StakeHolder and Business Problem

Stakeholder: The customer retention team at a telecommunications company.

Business Problem: Customer churn/customer cancelling their services represents revenue loss for syria telecom providers,as acquiring new customers is expensive than retaining existing ones. The goal is to build a predictive classification model in order to identify customers that are high risk churning.This will allow the retention team to target these customers with interventions, such as:

- personalized discounts
- upgraded plans
- improved customer support

This will help reduce overall churn rate from its current level of approximately 14.5% and improve long_term customer loyalty and profitability.

Objective:

Predict whether a customer will soon stop doing business with Syria Tel.

In [6]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [7]:

```
#display all the columns
pd.set_option('display.max_columns',None)
```

In [8]:

```
#Load Data
df = pd.read_csv('bigml_59c28831336c6604c800002a.csv')
df.head()
```

Out[8]:

	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	tot nig ca
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	197.4	99	16.78	244.7	
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	195.5	103	16.62	254.4	1
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	121.2	110	10.30	162.6	1
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	61.9	88	5.26	196.9	
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	148.3	122	12.61	186.9	1

In [9]:

```
#confirm number of rows
df.shape[0]
```

Out[9]:

3333

3333

In [10]:

```
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
```

EDA

In [11]:

```
#check for unique values
df.describe()
```

Out[11]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total eve calls	total eve charge
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.980348	100.114311	17.083540
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.713844	19.922625	4.310668
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.600000	87.000000	14.160000
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.400000	100.000000	17.120000
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.300000	114.000000	20.000000
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.700000	170.000000	30.910000

In [12]:

```
#check for null values
df.isna().sum()
```

Out[12]:

```
state                     0
```

```
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 [13]:

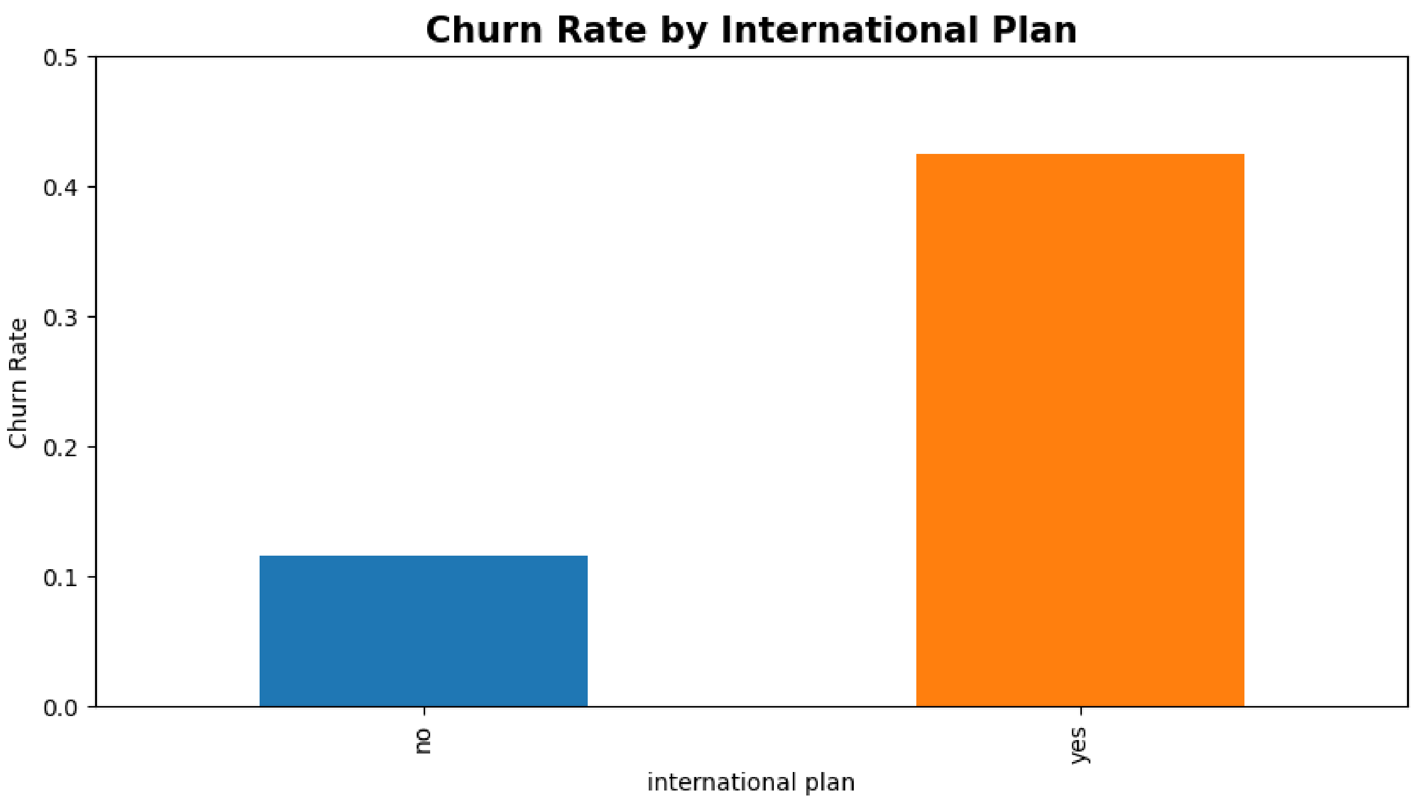
```
df['churn'].value_counts()
```

Out[13]:

```
churn
False    2850
True      483
Name: count, dtype: int64
```

In [14]:

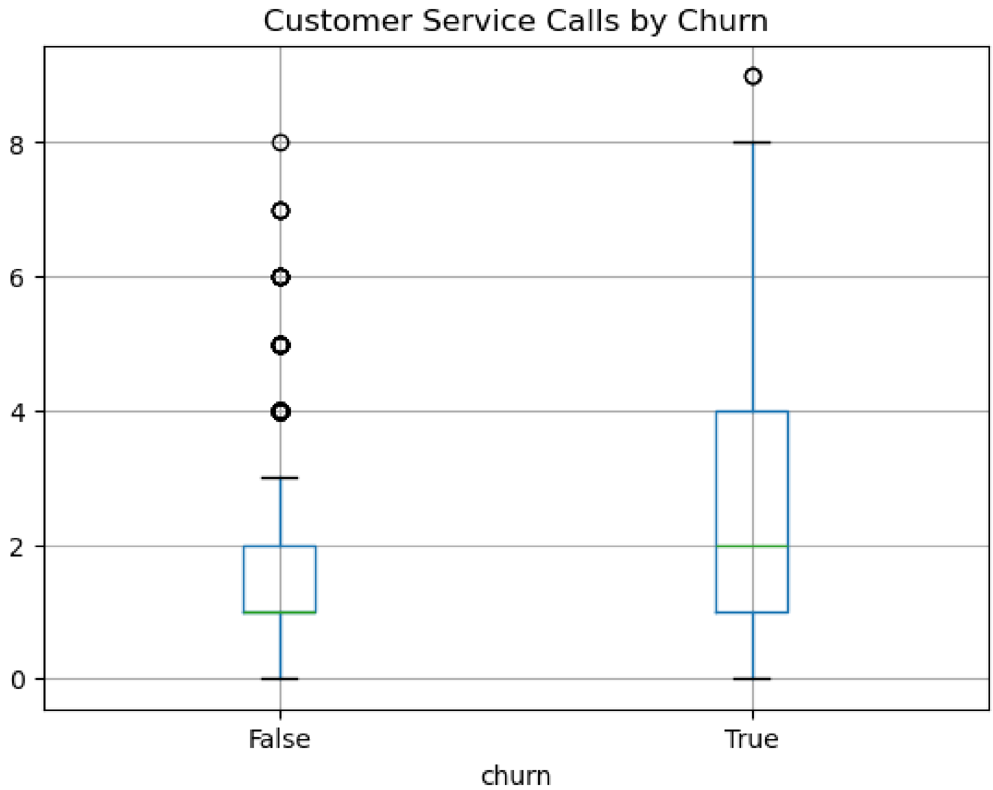
```
# 1. Churn by International Plan
plt.figure(figsize=(10,5))
df.groupby('international plan')['churn'].mean().plot(kind='bar', color=['#1f77b4','#ff7f0e'])
plt.title('Churn Rate by International Plan', fontsize=15, fontweight='bold')
plt.ylabel('Churn Rate')
plt.ylim(0, 0.5)
plt.show()
```



In [15]:

```
#customer service calls by churn
plt.figure(figsize=(8,6))
df.boxplot(column='customer service calls', by='churn')
plt.title('Customer Service Calls by Churn')
plt.suptitle('')
plt.show()
```

```
<Figure size 800x600 with 0 Axes>
```

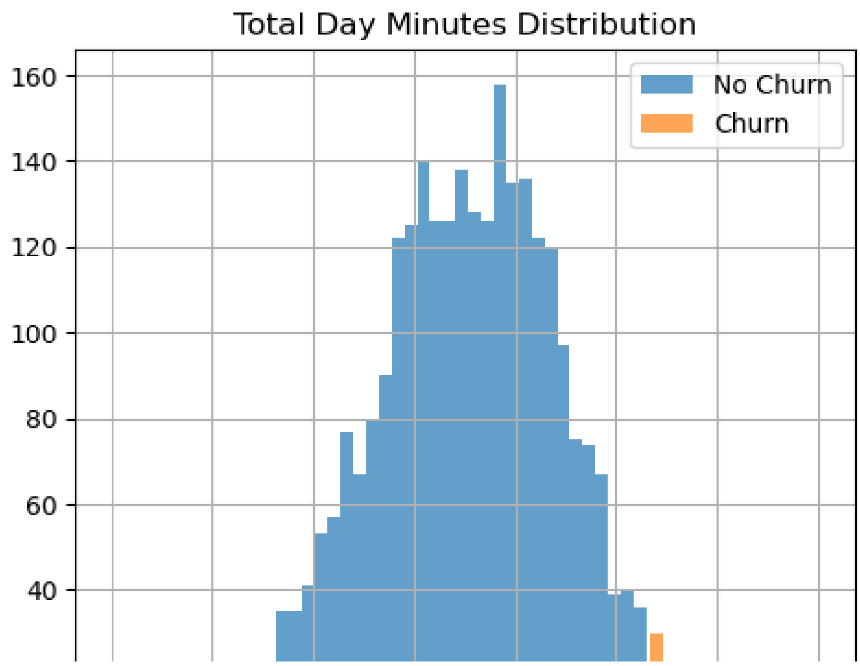


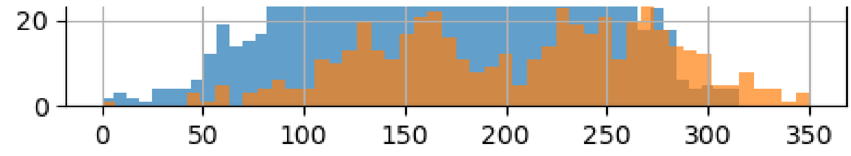
In [16]:

```
#Total Day Minutes Distribution by Churn
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
df[df['churn']==False]['total day minutes'].hist(bins=50, alpha=0.7, label='No Churn')
df[df['churn']==True]['total day minutes'].hist(bins=50, alpha=0.7, label='Churn')
plt.title('Total Day Minutes Distribution')
plt.legend()
```

Out[16]:

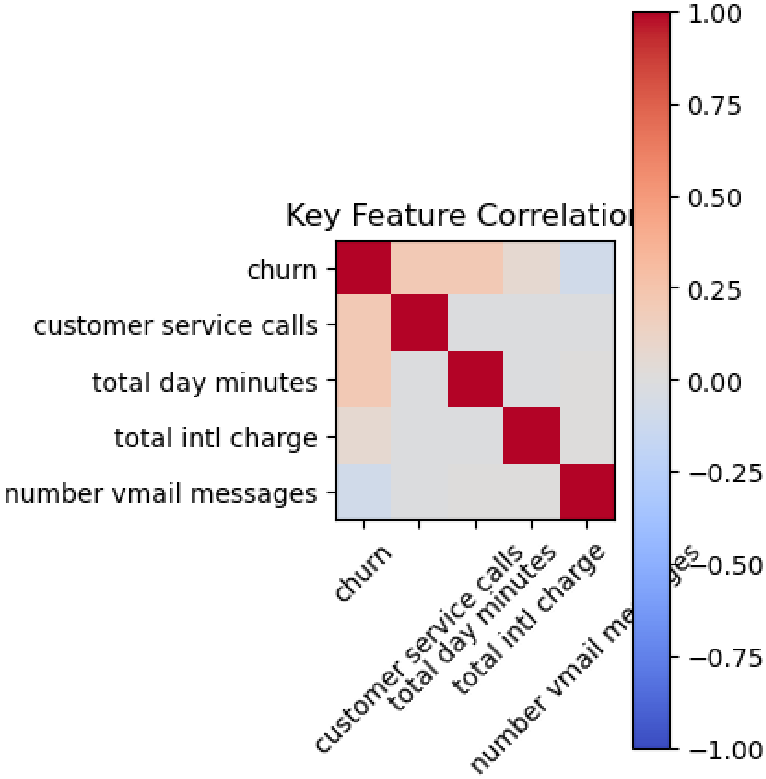
```
<matplotlib.legend.Legend at 0x1ba9e5b8ec0>
```





In [17]:

```
# 4. Correlation Heatmap (top features)
plt.subplot(1,2,2)
top_features = ['churn', 'customer service calls', 'total day minutes',
                'total intl charge', 'number vmail messages']
corr = df[top_features].corr()
plt.imshow(corr, cmap='coolwarm', vmin=-1, vmax=1)
plt.colorbar()
plt.xticks(range(len(top_features)), top_features, rotation=45)
plt.yticks(range(len(top_features)), top_features)
plt.title('Key Feature Correlations')
plt.tight_layout()
plt.show()
```



Post Analysis

Churn is driven by two things

- `Cost Sensitivity` **- Heavy daytime users(core business/personal use) get expensive bills which makes them leave.**
- `Service frustration` **- Customers who call support atmost times are likely to churn.**

International plan users are a high-risk ninche (42% churn) - they are price-sensitive and aware of alternatives.

Voice mail plan correlates more with settled customers.

The dataset shows clear actionable segments for retention

- **High day minutes and international plan**
- **Multiple customer service calls (>=3)**

Business takeaway: The Telco Business should focus on retaining daytime heavy users and frequent callers - these are the highest leverage points.

Modeling

We'll build two models:

- **Logistic Regression -> suited for classification when handling binary**
- **Decision Tree -> non linear model suited to capture interactions and easy to visualize**

The above models will be used to compare key metrics suitable for imbalanced data like this churn rate of `14.5%`

- **Accuracy: Overall correctness**
- **F1-Score: Harmonic mean of precision and recall**
- **ROC-AUC: Measures discrimination ability**

In [18]:

```
import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, f1_score, recall_score, precision_score,roc_a
uc_score, roc_curve,RocCurveDisplay,auc,classification_report
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV
```

In [19]:

```
#check the columns in the data set
df.columns
```

Out[19]:

```
Index(['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', 'total night charge',
       'total intl minutes', 'total intl calls', 'total intl charge',
       'customer service calls', 'churn'],
      dtype='object')
```

In [20]:

```
#data preparation - Drop unwanted columns

drop_cols = [ 'phone number', 'total day charge', 'total eve charge', 'total night charge
', 'total intl charge', 'area code']
df = df.drop(columns=drop_cols)
```

In [21]:

```
#convert churn to binary(0/1)
df['churn']=df['churn'].map({True: 1, False: 0})
```

In [22]:

```
#confirm the datatype of churn if its an int
type(df['churn'][0])
```

Out[22]:

```
numpy.int64
```

In [23]:

```
#confirm number of columns needed
df.shape[1]
```

Out[23]:

```
15
```

In [24]:

```
#Features and target
X = df.drop('churn',axis=1)
y = df['churn']
```

In [25]:

```
#preprocessing - categorical and numerical columns
cat_cols = ['state','international plan','voice mail plan']
num_cols = [col for col in X.columns if col not in cat_cols]
```

In [26]:

```
#preprocessing pipeline
preprocessor = ColumnTransformer(
    transformers = [
        ('num', StandardScaler(),num_cols),
        ('cat', OneHotEncoder(drop='first',handle_unknown='ignore'),cat_cols)
    ]
)
```

In [27]:

```
#split data (80/20, stratified)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
, stratify=y)
```

In [28]:

```
#build models using pipeline
log_Reg = Pipeline([
    ("preprocess", preprocessor),
    ("model", LogisticRegression(max_iter=1000))
])
log_Reg.fit(X_train,y_train)
y_pred_log = log_Reg.predict(X_test)
y_prob_log = log_Reg.predict_proba(X_test)[:,1]
```

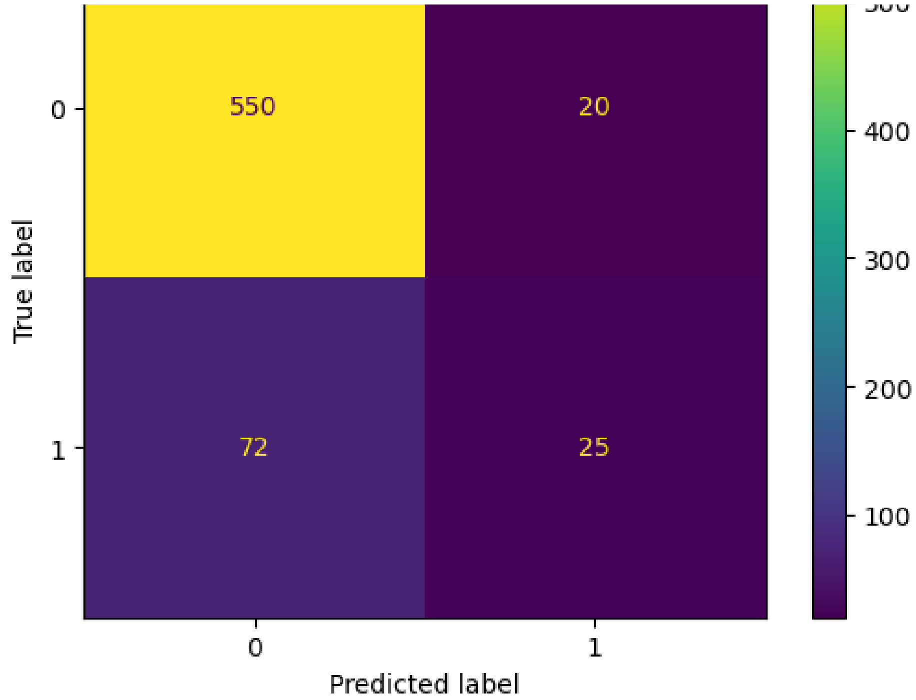
In [29]:

```
tree_model = Pipeline([
    ("preprocess", preprocessor),
    ("model", DecisionTreeClassifier(max_depth=5, random_state=42))
])
tree_model.fit(X_train, y_train)
y_pred_tree = tree_model.predict(X_test)
y_prob_tree = tree_model.predict_proba(X_test)[:, 1]
```

In [30]:

```
cm_log = confusion_matrix(y_test, y_pred_log)

print("Logistic Regression Confusion Matrix:")
#print(cm_log)

display = ConfusionMatrixDisplay(confusion_matrix= cm_log)
display.plot()
plt.show()
```

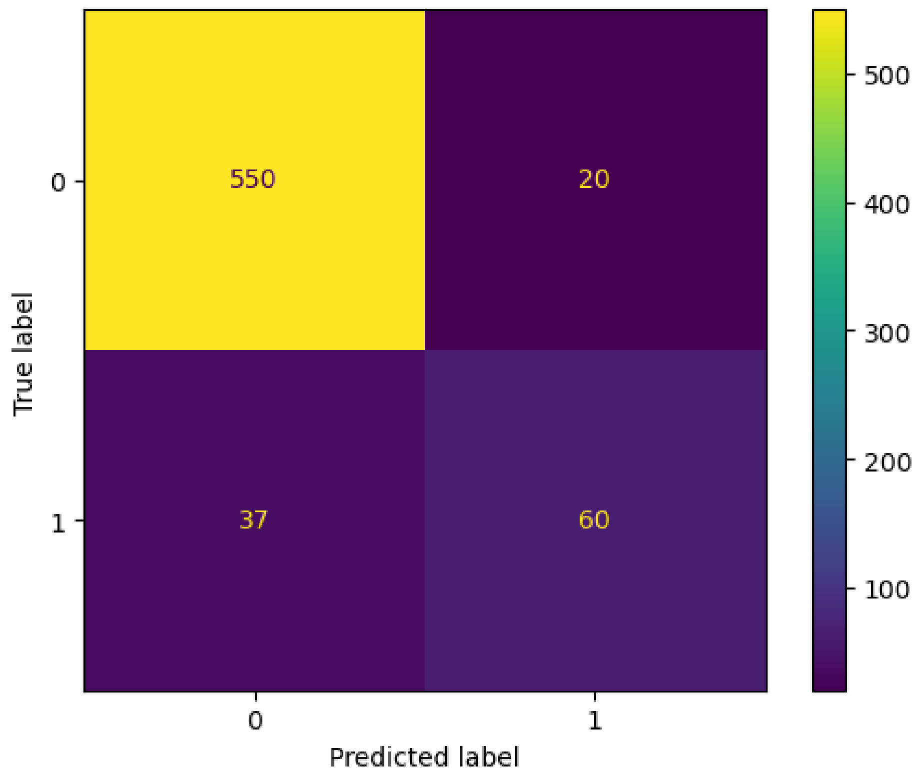
```
Logistic Regression Confusion Matrix:
```



In [31]:

```
cm_tree = confusion_matrix(y_test, y_pred_tree)

print("Decision Tree Matrix:")
#print(cm_tree)

display = ConfusionMatrixDisplay(confusion_matrix= cm_tree)
display.plot()
plt.show()
```

```
Decision Tree Matrix:
```



In [32]:

```
#check the values of churn
y_test.value_counts()
```

Out[32]:

```
churn
0     570
```

```
1      97
Name: count, dtype: int64
```

In [33]:

```
#check precision values for logistics
tn, fp, fn, tp = cm_log.ravel()
print("True Negatives:", tn)
print("False Positives:", fp)
print("False Negatives:", fn)
print("True Positives:", tp)
```

```
True Negatives: 550
False Positives: 20
False Negatives: 72
True Positives: 25
```

In [34]:

```
#check the precision values for decision tree
tn, fp, fn, tp = cm_tree.ravel()
print("True Negatives:", tn)
print("False Positives:", fp)
print("False Negatives:", fn)
print("True Positives:", tp)
```

```
True Negatives: 550
False Positives: 20
False Negatives: 37
True Positives: 60
```

In [35]:

```
print("----------------LogisticRegression----------------------")
print(f"Sklearn's accuracy:{accuracy_score(y_test,y_pred_log)}")
print(f"Sklearn's precision_score:{precision_score(y_test,y_pred_log)}")
print(f"Sklearn's recall_score:{recall_score(y_test,y_pred_log)}")
print(f"Sklearn's f1_score:{f1_score(y_test,y_pred_log)}")
```

```
----------------LogisticRegression----------------------
Sklearn's accuracy:0.8620689655172413
Sklearn's precision_score:0.5555555555555556
Sklearn's recall_score:0.25773195876288657
Sklearn's f1_score:0.352112676056338
```

In [36]:

```
print("---------------------Decion Tree------------------------")
print(f"Sklearn's accuracy:{accuracy_score(y_test,y_pred_tree)}")
print(f"Sklearn's precision_score:{precision_score(y_test,y_pred_tree)}")
print(f"Sklearn's recall_score:{recall_score(y_test,y_pred_tree)}")
print(f"Sklearn's f1_score:{f1_score(y_test,y_pred_tree)}")
```

```
---------------------Decion Tree------------------------
Sklearn's accuracy:0.9145427286356822
Sklearn's precision_score:0.75
Sklearn's recall_score:0.6185567010309279
Sklearn's f1_score:0.6779661016949152
```

In [37]:

```
print("---------Logistic Regression Metrics-----------")
print(classification_report(y_test,y_pred_log))
print("-----------DecisionTree-----------------")
print(classification_report(y_test,y_pred_tree))
```

```
---------Logistic Regression Metrics-----------
              precision    recall  f1-score   support

           0       0.88      0.96      0.92       570
           1       0.56      0.26      0.35        97
```

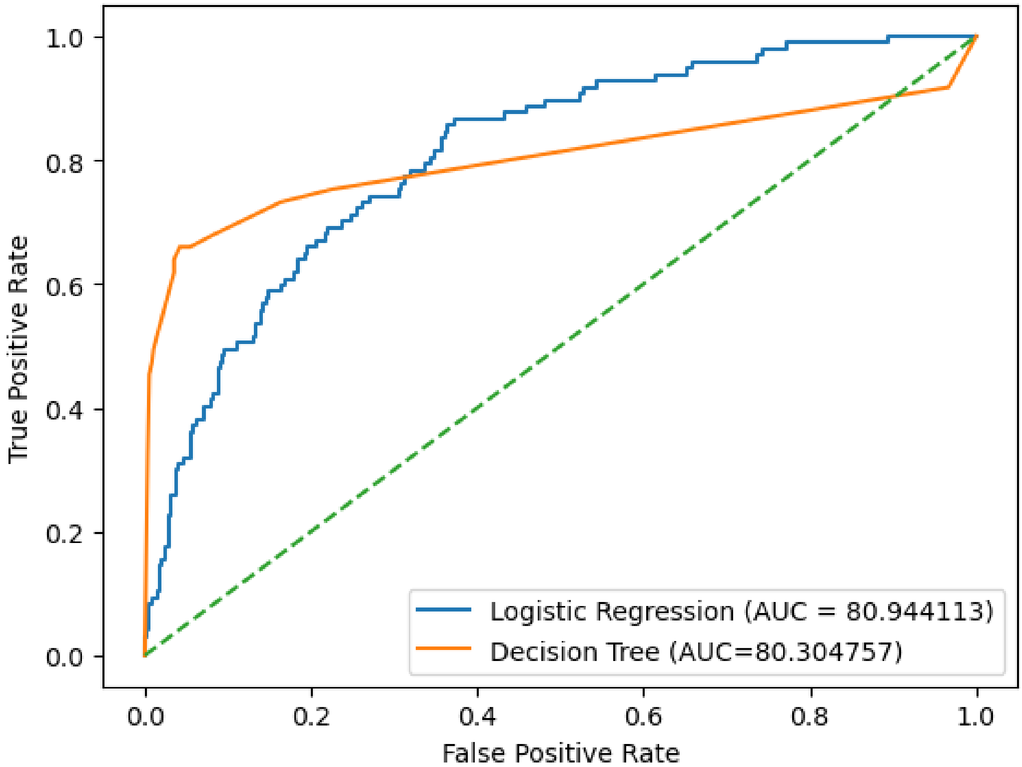
```
    accuracy                           0.86       667
   macro avg       0.72      0.61      0.64       667
weighted avg       0.84      0.86      0.84       667

-----------DecisionTree----------------
              precision    recall  f1-score   support

           0       0.94      0.96      0.95       570
           1       0.75      0.62      0.68        97

    accuracy                           0.91       667
   macro avg       0.84      0.79      0.81       667
weighted avg       0.91      0.91      0.91       667
```

In [38]:

```
lr_fpr, lr_tpr, _ = roc_curve(y_test, y_prob_log)
dt_fpr, dt_tpr, _ = roc_curve(y_test, y_prob_tree)

lr_auc = auc(lr_fpr, lr_tpr)
dt_auc = auc(dt_fpr, dt_tpr)
```

In [58]:

```
#plot auc for logistic regression and decision tree
plt.plot(lr_fpr,lr_tpr,label=f'Logistic Regression (AUC = {lr_auc*100:2f})')
plt.plot(dt_fpr,dt_tpr,label=f'Decision Tree (AUC={dt_auc*100:2f})')
plt.plot([0,1],[0,1],linestyle='--')

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```



In [40]:

```
#compare roc accuracy from both sides

roc_log = roc_auc_score(y_test,y_prob_log)
roc_tree = roc_auc_score(y_test,y_prob_tree)

print("\nComparison:")
if roc_tree > roc_log:
```

```
    print("Decision Tree is better based on ROC AUC.")
else:
    print("Logistic Regression is better based on ROC AUC.")
```

```
Comparison:
Logistic Regression is better based on ROC AUC.
```

Tuning

In [43]:

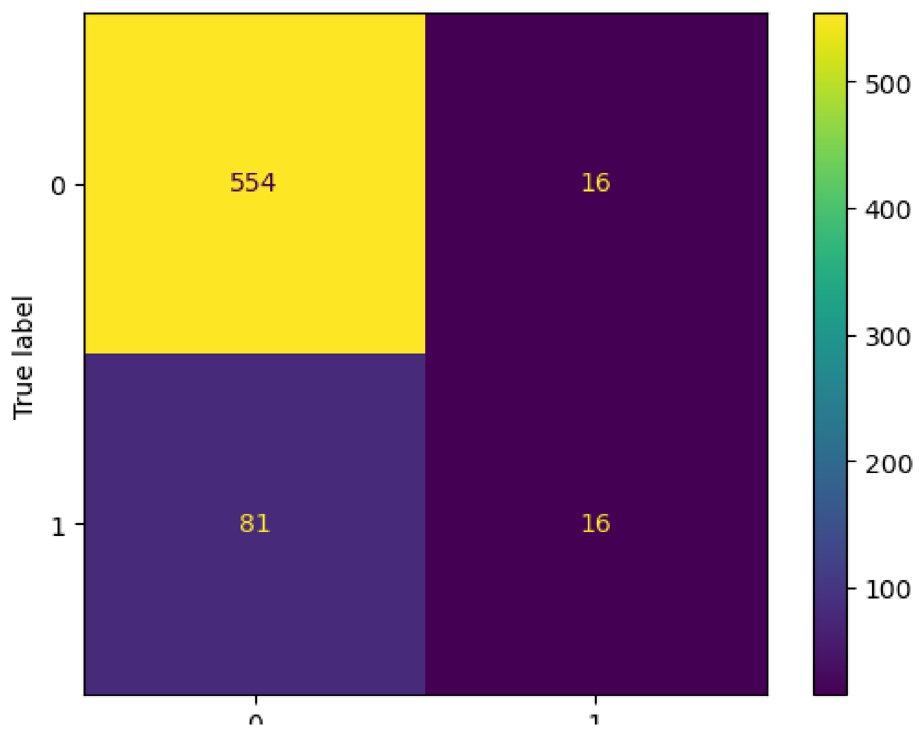
```
lr_params = {'model__C': [0.01, 0.1, 1, 10, 100]}
lr_grid = GridSearchCV(log_Reg, lr_params, cv=5, scoring='roc_auc')
lr_grid.fit(X_train, y_train)
print('Best LR Params:', lr_grid.best_params_)
lr_tuned_pred = lr_grid.predict(X_test)
lr_tuned_prob = lr_grid.predict_proba(X_test)[:, 1]
print('Tuned LR - Acc:', accuracy_score(y_test, lr_tuned_pred), 'F1:', f1_score(y_test,
lr_tuned_pred), 'AUC:', roc_auc_score(y_test, lr_tuned_prob))

dt_params = {'model__max_depth': [3, 5, 7, 10], 'model__min_samples_split': [2, 5, 10],
'model__min_samples_leaf': [1, 2, 4]}
dt_grid = GridSearchCV(tree_model, dt_params, cv=5, scoring='roc_auc')
dt_grid.fit(X_train, y_train)
print('Best DT Params:', dt_grid.best_params_)
dt_tuned_pred = dt_grid.predict(X_test)
dt_tuned_prob = dt_grid.predict_proba(X_test)[:, 1]
print('Tuned DT - Acc:', accuracy_score(y_test, dt_tuned_pred), 'F1:', f1_score(y_test,
dt_tuned_pred), 'AUC:', roc_auc_score(y_test, dt_tuned_prob))
```

```
Best LR Params: {'model__C': 0.1}
Tuned LR - Acc: 0.8545727136431784 F1: 0.24806201550387597 AUC: 0.8155181768855128
Best DT Params: {'model__max_depth': 5, 'model__min_samples_leaf': 1, 'model__min_samples
_split': 5}
Tuned DT - Acc: 0.9145427286356822 F1: 0.6779661016949152 AUC: 0.8030475673720383
```

In [50]:

```
cm_tuned_Lr = confusion_matrix(y_test, lr_tuned_pred)
print("Decision Tree Matrix:")
#print(cm_tree)
display = ConfusionMatrixDisplay(confusion_matrix= cm_tuned_Lr )
display.plot()
plt.show()
```

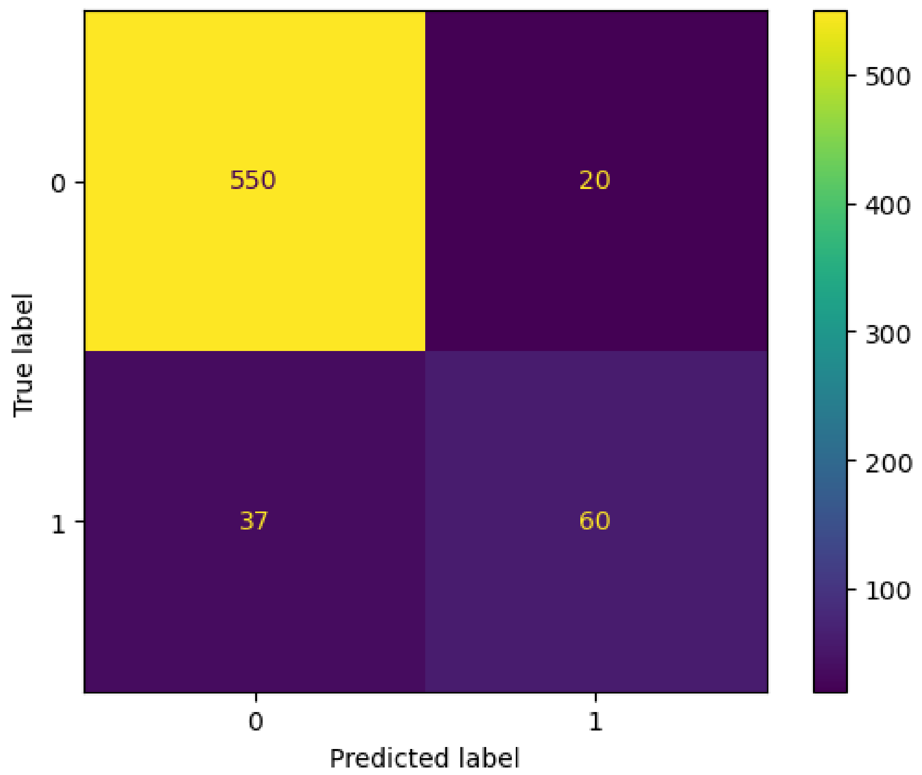
```
Decision Tree Matrix:
```



In [51]:

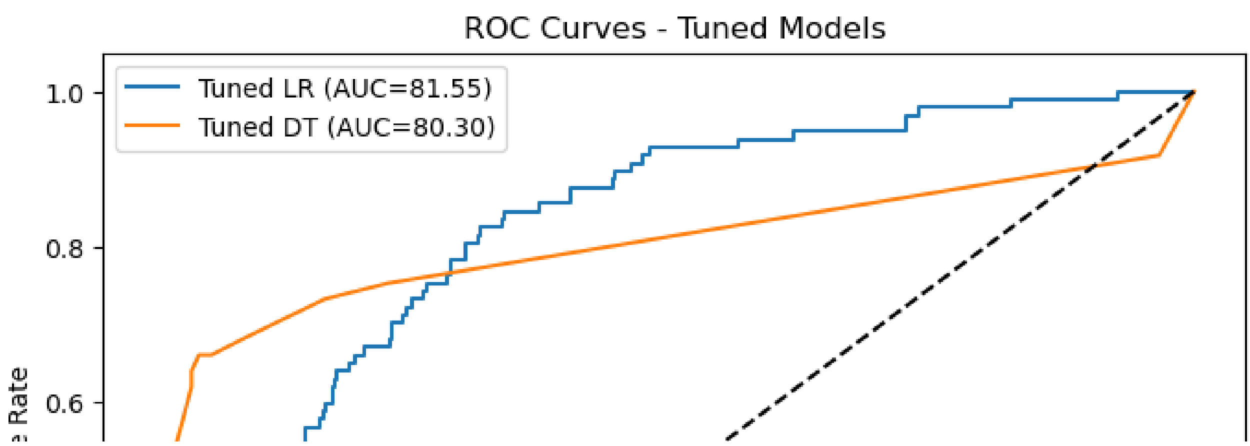
```
cm_tuned_tree = confusion_matrix(y_test, dt_tuned_pred)
print("Decision Tree Matrix:")
#print(cm_tree)
display = ConfusionMatrixDisplay(confusion_matrix= cm_tuned_tree)
display.plot()
plt.show()
```

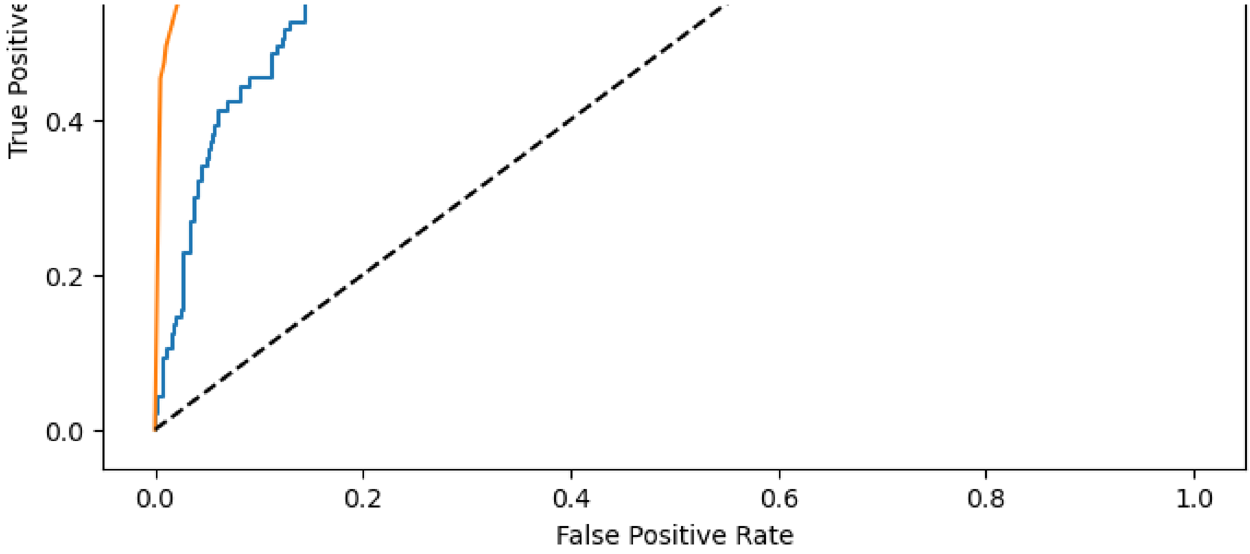
```
Decision Tree Matrix:
```



In [65]:

```
# ROC Curves (higher curve/area = better model)
fpr_lr, tpr_lr, _ = roc_curve(y_test, lr_tuned_prob)
fpr_dt, tpr_dt, _ = roc_curve(y_test, dt_tuned_prob)
tuned_lr_auc = auc(fpr_lr, tpr_lr)
tuned_dt_auc = auc(fpr_dt, tpr_dt)
plt.figure(figsize=(8, 6))
plt.plot(fpr_lr, tpr_lr, label=f'Tuned LR (AUC={tuned_lr_auc*100:.2f})')
plt.plot(fpr_dt, tpr_dt, label=f'Tuned DT (AUC={tuned_dt_auc*100:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves - Tuned Models')
plt.legend()
plt.show()
```





In [62]:

```
#compare roc accuracy from both sides

roc_tuned_log =  roc_auc_score(y_test, lr_tuned_prob)
roc_tuned_tree = roc_auc_score(y_test, dt_tuned_prob)

print("\nComparison:")
if roc_tuned_tree > roc_tuned_log:
    print("Decision Tree is better based on tuned ROC AUC.")
else:
    print("Logistic Regression is better based on tuned ROC AUC.")
```

```
Comparison:
Logistic Regression is better based on tuned ROC AUC.
```