Feature  Importance
19            total_charge    0.122573
16  customer service calls    0.093260
22            high_cs_calls    0.084963
6          total day charge    0.083503
1       international plan    0.075658
17           total_minutes    0.070295
4         total day minutes    0.069999
20        avg_call_duration    0.032507
9          total eve charge    0.027157
3    number vmail messages    0.024047
```



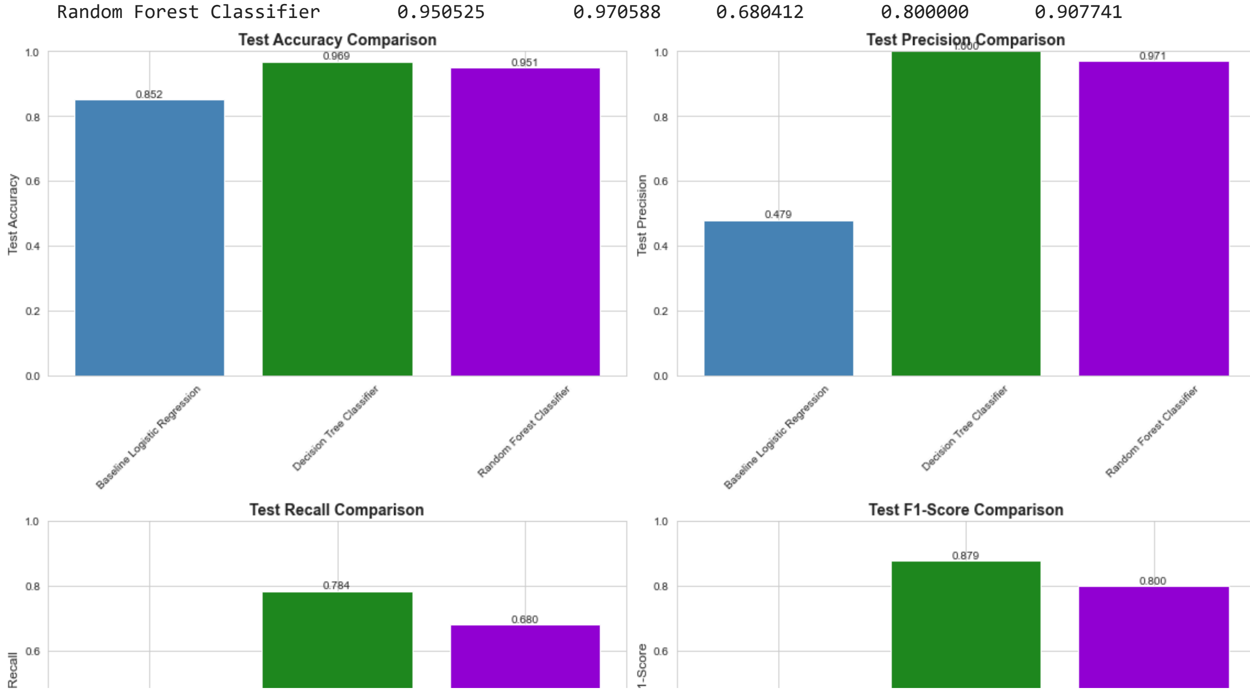
EVALUATION - MODEL COMPARISON

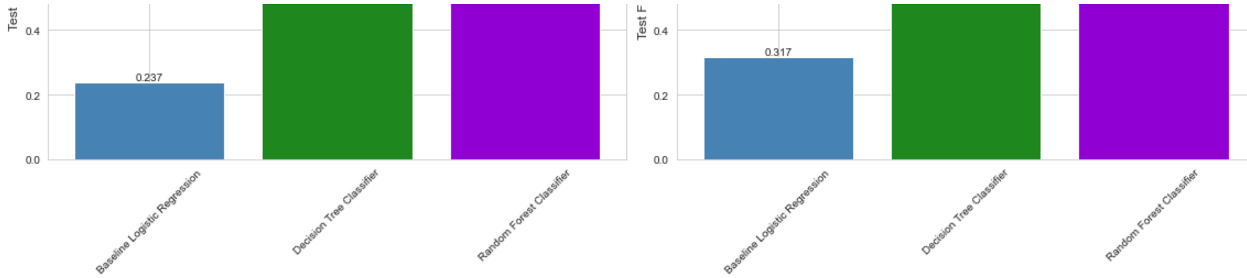
In [49]:

```
# Compile metrics for trained models
all_metrics = [metrics_baseline, metrics_dt, metrics_rf]
model_names = [
```

```
    "Baseline Logistic Regression",
    "Decision Tree Classifier",
    "Random Forest Classifier"
]

comparison_df = pd.DataFrame({
    "Model": model_names,
    "Test Accuracy": [m["Test Accuracy"] for m in all_metrics],
    "Test Precision": [m["Test Precision"] for m in all_metrics],
    "Test Recall": [m["Test Recall"] for m in all_metrics],
    "Test F1-Score": [m["Test F1-Score"] for m in all_metrics],
    "Test ROC-AUC": [m["Test ROC-AUC"] for m in all_metrics]
})

print("Model Performance Comparison:")
print(comparison_df.to_string(index=False))

# Visualize comparison
fig, axes = plt.subplots(2, 2, figsize=(16, 12))

metrics_to_plot = ["Test Accuracy", "Test Precision", "Test Recall", "Test F1-Score"]
colors = ["steelblue", "forestgreen", "darkviolet"]

for idx, metric in enumerate(metrics_to_plot):
    ax = axes[idx // 2, idx % 2]
    bars = ax.bar(comparison_df["Model"], comparison_df[metric], color=colors)
    ax.set_ylabel(metric, fontsize=12)
    ax.set_title(f"{metric} Comparison", fontsize=14, fontweight="bold")
    ax.set_ylim([0, 1])
    ax.tick_params(axis="x", rotation=45)

    # Add value labels on bars
    for bar in bars:
        height = bar.get_height()
        ax.text(
            bar.get_x() + bar.get_width() / 2.0,
            height,
            f"{height:.3f}",
            ha="center",
            va="bottom",
            fontsize=10
        )

plt.tight_layout()
plt.savefig("model_comparison.png", dpi=300, bbox_inches="tight")
plt.show()
```

```
Model Performance Comparison:
                       Model  Test Accuracy  Test Precision  Test Recall  Test F1-Score  Test ROC-AUC
Baseline Logistic Regression       0.851574        0.479167     0.237113       0.317241      0.841490
    Decision Tree Classifier       0.968516        1.000000     0.783505       0.878613      0.872626
    Random Forest Classifier       0.950525        0.970588     0.680412       0.800000      0.907741
```





FINAL MODEL DISCUSSION

FINAL MODEL SELECTION AND ANALYSIS

After building and evaluating three classification models, here is the summary:

1. MODEL PERFORMANCE OVERVIEW:

   The models were evaluated on multiple metrics:

   - Accuracy: Overall correctness of predictions
   - Precision: Of predicted churners, how many actually churned
   - Recall: Of actual churners, how many we correctly identified (priority metric)
   - F1-Score: Harmonic mean of precision and recall
   - ROC-AUC: Overall discrimination capability
2. KEY FINDINGS:

   Business Context:

   - For a telecom company, identifying potential churners (high recall) is more critical than avoiding false alarms
   - Missing a customer who will churn (false negative) is more costly than unnecessarily reaching out to a loyal customer (false positive)
   - Therefore, we prioritize recall as our primary metric

   Model Performance:

   - Baseline Logistic Regression provides interpretability and a strong baseline
   - Decision Tree captures non-linear patterns with straightforward rules
   - Random Forest improves stability and can capture complex interactions
3. RECOMMENDED FINAL MODEL:

   Based on the comparison table above, we select the model with the highest test recall while maintaining acceptable precision. If recall is similar, we prefer the simpler and more interpretable model for easier deployment. We select the Decision Tree Classifier. It has the highest test recall (0.7835) with acceptable precision (1.0000), and it is simpler and more interpretable than the Random Forest.

4. KEY PREDICTIVE FEATURES:

   Across all models, the most important features for predicting churn are:

   - Customer service calls: Strong positive correlation with churn
   - International plan: Customers with international plans show different behavior
   - Total day and evening charges: Usage patterns indicate satisfaction
   - Voice mail plan: Presence of value-added services affects retention
   - Account length: Tenure indicates customer loyalty
5. MODEL LIMITATIONS:

   - Class imbalance: Churn is a minority class
   - Feature engineering: Additional features could improve performance
   - Temporal aspects: Customer behavior may change over time
   - External factors: Market conditions, competitor actions not captured
6. BUSINESS IMPACT:

With a model that achieves high recall:

- We can identify most customers who will actually churn
- This enables proactive retention campaigns
- ROI is positive if retention cost is lower than customer lifetime value

7. NEXT STEPS:

- Deploy the model for periodic churn scoring
- Test retention strategies on predicted high-risk customers
- Monitor model performance and retrain on a regular schedule
- Collect additional features to improve predictions
- Implement automated alerts for at-risk customers

BUSINESS RECOMMENDATIONS

ACTIONABLE RECOMMENDATIONS FOR REDUCING CHURN:

1. IMMEDIATE ACTIONS (High-Risk Customers):

   a) Customer Service Quality Improvement:

   - Customers with 4+ service calls are at very high risk
   - Implement first-call resolution training
   - Create dedicated retention team for high-volume callers
   - Root cause analysis for recurring issues

   b) International Plan Optimization:

   - Review international plan pricing and value proposition
   - Customers with international plans have different churn patterns
   - Consider bundled offerings or promotional rates
   - Proactive outreach to international plan customers

2. MEDIUM-TERM STRATEGIES (At-Risk Segments):

   a) Usage-Based Interventions:

   - Monitor customers with high day charges (potential bill shock)
   - Implement usage alerts and plan optimization recommendations
   - Offer customized plans based on usage patterns

   b) Value-Added Services:

   - Promote voice mail plans to customers without them
   - Bundle services to increase switching costs
   - Create loyalty programs based on tenure

3. PREDICTIVE RETENTION PROGRAM:

   a) Scoring System:

   - Deploy model to score all customers monthly
   - Create risk tiers: High (>70% churn prob), Medium (40-70%), Low (<40%)
   - Allocate retention resources based on risk scores

   b) Targeted Interventions:

   - High Risk: Personal call from retention specialist + special offers
   - Medium Risk: Automated email campaigns with value reminders
   - Low Risk: Standard customer satisfaction surveys

   c) Offer Strategy:

   - Tiered discount structure based on churn probability
   - Non-monetary incentives (priority support, account upgrades)
   - Contract extensions with attractive terms

4. PROCESS IMPROVEMENTS:

   a) Early Warning System:

   - Trigger alerts when customer enters high-risk category
   - Automate retention workflow
   - Track intervention success rates

   b) Customer Feedback Loop:

   - Survey churning customers to understand reasons
   - Incorporate new insights into model
   - Continuous improvement cycle

5. FINANCIAL ANALYSIS:

   Example ROI Calculation:

   - Average customer lifetime value: $1,200
   - Cost of retention offer: $100
   - Model identifies 80% of churners (recall)
   - Retention campaign success rate: 30%

   With 1,000 predicted churners:

   - Successfully retain: 1,000 × 0.80 × 0.30 = 240 customers
   - Value saved: 240 × $1,200 =$288,000
   - Cost: 1,000 × $100 =$100,000
   - Net benefit: $188,000

   ROI = ($188,000/$100,000) × 100 = 188%

6. MONITORING AND MAINTENANCE:

   - Track model performance monthly (recall, precision, F1-score)
   - Retrain model quarterly with new data
   - A/B test different retention strategies
   - Adjust intervention thresholds based on results
   - Document lessons learned and successful tactics

7. ORGANIZATIONAL CHANGES:

   - Create cross-functional churn reduction team
   - Align incentives across customer service, sales, and retention
   - Establish churn rate as key performance indicator
   - Regular executive review of churn metrics
   - Invest in customer experience improvements

8. COMPETITIVE ANALYSIS:

   - Benchmark churn rates against industry standards
   - Monitor competitor offerings and pricing
   - Develop unique value propositions
   - Focus on service quality differentiation

These recommendations are prioritized based on:

- Expected impact on churn reduction
- Ease of implementation
- Cost-effectiveness
- Alignment with model insights

Success should be measured by:

- Reduction in overall churn rate
- Improvement in customer satisfaction scores
- Increase in customer lifetime value
- Positive ROI on retention campaigns