Customer Churn Prediction – EDA & Modeling

This notebook performs exploratory data analysis (EDA), feature engineering, model training, and evaluation for the **Customer Churn Prediction** project.
It uses **Scikit-learn**, **XGBoost**, and **SHAP** (optional) and is designed to work with the Telco Customer Churn dataset.

In [2]:
```
# --- Imports & Configuration ---
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.metrics import roc_auc_score, roc_curve, precision_recall_curve, class

from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier

import joblib

# Try to import shap (optional for explainability)
try:
    import shap
    SHAP_AVAILABLE = True
except Exception:
    SHAP_AVAILABLE = False

plt.rcParams['figure.figsize'] = (8, 5)

# Path to data relative to this notebook (assuming repo layout)
DATA_PATH = '../data/telco_churn.csv'  # <-- change if different
ARTIFACT_DIR = '../artifacts'
os.makedirs(ARTIFACT_DIR, exist_ok=True)

print('SHAP available:', SHAP_AVAILABLE)
print('Data path:', DATA_PATH)
```

```
SHAP available: True
Data path: ../data/telco_churn.csv
```

1. Load & Preview Data

In [3]:
```
# --- Load & Preview ---
df = pd.read_csv(DATA_PATH)

# Clean up TotalCharges if present (coerce to numeric)
if 'TotalCharges' in df.columns:
    df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')

print('Shape:', df.shape)
df.head()
```

```
Shape: (7043, 21)
```

Out[3]:

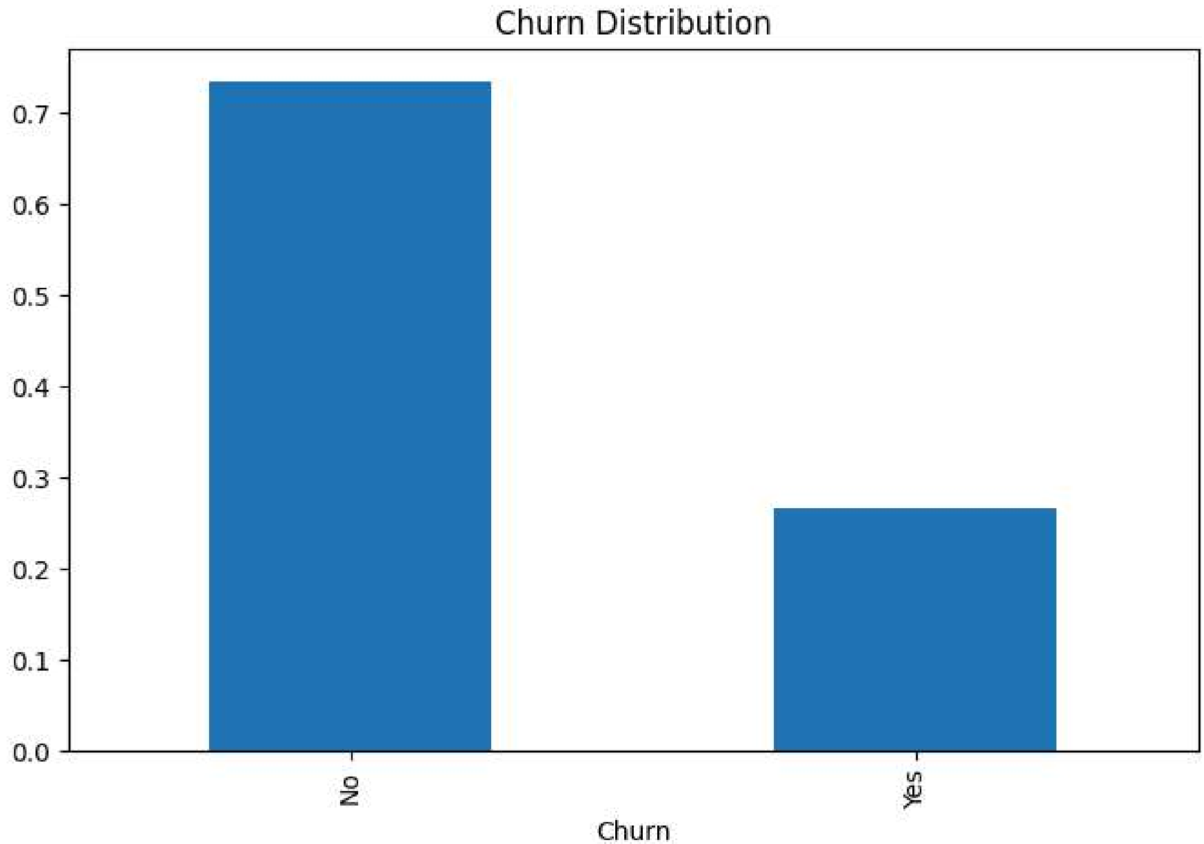
	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Multipl
0	7590-VHVEG	Female	0	Yes	No	1	No	No
1	5575-GNVDE	Male	0	No	No	34	Yes	
2	3668-QPYBK	Male	0	No	No	2	Yes	
3	7795-CFOCW	Male	0	No	No	45	No	No
4	9237-HQITU	Female	0	No	No	2	Yes	

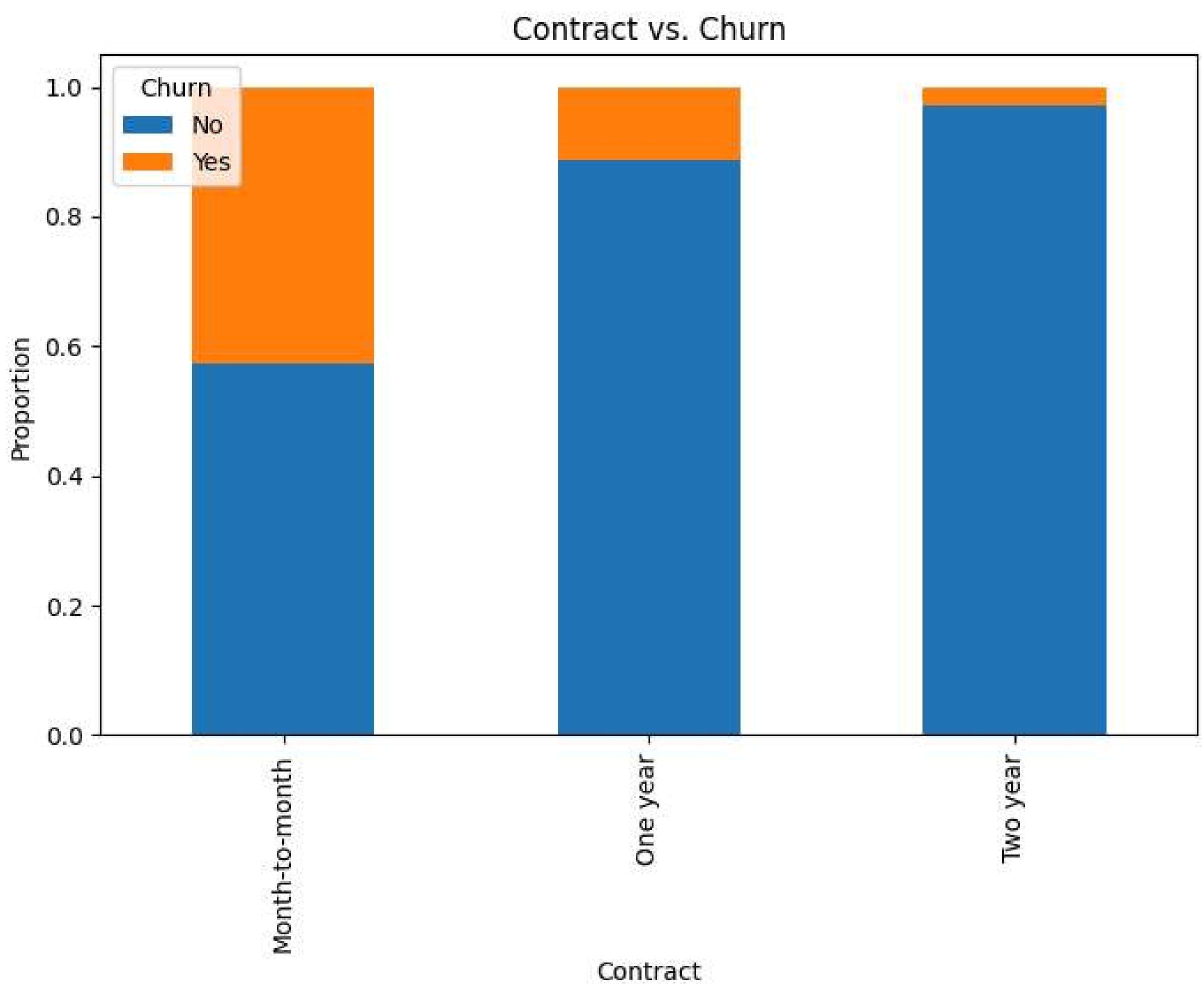
5 rows × 21 columns

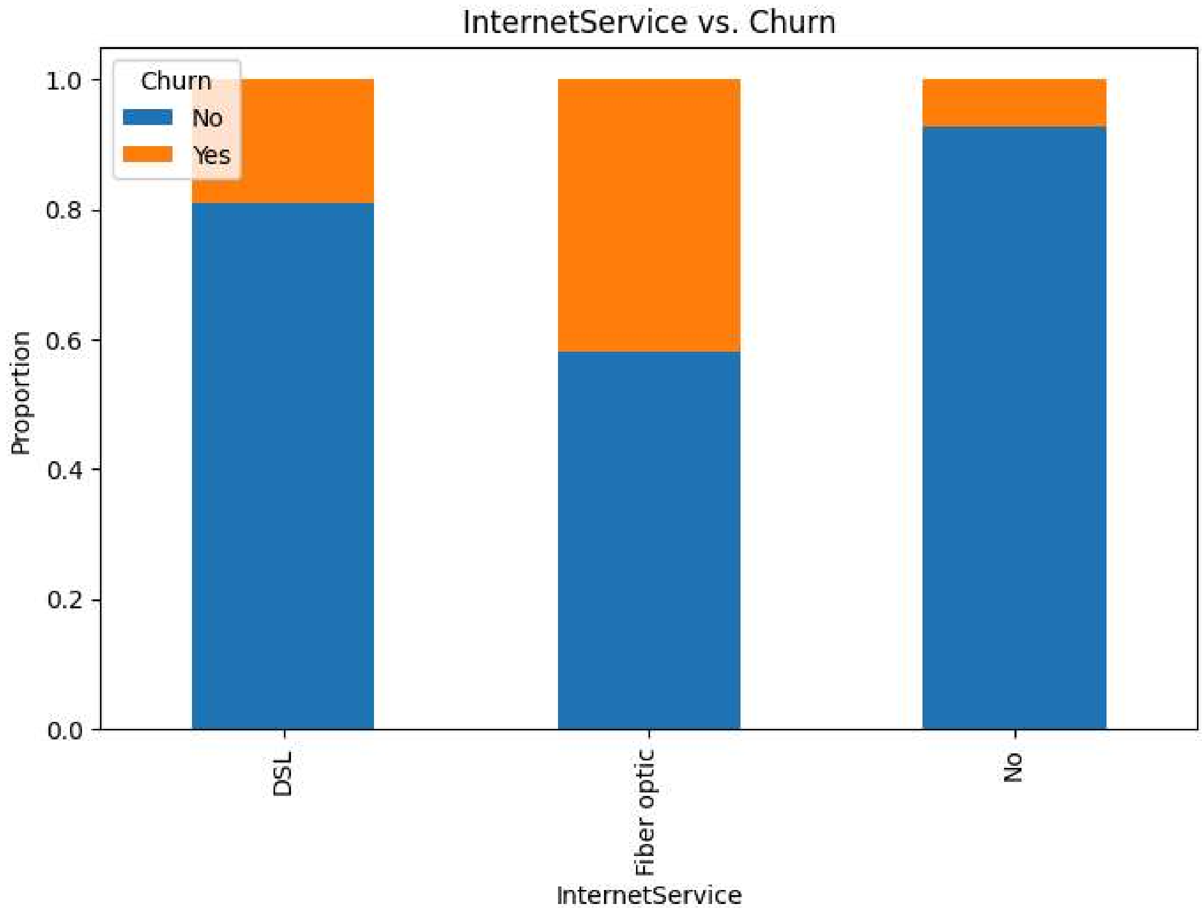
2. Basic EDA

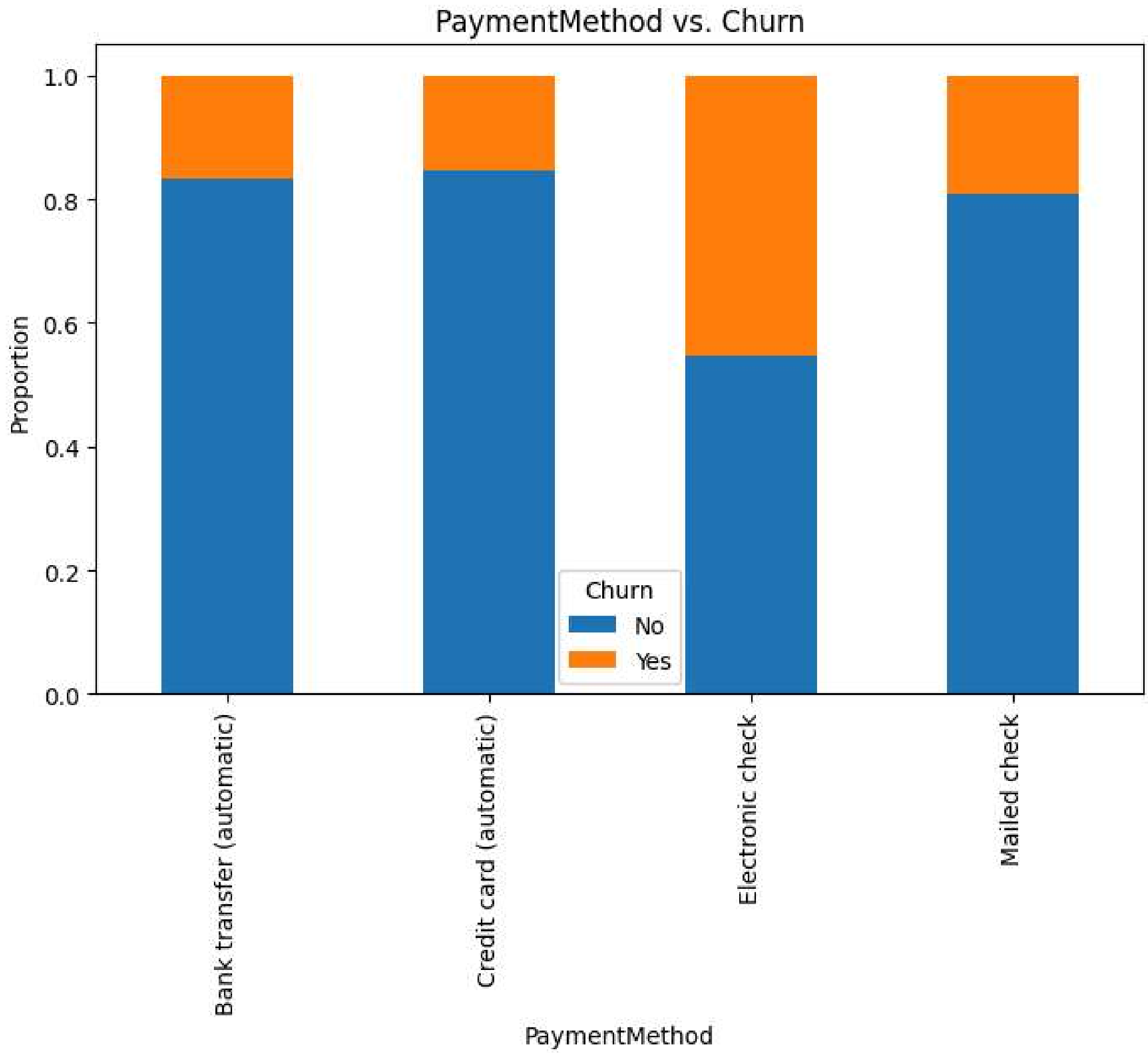
In [4]:
```
# Target distribution
target_col = 'Churn'   # assumes Yes/No
if target_col in df.columns:
    print(df[target_col].value_counts(dropna=False))
    df[target_col].value_counts(normalize=True).plot(kind='bar', title='Churn Distr

# Example relationships (customize as needed)
for col in ['Contract', 'InternetService', 'PaymentMethod']:
    if col in df.columns and target_col in df.columns:
        ct = pd.crosstab(df[col], df[target_col], normalize='index')
        ct.plot(kind='bar', stacked=True, title=f'{col} vs. Churn'); plt.ylabel('Pr
```

```
Churn
No      5174
Yes     1869
Name: count, dtype: int64
```


Churn Distribution
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
No
Yes
Churn


Contract vs. Churn
Churn
No
Yes
1.0
0.8
0.6
0.4
0.2
0.0
Proportion
Month-to-month
One year
Two year
Contract


InternetService vs. Churn
Churn
No
Yes
1.0
0.8
0.6
0.4
0.2
0.0
Proportion
DSL
Fiber optic
No
InternetService



3. Train/Test Split & Preprocessing

In [5]:
```
# --- Split X, y ---
y = (df[target_col].astype(str).str.lower() == 'yes').astype(int)
X = df.drop(columns=[target_col])

# Identify dtypes
numeric_cols = X.select_dtypes(include=['int64', 'float64']).columns.tolist()
categorical_cols = X.select_dtypes(exclude=['int64', 'float64']).columns.tolist()

# Preprocessor: impute, scale numeric; one-hot encode categoricals
numeric_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='median')),
    ('scaler', StandardScaler(with_mean=False))
])

categorical_transformer = Pipeline(steps=[
    ('imputer', SimpleImputer(strategy='most_frequent')),
    ('encoder', OneHotEncoder(handle_unknown='ignore'))
])
```

```
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numeric_cols),
        ('cat', categorical_transformer, categorical_cols)
    ],
    remainder='drop'
)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y
X_train.shape, X_test.shape
```

Out[5]:
```
((5634, 20), (1409, 20))
```

4. Baseline Models & Cross-Validation

In [6]:
```
# Define candidate models
models = {
    'logreg': LogisticRegression(max_iter=1000),
    'rf': RandomForestClassifier(n_estimators=300, n_jobs=-1, random_state=42),
    'xgb': XGBClassifier(
        n_estimators=500, eval_metric='auc', tree_method='hist', n_jobs=-1, random_
    )
}

cv_results = {}
for name, clf in models.items():
    pipe = Pipeline([('prep', preprocessor), ('clf', clf)])
    scores = cross_val_score(pipe, X_train, y_train, scoring='roc_auc', cv=3, n_job
    cv_results[name] = (scores.mean(), scores.std())
    print(f'{name}: ROC-AUC {scores.mean():.3f} ± {scores.std():.3f}')

cv_results
```

```
logreg: ROC-AUC 0.846 ± 0.014
rf: ROC-AUC 0.834 ± 0.014
xgb: ROC-AUC 0.808 ± 0.007
```

Out[6]:
```
{'logreg': (np.float64(0.8456947918571416), np.float64(0.013984338004309446)),
 'rf': (np.float64(0.8338053202236523), np.float64(0.014096514049514288)),
 'xgb': (np.float64(0.8079149543976988), np.float64(0.007388764145710784))}
```

5. Hyperparameter Tuning (XGBoost)

In [7]:
```
param_grid = {
    'clf__max_depth': [4, 6, 8],
    'clf__learning_rate': [0.03, 0.1],
    'clf__subsample': [0.8, 1.0]
}

xgb_pipe = Pipeline([('prep', preprocessor),
                     ('clf', XGBClassifier(n_estimators=500, eval_metric='auc', tre

gs = GridSearchCV(xgb_pipe, param_grid, cv=3, scoring='roc_auc', n_jobs=-1, verbose
```

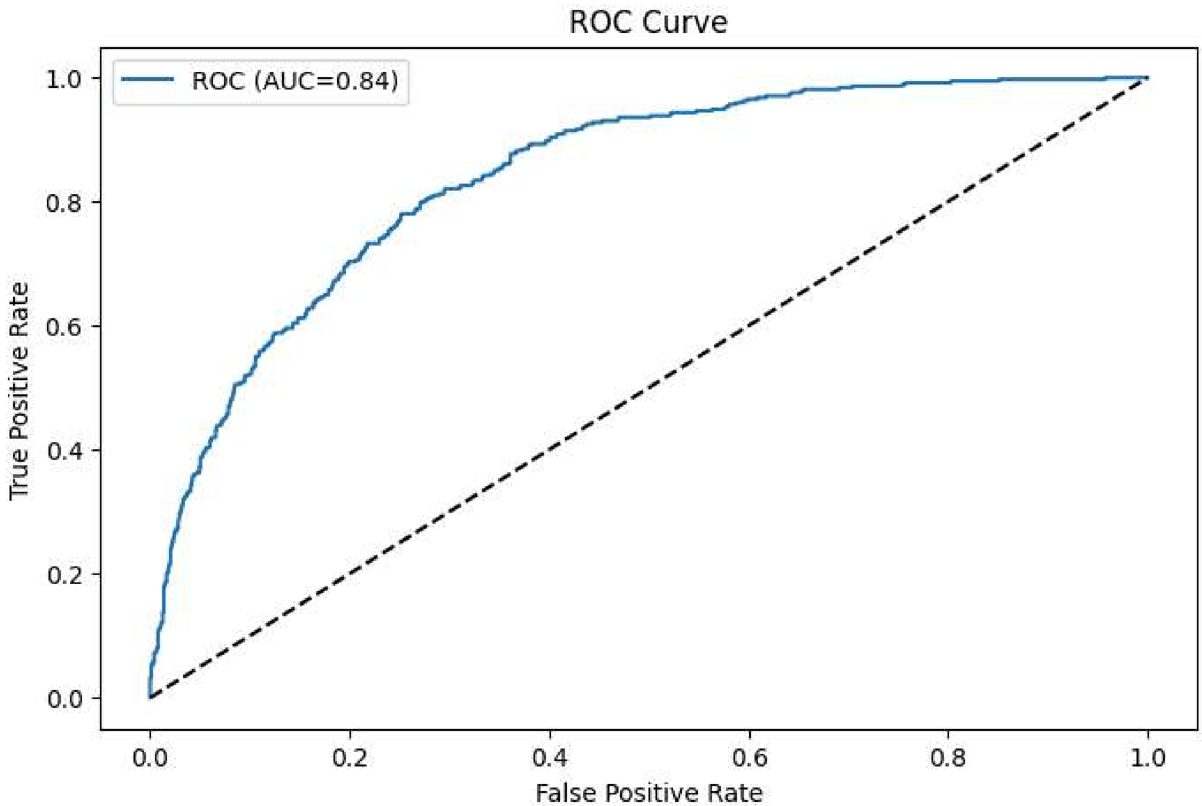
```python
gs.fit(X_train, y_train)

print('Best params:', gs.best_params_)
print('Best CV ROC-AUC:', gs.best_score_)

best_model = gs.best_estimator_
```

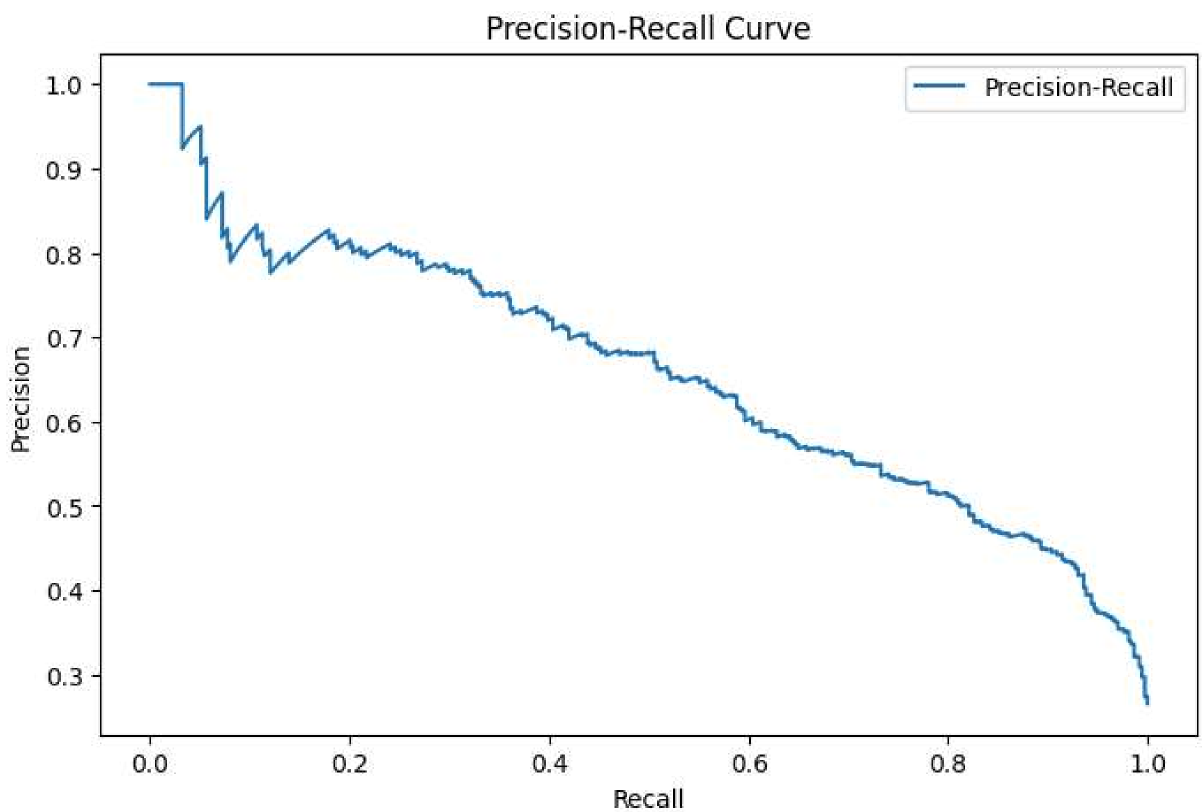
```
Fitting 3 folds for each of 12 candidates, totalling 36 fits
Best params: {'clf__learning_rate': 0.03, 'clf__max_depth': 4, 'clf__subsample': 0.
8}
Best CV ROC-AUC: 0.8454396129493144
```

6. Evaluation on Holdout Set

In [8]:
```python
y_proba = best_model.predict_proba(X_test)[:, 1]
y_pred = (y_proba >= 0.5).astype(int)

auc = roc_auc_score(y_test, y_proba)
print('Holdout ROC-AUC:', round(auc, 3))
print('\nClassification Report\n', classification_report(y_test, y_pred))

# ROC curve
fpr, tpr, _ = roc_curve(y_test, y_proba)
plt.plot(fpr, tpr, label=f'ROC (AUC={auc:.2f})')
plt.plot([0,1],[0,1],'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()

# Precision-Recall curve
prec, rec, _ = precision_recall_curve(y_test, y_proba)
plt.plot(rec, prec, label='Precision-Recall')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend()
plt.show()
```

```
Holdout ROC-AUC: 0.842

Classification Report
               precision    recall  f1-score   support

           0       0.84      0.90      0.87      1035
           1       0.66      0.52      0.58       374

    accuracy                           0.80      1409
   macro avg       0.75      0.71      0.73      1409
weighted avg       0.79      0.80      0.79      1409
```

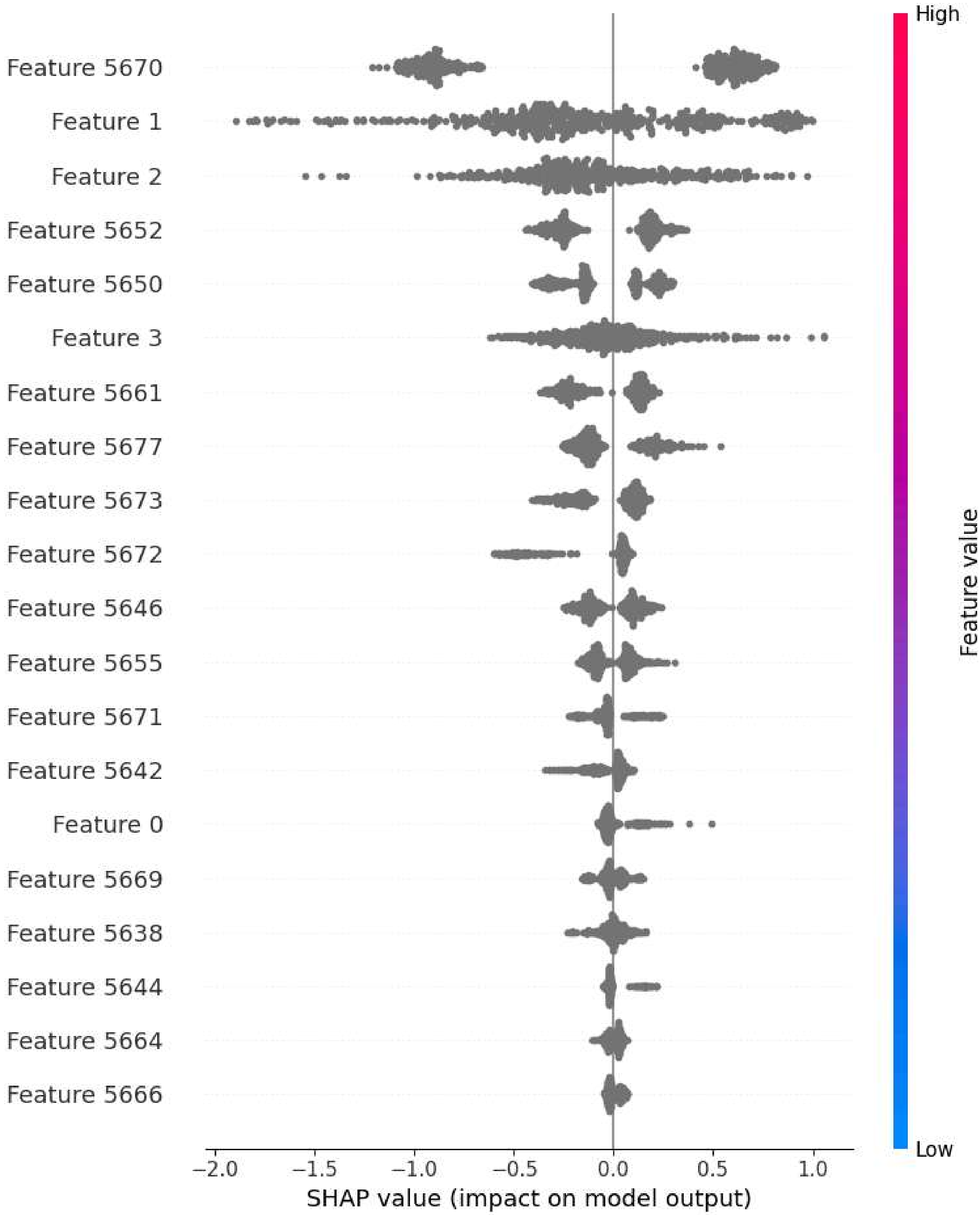




7. Explainability (SHAP)

In [9]:
```
if SHAP_AVAILABLE:
    # Take a small sample to speed up plotting if needed
```

```
    X_sample = X_test.sample(min(500, len(X_test)), random_state=42)
    # Extract the underlying trained XGB model after preprocessing
    # We can transform X_sample with the preprocessor to a numeric matrix
    X_mat = best_model.named_steps['prep'].transform(X_sample)
    xgb_clf = best_model.named_steps['clf']

    explainer = shap.TreeExplainer(xgb_clf)
    shap_values = explainer.shap_values(X_mat)

    shap.summary_plot(shap_values, X_mat, show=True)
else:
    print("SHAP not installed. To enable, install shap and rerun this cell.")
```



8. Save Trained Model

In [10]:
```
model_path = os.path.join(ARTIFACT_DIR, 'xgb_nb_model.joblib')
joblib.dump(best_model, model_path)
model_path
```

Out[10]: `'../artifacts\\xgb_nb_model.joblib'`

In [ ]: