In [25]:
```
import pandas as pd
import numpy as np
import missingno as msno
import plotly.express as px
```

Data Cleaning

In [26]:
```
df = pd.read_csv('C:/Users/19229/OneDrive/Desktop/data1030-fall2025/data1030-pro
df.shape
df.head()
df.dtypes
#df = df.drop(['customerID'], axis = 1), already done
```

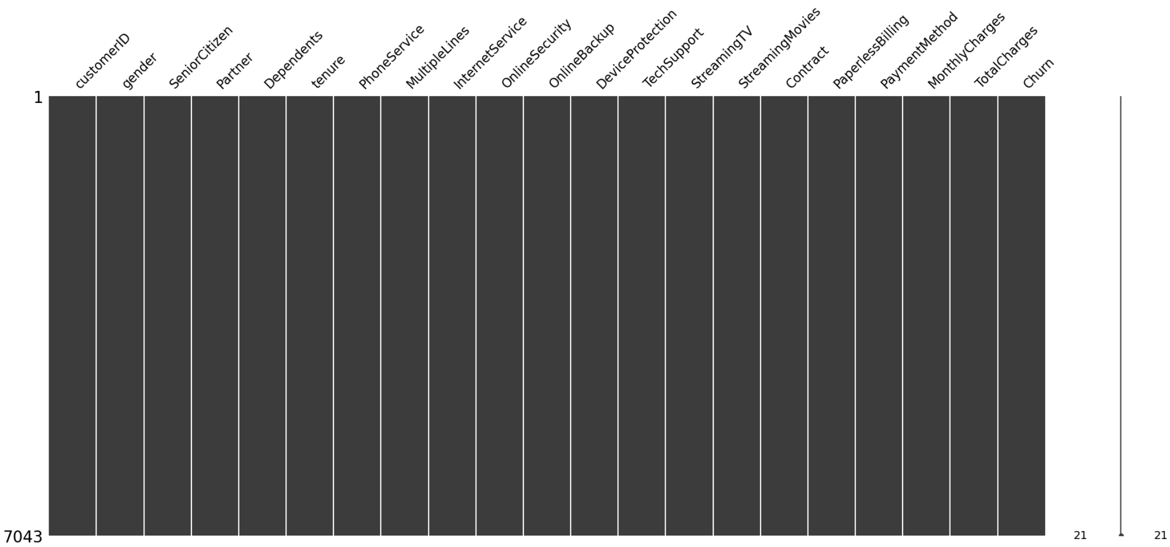
Out[26]:
```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

In [27]:
```
msno.matrix(df)
df['TotalCharges'] = pd.to_numeric(df.TotalCharges, errors='coerce')
print(df.isnull().sum())
df[np.isnan(df['TotalCharges'])]
df['TotalCharges'] = df['TotalCharges'].fillna(df['TotalCharges'].mean())
print(df.isnull().sum())

df["SeniorCitizen"] = df["SeniorCitizen"].map({0:"No", 1:"Yes"}).astype("categor
numerical_cols = ['tenure', 'MonthlyCharges', 'TotalCharges']
df[numerical_cols].describe()
```

```
customerID           0
gender               0
SeniorCitizen        0
Partner              0
Dependents           0
tenure               0
PhoneService         0
MultipleLines        0
InternetService      0
OnlineSecurity       0
OnlineBackup         0
DeviceProtection     0
TechSupport          0
StreamingTV          0
StreamingMovies      0
Contract             0
PaperlessBilling     0
PaymentMethod        0
MonthlyCharges       0
TotalCharges        11
Churn                0
dtype: int64
customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

Out[27]:

	tenure	MonthlyCharges	TotalCharges
count	7043.000000	7043.000000	7043.000000
mean	32.371149	64.761692	2283.300441
std	24.559481	30.090047	2265.000258
min	0.000000	18.250000	18.800000
25%	9.000000	35.500000	402.225000
50%	29.000000	70.350000	1400.550000
75%	55.000000	89.850000	3786.600000
max	72.000000	118.750000	8684.800000



EDA

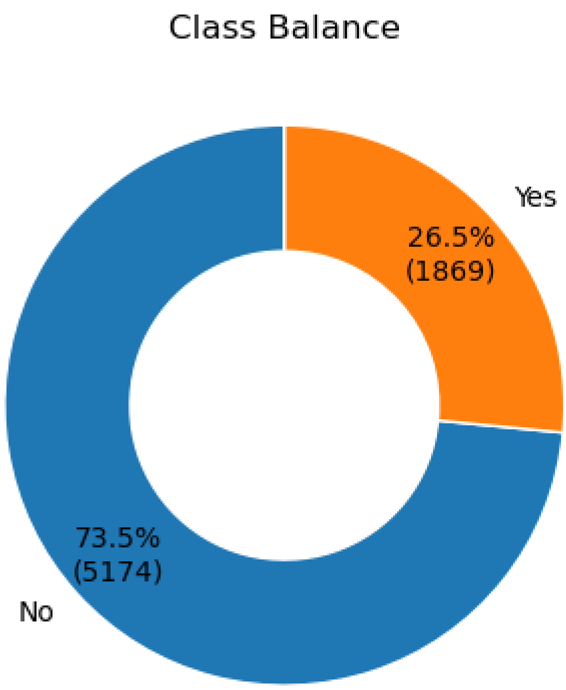
In [28]:
```
import matplotlib.pyplot as plt
import os
plt.rcParams["figure.figsize"] = (7,4)

os.makedirs("reports/figures", exist_ok=True)

target = "Churn"

_churn_num = df[target].map({"No":0, "Yes":1})#temperory switch to 0/1 for matri
```

In [29]:
```
print("Shape:", df.shape)
print("Missing per column after cleaning:\n", df.isna().sum()[df.isna().sum()>0]
print("Churn distribution:\n", df[target].value_counts())
print("Positive rate:", _churn_num.mean().round(3))
print("\nNumeric summary:\n", df[numerical_cols].describe().T)
```

```
Shape: (7043, 21)
Missing per column after cleaning:
 Series([], dtype: int64)
Churn distribution:
 Churn
No     5174
Yes    1869
Name: count, dtype: int64
Positive rate: 0.265

Numeric summary:
                 count         mean          std    min      25%      50%  \
tenure          7043.0    32.371149    24.559481   0.00    9.000    29.00
MonthlyCharges  7043.0    64.761692    30.090047  18.25   35.500    70.35
TotalCharges    7043.0  2283.300441  2265.000258  18.80  402.225  1400.55

                    75%      max
tenure            55.00    72.00
MonthlyCharges    89.85   118.75
TotalCharges    3786.60  8684.80
```

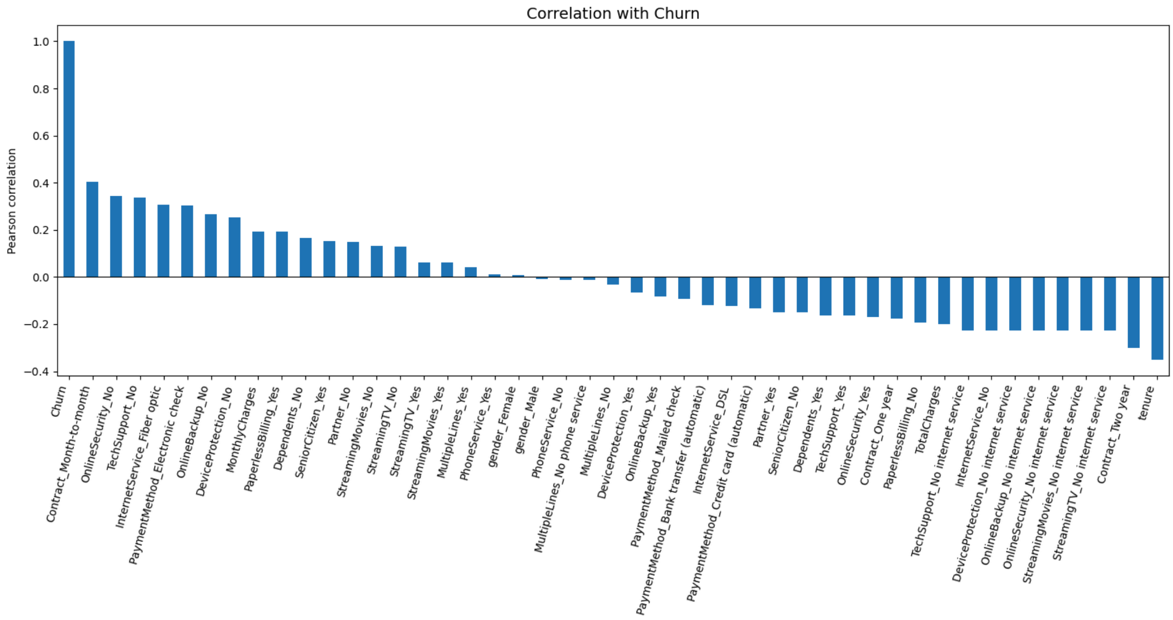
In [30]:
```
counts = df[target].value_counts().reindex(["No","Yes"])
labels = counts.index
```

```
vals = counts.values
total = counts.sum()

fig, ax = plt.subplots(figsize=(6,4))
ax.pie(
    vals,
    labels=labels,
    autopct=lambda p: f"{p:.1f}%\n({int(round(p*total/100))})",
    startangle=90,
    pctdistance=0.8,
    wedgeprops={"width":0.45, "edgecolor":"white"}
)
ax.set_title("Class Balance")
ax.set_aspect("equal")
plt.tight_layout()
plt.show()
```

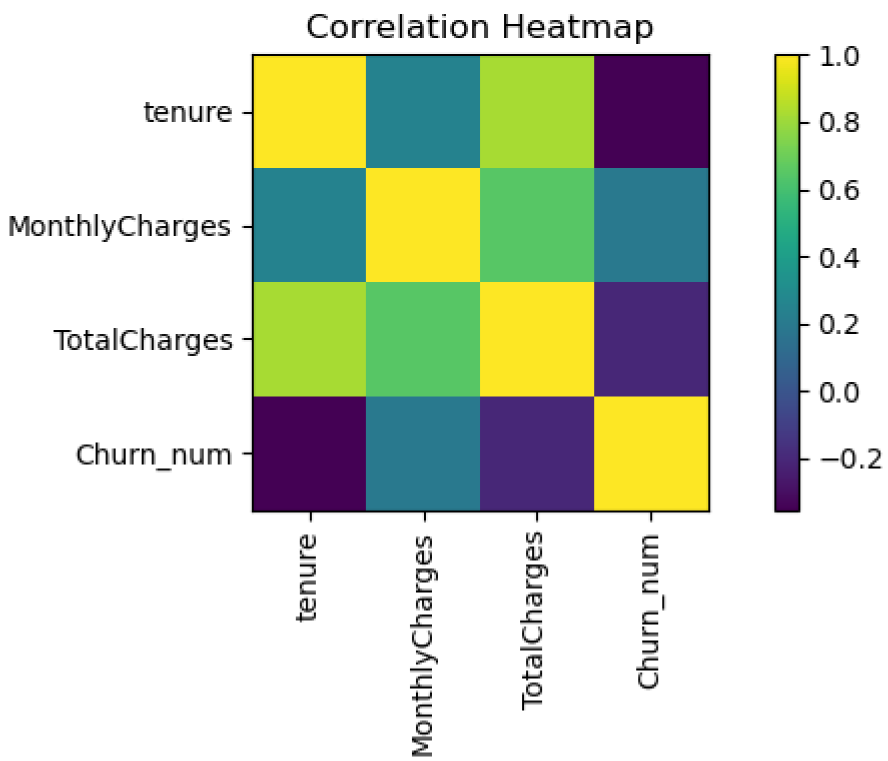


In [31]:
```
data = df.copy()
data["Churn"] = data["Churn"].map({"No":0, "Yes":1}).astype(int)
if "customerID" in data.columns:
    data = data.drop(columns=["customerID"])

dummies = pd.get_dummies(data, dtype=int)

y = dummies["Churn"]
X = dummies.drop(columns="Churn")
corr = X.corrwith(y)

corr_with_target = pd.concat([pd.Series({"Churn": 1.0}), corr])

corr_sorted = corr_with_target.sort_values(ascending=False)

plt.figure(figsize=(15, 8))
corr_sorted.plot(kind="bar")
plt.axhline(0, color="black", linewidth=0.8)
plt.title("Correlation with Churn", fontsize=14)
```

```
plt.ylabel("Pearson correlation")
plt.xticks(rotation=75, ha="right")
plt.tight_layout()
plt.show()
```

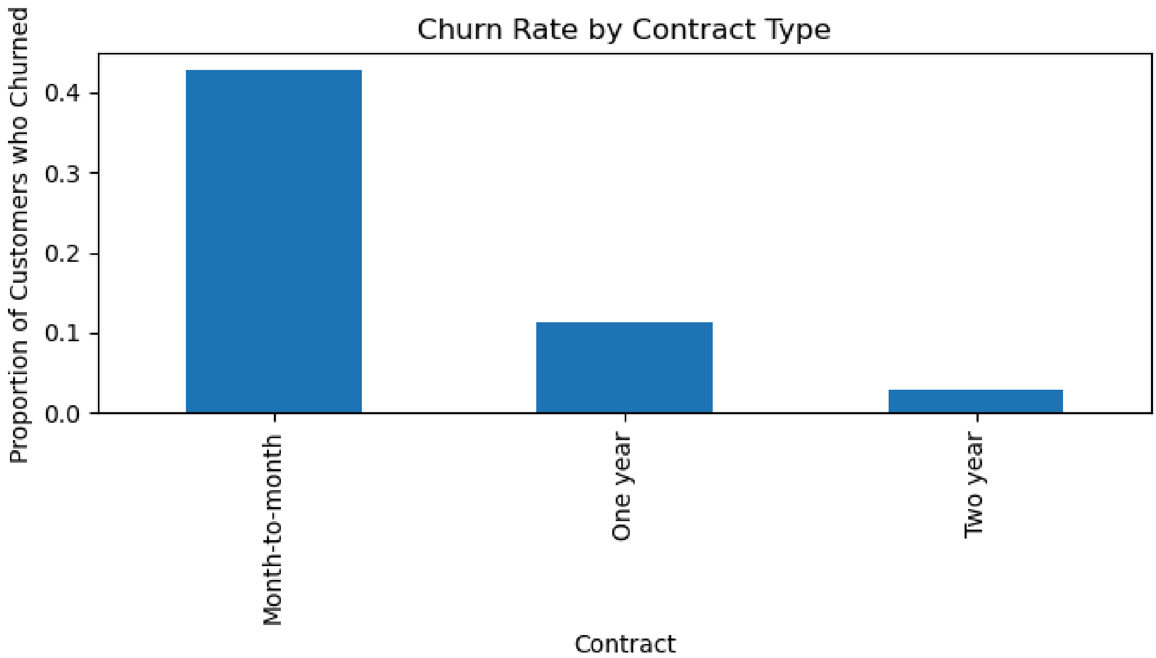


In [32]:
```
corr_df = df[numerical_cols].copy()
corr_df["Churn_num"] = _churn_num
corr = corr_df.corr()

plt.imshow(corr, interpolation="nearest")
plt.title("Correlation Heatmap")
plt.colorbar()
plt.xticks(range(len(corr.columns)), corr.columns, rotation=90)
plt.yticks(range(len(corr.index)), corr.index)
plt.tight_layout(); plt.savefig("reports/figures/eda_corr_heatmap.png", dpi=200)
plt.show()

print("Top correlation with Churn_num:\n", corr["Churn_num"].drop("Churn_num").a
```



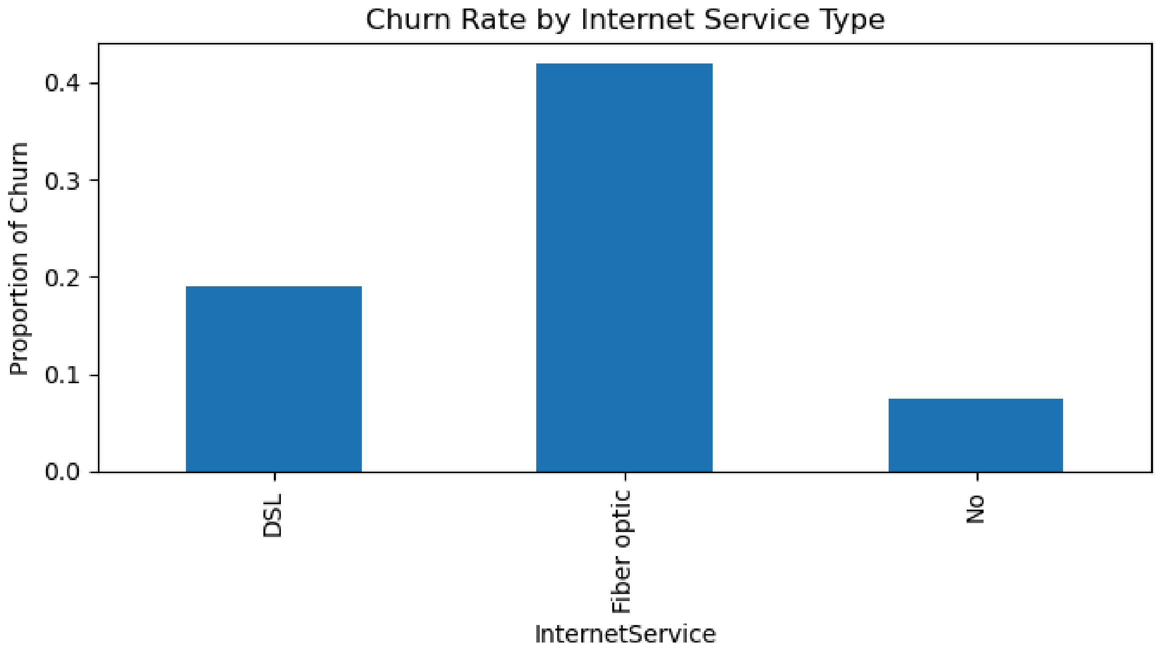

```
Top correlation with Churn_num:
 tenure            0.352229
TotalCharges      0.199428
MonthlyCharges    0.193356
Name: Churn_num, dtype: float64
```

In [33]:
```
churn_by_contract = df.groupby('Contract')['Churn'].value_counts(normalize=True)
churn_by_contract.plot(kind='bar')
plt.title('Churn Rate by Contract Type')
plt.ylabel('Proportion of Customers who Churned')
plt.tight_layout();
plt.show()
```

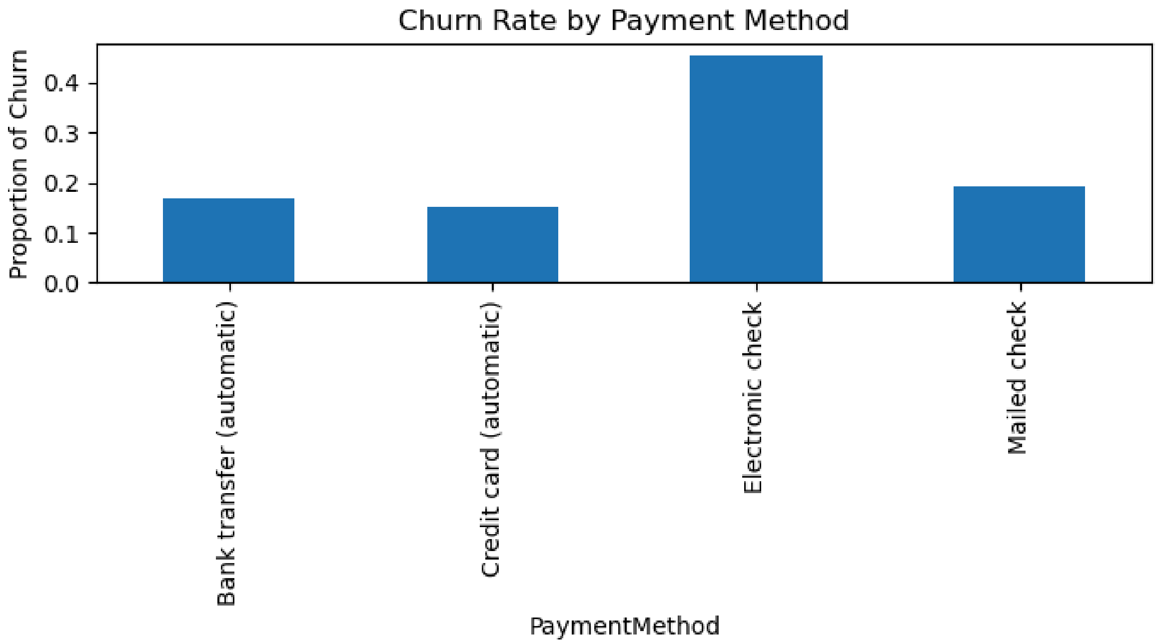


In [34]:
```
churn_by_service = df.groupby('InternetService')['Churn'].value_counts(normalize
churn_by_service.plot(kind='bar')
plt.title('Churn Rate by Internet Service Type')
```

```
plt.ylabel('Proportion of Churn')
plt.tight_layout(); plt.show()
```

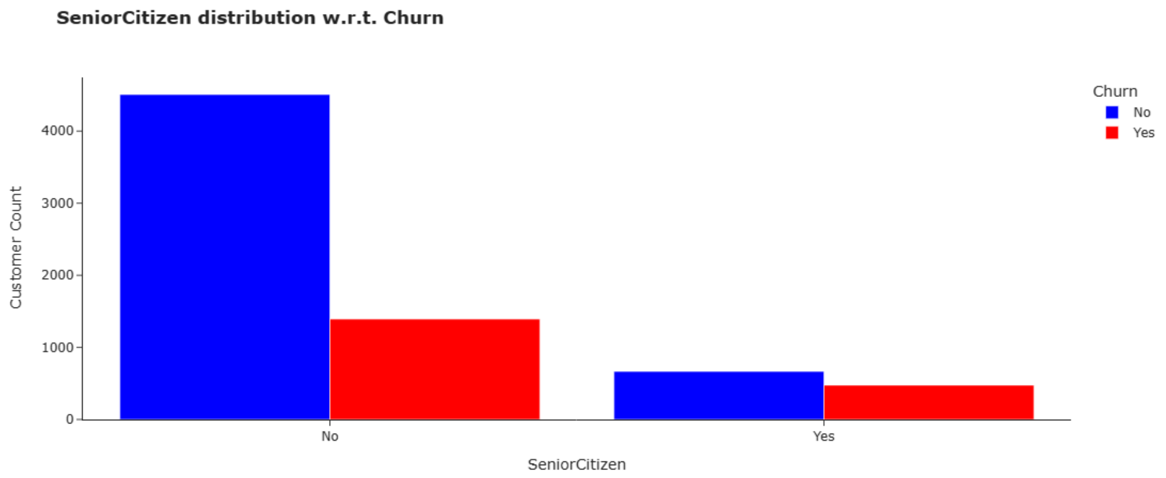


In [35]:
```
churn_by_payment = df.groupby('PaymentMethod')['Churn'].value_counts(normalize=T
churn_by_payment.plot(kind='bar')
plt.title('Churn Rate by Payment Method')
plt.ylabel('Proportion of Churn')
plt.tight_layout(); plt.show()
```

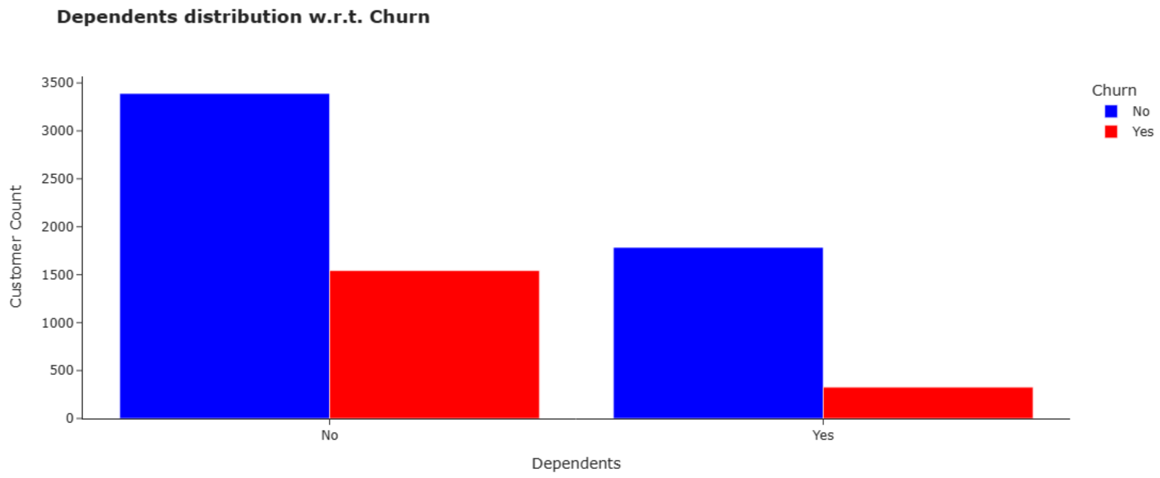


In [36]:
```
top_cat = "SeniorCitizen"
color_map = {"Yes": "red", "No": "blue"}

fig = px.histogram(
    df,
    x=top_cat,
    color="Churn",
    barmode="group",
    title=f"<b>{top_cat} distribution w.r.t. Churn</b>",
    color_discrete_map=color_map
```

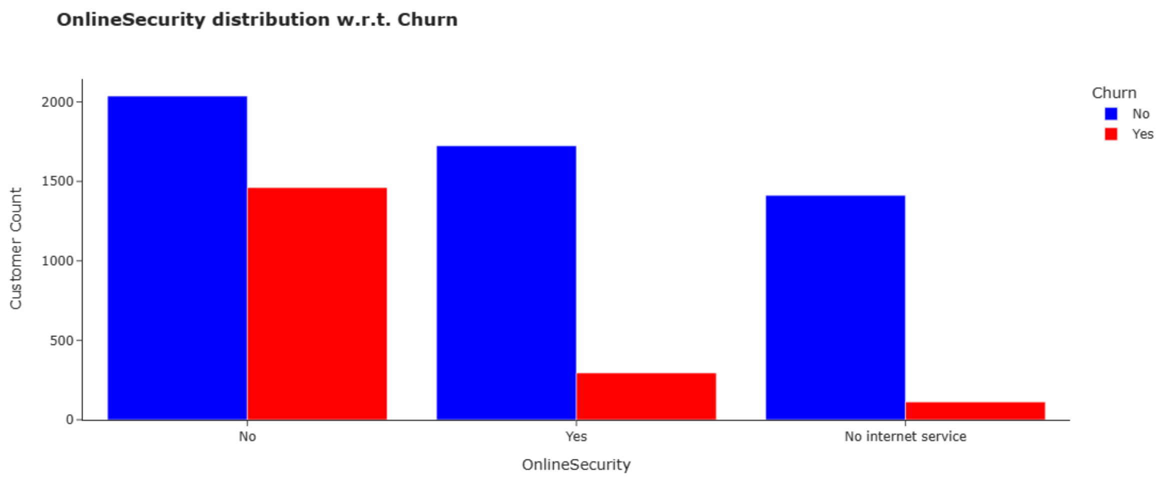
```
)

fig.update_layout(
    width=700,
    height=500,
    bargap=0.15,
    xaxis_title=top_cat,
    yaxis_title="Customer Count",
    legend_title="Churn",
    template="simple_white"
)

fig.show()
```



In [37]:
```
import plotly.express as px
top_cat = "Dependents"
color_map = {"Yes": "red", "No": "blue"}

fig = px.histogram(
    df,
    x=top_cat,
    color="Churn",
    barmode="group",
    title=f"<b>{top_cat} distribution w.r.t. Churn</b>",
    color_discrete_map=color_map
)

fig.update_layout(
    width=700,
    height=500,
    bargap=0.15,
    xaxis_title=top_cat,
    yaxis_title="Customer Count",
    legend_title="Churn",
    template="simple_white"
)

fig.show()
```

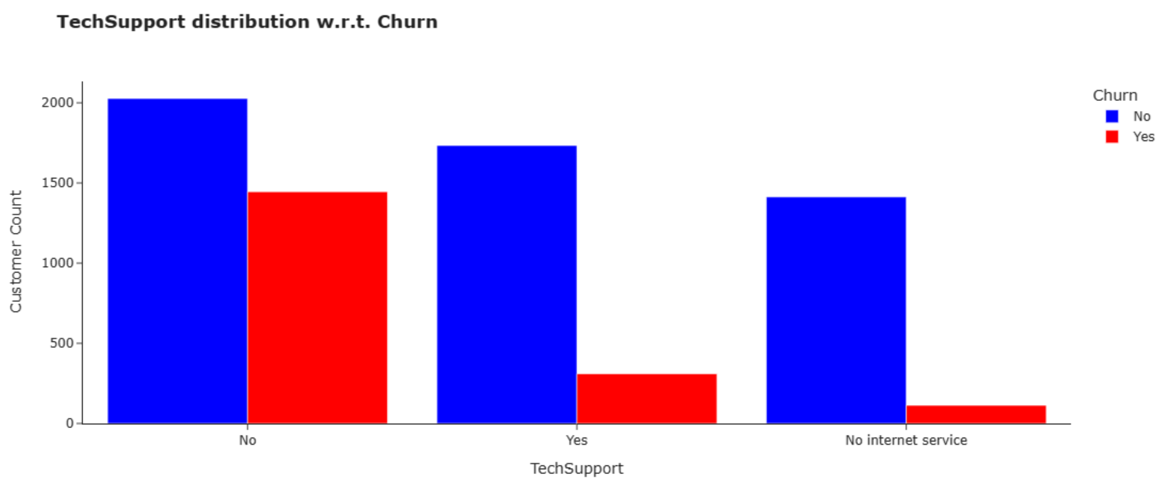


In [38]:
```
top_cat = "OnlineSecurity"
color_map = {"Yes": "red", "No": "blue"}

fig = px.histogram(
    df,
    x=top_cat,
    color="Churn",
    barmode="group",
    title=f"<b>{top_cat} distribution w.r.t. Churn</b>",
    color_discrete_map=color_map
)

fig.update_layout(
    width=700,
    height=500,
    bargap=0.15,
    xaxis_title=top_cat,
    yaxis_title="Customer Count",
    legend_title="Churn",
    template="simple_white"
)

fig.show()
```



In [39]:
```
top_cat = "TechSupport"
color_map = {"Yes": "red", "No": "blue"}
```

```
fig = px.histogram(
    df,
    x=top_cat,
    color="Churn",
    barmode="group",
    title=f"<b>{top_cat} distribution w.r.t. Churn</b>",
    color_discrete_map=color_map
)

fig.update_layout(
    width=700,
    height=500,
    bargap=0.15,
    xaxis_title=top_cat,
    yaxis_title="Customer Count",
    legend_title="Churn",
    template="simple_white"
)

fig.show()
```

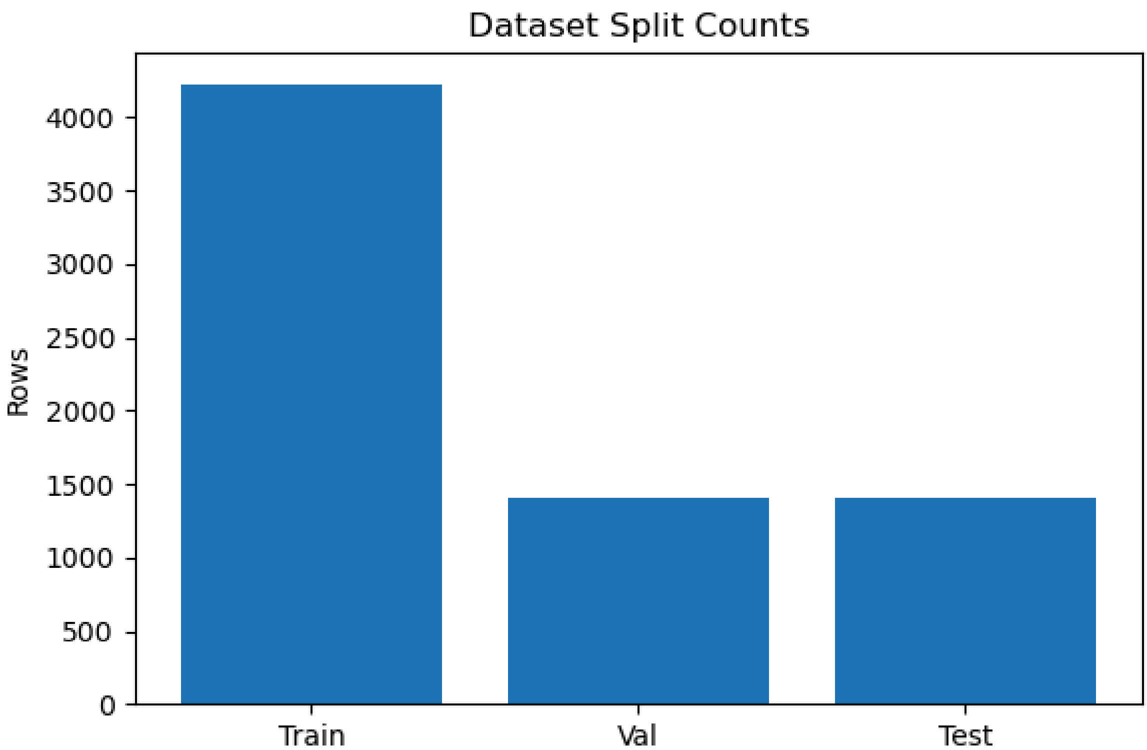


Preprocessing

In [40]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
import matplotlib.pyplot as plt

y = df["Churn"].map({"No":0, "Yes":1}).astype(int)
X = df.drop(columns=["Churn","customerID"], errors="ignore")

num_cols = X.select_dtypes(include=[np.number]).columns.tolist()
cat_cols = X.select_dtypes(include=["object","category","bool"]).columns.tolist(

X_tmp, X_test, y_tmp, y_test = train_test_split(X, y, test_size=0.20, stratify=y
X_train, X_val,  y_train, y_val = train_test_split(X_tmp, y_tmp, test_size=0.25,

print(f"Train: {X_train.shape}, Val: {X_val.shape}, Test: {X_test.shape}")
```

```
print(f"Pos rate train/val/test: {y_train.mean():.3f}/{y_val.mean():.3f}/{y_test

numeric_pipe = Pipeline([("imputer", SimpleImputer(strategy="mean")),
                         ("scaler", StandardScaler())])
categorical_pipe = Pipeline([("imputer", SimpleImputer(strategy="most_frequent")
                             ("onehot", OneHotEncoder(handle_unknown="ignore"))]

preprocess = ColumnTransformer([("num", numeric_pipe, num_cols),
                                ("cat", categorical_pipe, cat_cols)])

X_train_p = preprocess.fit_transform(X_train)
X_val_p   = preprocess.transform(X_val)
X_test_p  = preprocess.transform(X_test)

ohe = preprocess.named_transformers_["cat"].named_steps["onehot"]
ohe_names = ohe.get_feature_names_out(cat_cols)
feature_names = np.r_[num_cols, ohe_names]

print("Processed shapes:", X_train_p.shape, X_val_p.shape, X_test_p.shape)
print("Total features after preprocessing:", len(feature_names))

sizes = {"Train": len(X_train), "Val": len(X_val), "Test": len(X_test)}
plt.figure(figsize=(6,4))
plt.bar(list(sizes.keys()), list(sizes.values()))
plt.title("Dataset Split Counts")
plt.ylabel("Rows")
plt.tight_layout()
plt.show()
```

```
Train: (4225, 19), Val: (1409, 19), Test: (1409, 19)
Pos rate train/val/test: 0.265/0.265/0.265
Processed shapes: (4225, 46) (1409, 46) (1409, 46)
Total features after preprocessing: 46
```



In [58]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split, cross_val_score
```

```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
import xgboost as xgb
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, roc_auc_score, confusion_matrix,
                             classification_report)
from sklearn.inspection import permutation_importance
import shap
import matplotlib.pyplot as plt
import seaborn as sns

# Model Training

# Baseline: predict majority class
baseline_accuracy = 1 - y_train.mean()  # Assuming no churn is majority
print(f"BASELINE ACCURACY (predict majority class): {baseline_accuracy:.4f}")

models = {
    "Logistic Regression": LogisticRegression(max_iter=1000, random_state=123),
    "Decision Tree": DecisionTreeClassifier(random_state=123),
    "Random Forest": RandomForestClassifier(n_estimators=100, random_state=123),
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=100, random_sta
}

param_grids = {
    "Logistic Regression": [
        {"C": 0.01, "solver": "lbfgs"},
        {"C": 0.1, "solver": "lbfgs"},
        {"C": 1.0, "solver": "lbfgs"},
        {"C": 10.0, "solver": "lbfgs"}
    ],
    "Decision Tree": [
        {"max_depth": 5, "min_samples_split": 20},
        {"max_depth": 10, "min_samples_split": 20},
        {"max_depth": 15, "min_samples_split": 10},
        {"max_depth": None, "min_samples_split": 10}
    ],
    "Random Forest": [
        {"n_estimators": 50, "max_depth": 10, "min_samples_split": 20},
        {"n_estimators": 100, "max_depth": 15, "min_samples_split": 10},
        {"n_estimators": 200, "max_depth": 20, "min_samples_split": 5}
    ],
    "Gradient Boosting": [
        {"n_estimators": 50, "learning_rate": 0.1, "max_depth": 3},
        {"n_estimators": 100, "learning_rate": 0.1, "max_depth": 3},
        {"n_estimators": 100, "learning_rate": 0.05, "max_depth": 5}
    ]
}


# Training and Evaluation

results = []
best_models = {}
```

```
for model_name, base_model in models.items():
    print(f"\nTraining {model_name}...")

    best_score = 0
    best_params = None
    best_model_instance = None

    for params in param_grids[model_name]:
        model = base_model.__class__(**params, random_state=123)
        model.fit(X_train_p, y_train)
        val_score = roc_auc_score(y_val, model.predict_proba(X_val_p)[:, 1])

        if val_score > best_score:
            best_score = val_score
            best_params = params
            best_model_instance = model

    cv_scores = cross_val_score(
        best_model_instance, X_train_p, y_train,
        cv=5, scoring='roc_auc', n_jobs=-1
    )

    test_scores = []
    if model_name in ["Random Forest", "Gradient Boosting"]:
        for seed in range(123, 128):
            temp_model = best_model_instance.__class__(**best_params, random_sta
            temp_model.fit(X_train_p, y_train)
            test_pred_proba = temp_model.predict_proba(X_test_p)[:, 1]
            test_scores.append(roc_auc_score(y_test, test_pred_proba))
    else:
        test_pred_proba = best_model_instance.predict_proba(X_test_p)[:, 1]
        test_scores = [roc_auc_score(y_test, test_pred_proba)]

    y_test_pred = best_model_instance.predict(X_test_p)
    y_test_proba = best_model_instance.predict_proba(X_test_p)[:, 1]

    test_accuracy = accuracy_score(y_test, y_test_pred)
    test_precision = precision_score(y_test, y_test_pred)
    test_recall = recall_score(y_test, y_test_pred)
    test_f1 = f1_score(y_test, y_test_pred)
    test_auc = roc_auc_score(y_test, y_test_proba)

    results.append({
        "Model": model_name,
        "Best Params": str(best_params),
        "CV AUC": f"{cv_scores.mean():.4f}±{cv_scores.std():.4f}",
        "Test Accuracy": test_accuracy,
        "Test Precision": test_precision,
        "Test Recall": test_recall,
        "Test F1": test_f1,
        "Test AUC": test_auc,
        "Test AUC(mean,std)": f"{np.mean(test_scores):.4f}±{np.std(test_scores):
    })

    best_models[model_name] = best_model_instance

    print(f"  Best params: {best_params}")
    print(f"  CV AUC: {cv_scores.mean():.4f} ± {cv_scores.std():.4f}")
    print(f"  Test AUC: {np.mean(test_scores):.4f} ± {np.std(test_scores):.4f}")
```

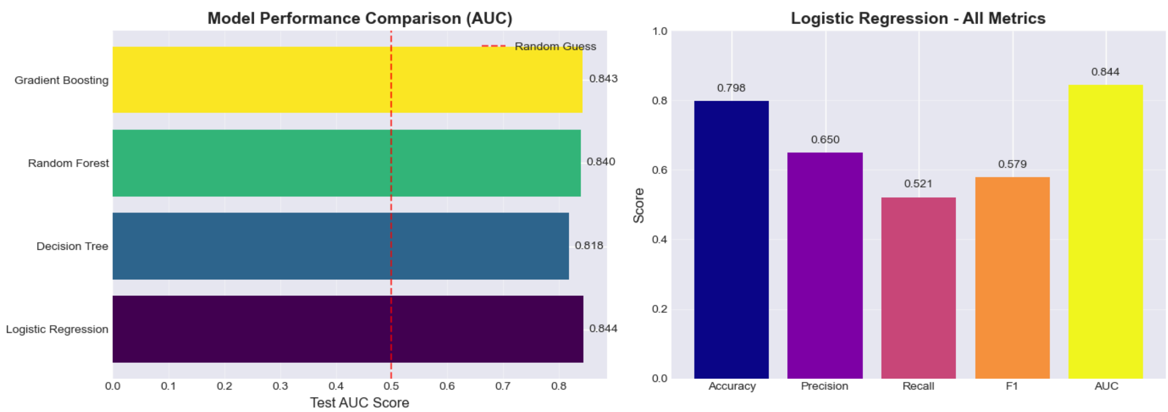
```
# Performance Comparison Table

results_df = pd.DataFrame(results)

print("MODEL PERFORMANCE SUMMARY")
print(results_df.to_string(index=False))

# Find best model
best_model_name = results_df.loc[results_df["Test AUC"].idxmax(), "Model"]
best_model = best_models[best_model_name]
print(f"Best Model: {best_model_name} (Test AUC: {results_df['Test AUC'].max():.

best_accuracy = results_df.loc[results_df["Test AUC"].idxmax(), "Test Accuracy"]
std_above_baseline = (best_accuracy - baseline_accuracy) / (baseline_accuracy *
print(f"Best model is {std_above_baseline:.2f} standard deviations above baselin


# Visualization

fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# AUC comparison
ax1 = axes[0]
models_list = results_df["Model"].tolist()
auc_scores = results_df["Test AUC"].tolist()
colors = plt.cm.viridis(np.linspace(0, 1, len(models_list)))

bars = ax1.barh(models_list, auc_scores, color=colors)
ax1.axvline(x=0.5, color='red', linestyle='--', label='Random Guess', alpha=0.7)
ax1.set_xlabel('Test AUC Score', fontsize=12)
ax1.set_title('Model Performance Comparison (AUC)', fontsize=14, fontweight='bol
ax1.legend()
ax1.grid(axis='x', alpha=0.3)
for i, (bar, score) in enumerate(zip(bars, auc_scores)):
    ax1.text(score + 0.01, i, f'{score:.3f}', va='center', fontsize=10)

# Multiple metrics for best model
ax2 = axes[1]
best_idx = results_df["Test AUC"].idxmax()
metrics = ['Accuracy', 'Precision', 'Recall', 'F1', 'AUC']
values = [
    results_df.loc[best_idx, 'Test Accuracy'],
    results_df.loc[best_idx, 'Test Precision'],
    results_df.loc[best_idx, 'Test Recall'],
    results_df.loc[best_idx, 'Test F1'],
    results_df.loc[best_idx, 'Test AUC']
]
colors2 = plt.cm.plasma(np.linspace(0, 1, len(metrics)))
bars2 = ax2.bar(metrics, values, color=colors2)
ax2.set_ylabel('Score', fontsize=12)
ax2.set_title(f'{best_model_name} - All Metrics', fontsize=14, fontweight='bold'
ax2.set_ylim([0, 1])
ax2.grid(axis='y', alpha=0.3)
for bar, val in zip(bars2, values):
    height = bar.get_height()
    ax2.text(bar.get_x() + bar.get_width()/2., height + 0.02,
             f'{val:.3f}', ha='center', va='bottom', fontsize=10)
```

```
plt.tight_layout()
plt.show()

# Feature Importance (3+ Methods)

print("FEATURE IMPORTANCE ANALYSIS")

# Built-in feature importance
if hasattr(best_model, 'feature_importances_'):
    importance_builtin = best_model.feature_importances_
    feature_imp_df = pd.DataFrame({
        'Feature': feature_names,
        'Importance': importance_builtin
    }).sort_values('Importance', ascending=False)

    print("Top 10 Features (Built-in Importance):")
    print(feature_imp_df.head(10).to_string(index=False))
    print()

    plt.figure(figsize=(10, 6))
    top_n = 15
    top_features = feature_imp_df.head(top_n)
    plt.barh(range(top_n), top_features['Importance'].values)
    plt.yticks(range(top_n), top_features['Feature'].values)
    plt.xlabel('Feature Importance', fontsize=12)
    plt.title(f'Top {top_n} Features - Built-in Importance ({best_model_name})',
              fontsize=14, fontweight='bold')
    plt.gca().invert_yaxis()
    plt.tight_layout()
    plt.show()

# Permutation Importance
print("\n Permutation Importance")
perm_importance = permutation_importance(
    best_model, X_test_p, y_test,
    n_repeats=10, random_state=123, n_jobs=-1
)

perm_imp_df = pd.DataFrame({
    'Feature': feature_names,
    'Importance': perm_importance.importances_mean,
    'Std': perm_importance.importances_std
}).sort_values('Importance', ascending=False)

print("\nTop 10 Features (Permutation Importance):")
print(perm_imp_df.head(10).to_string(index=False))

plt.figure(figsize=(10, 6))
top_n = 15
top_features_perm = perm_imp_df.head(top_n)
y_pos = range(top_n)
plt.barh(y_pos, top_features_perm['Importance'].values,
         xerr=top_features_perm['Std'].values, alpha=0.7)
plt.yticks(y_pos, top_features_perm['Feature'].values)
plt.xlabel('Permutation Importance', fontsize=12)
plt.title(f'Top {top_n} Features - Permutation Importance',
          fontsize=14, fontweight='bold')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```

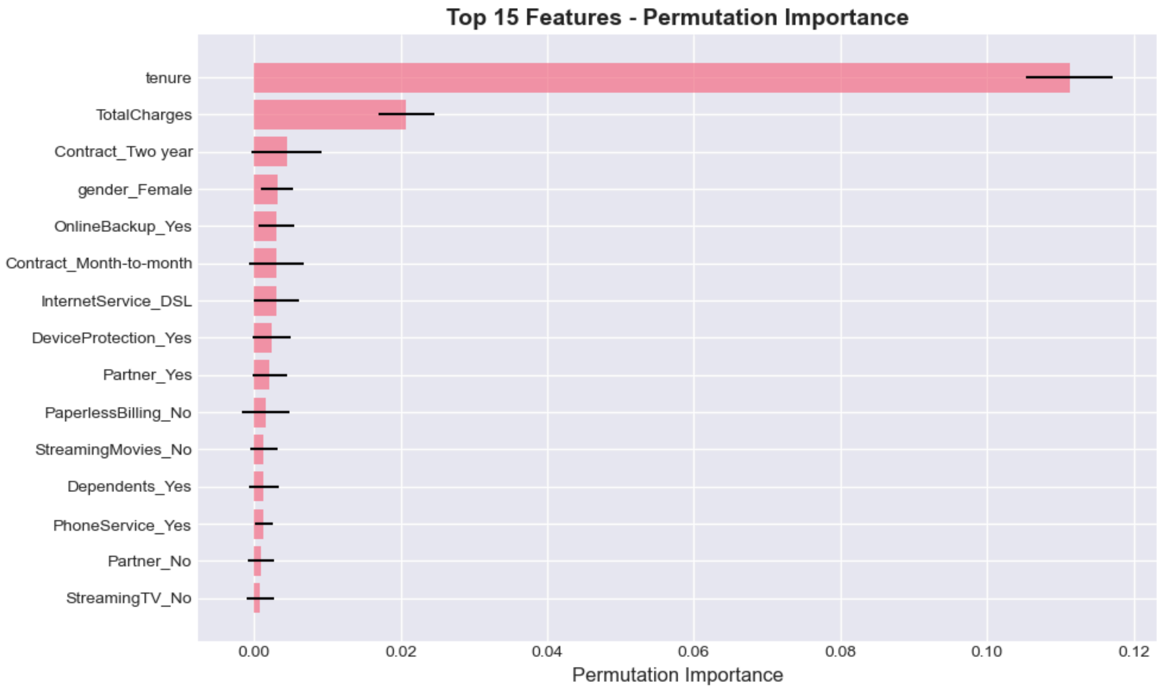
```python
# Coefficients for Logistic Regression or alternative method
if "Logistic" in best_model_name:
    coef_importance = np.abs(best_models["Logistic Regression"].coef_[0])
    coef_imp_df = pd.DataFrame({
        'Feature': feature_names,
        'Importance': coef_importance
    }).sort_values('Importance', ascending=False)

    print("\nTop 10 Features (Coefficient Magnitude - Logistic Regression):")
    print(coef_imp_df.head(10).to_string(index=False))

    plt.figure(figsize=(10, 6))
    top_n = 15
    top_features_coef = coef_imp_df.head(top_n)
    plt.barh(range(top_n), top_features_coef['Importance'].values, color='coral'
    plt.yticks(range(top_n), top_features_coef['Feature'].values)
    plt.xlabel('Absolute Coefficient Value', fontsize=12)
    plt.title(f'Top {top_n} Features - Coefficient Magnitude',
              fontsize=14, fontweight='bold')
    plt.gca().invert_yaxis()
    plt.tight_layout()
    plt.show()

# SHAP Values for Local Interpretability

print("SHAP ANALYSIS")

if best_model_name in ["Random Forest", "Gradient Boosting", "Decision Tree"]:
    X_shap = X_test_p
    explainer = shap.TreeExplainer(best_model)
    shap_values = explainer.shap_values(X_shap)
else:
    X_shap = X_test_p[:100]
    background = shap.sample(X_train_p, 100)
    explainer = shap.KernelExplainer(best_model.predict_proba, background)
    shap_values = explainer.shap_values(X_shap)

shap_values_arr = np.array(shap_values)

if isinstance(shap_values, list):
    shap_values_plot = shap_values[1]
    base_val = explainer.expected_value[1]
else:
    if shap_values_arr.ndim == 3:
        shap_values_plot = shap_values_arr[:, :, 1]
        if hasattr(explainer.expected_value, "__len__"):
            base_val = explainer.expected_value[1]
        else:
            base_val = explainer.expected_value
    else:
        shap_values_plot = shap_values_arr
        if hasattr(explainer.expected_value, "__len__"):
            base_val = explainer.expected_value[1]
        else:
            base_val = explainer.expected_value

if hasattr(X_shap, "toarray"):
    X_shap_plot = X_shap.toarray()
else:
```

```
    X_shap_plot = X_shap

plt.figure(figsize=(10, 8))
shap.summary_plot(
    shap_values_plot,
    X_shap_plot,
    feature_names=feature_names,
    show=False
)
plt.title(
    'SHAP Summary Plot - Feature Impact on Predictions',
    fontsize=14,
    fontweight='bold',
    pad=20
)
plt.tight_layout()
plt.show()

# SHAP Bar Plot
plt.figure(figsize=(10, 6))
shap.summary_plot(
    shap_values_plot,
    X_shap_plot,
    feature_names=feature_names,
    plot_type="bar",
    show=False
)
plt.title(
    'SHAP Feature Importance - Mean Absolute Impact',
    fontsize=14,
    fontweight='bold'
)
plt.tight_layout()
plt.show()

# waterfall plot for a single instance

sample_idx = 0

sample_data = X_shap[sample_idx]
if hasattr(sample_data, "toarray"):
    sample_data = sample_data.toarray().ravel()

values_1d = shap_values_plot[sample_idx]

shap_expl = shap.Explanation(
    values=values_1d,
    base_values=base_val,
    data=sample_data,
    feature_names=feature_names
)

shap.plots.waterfall(shap_expl, max_display=15)

print("\nKey Findings:")
print(f"1. Best Model: {best_model_name}")
print(f"2. Test AUC: {results_df['Test AUC'].max():.4f}")
print(f"3. Performance is {std_above_baseline:.2f} std above baseline")
print(f"4. Most important features identified through multiple methods")
print(f"5. SHAP analysis provides local explanations for individual predictions"
```

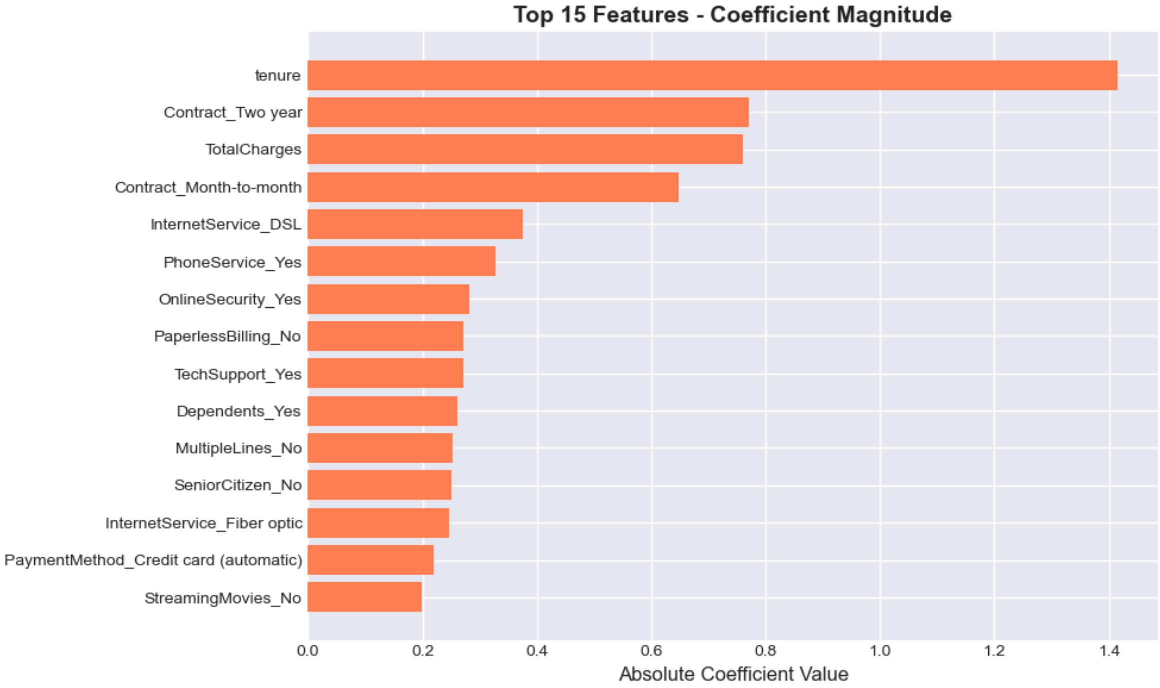
```
BASELINE ACCURACY (predict majority class): 0.7347

Training Logistic Regression...
  Best params: {'C': 10.0, 'solver': 'lbfgs'}
  CV AUC: 0.8406 ± 0.0134
  Test AUC: 0.8437 ± 0.0000

Training Decision Tree...
  Best params: {'max_depth': 5, 'min_samples_split': 20}
  CV AUC: 0.8214 ± 0.0097
  Test AUC: 0.8183 ± 0.0000

Training Random Forest...
  Best params: {'n_estimators': 50, 'max_depth': 10, 'min_samples_split': 20}
  CV AUC: 0.8415 ± 0.0157
  Test AUC: 0.8390 ± 0.0011

Training Gradient Boosting...
  Best params: {'n_estimators': 50, 'learning_rate': 0.1, 'max_depth': 3}
  CV AUC: 0.8433 ± 0.0142
  Test AUC: 0.8428 ± 0.0000
MODEL PERFORMANCE SUMMARY
              Model                                                      Best Param
s         CV AUC  Test Accuracy  Test Precision  Test Recall  Test F1  Test AUC Te
st AUC(mean,std)
Logistic Regression                                 {'C': 10.0, 'solver': 'lbfg
s'} 0.8406±0.0134       0.798439        0.650000     0.521390 0.578635   0.843724
0.8437±0.0000
      Decision Tree                     {'max_depth': 5, 'min_samples_split': 2
0} 0.8214±0.0097       0.791341        0.613636     0.577540 0.595041   0.818321
0.8183±0.0000
      Random Forest {'n_estimators': 50, 'max_depth': 10, 'min_samples_split': 2
0} 0.8415±0.0157       0.798439        0.659574     0.497326 0.567073   0.839583
0.8390±0.0011
  Gradient Boosting     {'n_estimators': 50, 'learning_rate': 0.1, 'max_depth':
3} 0.8433±0.0142       0.801987        0.664360     0.513369 0.579186   0.842808
0.8428±0.0000
Best Model: Logistic Regression (Test AUC: 0.8437)
Best model is 0.14 standard deviations above baseline
```



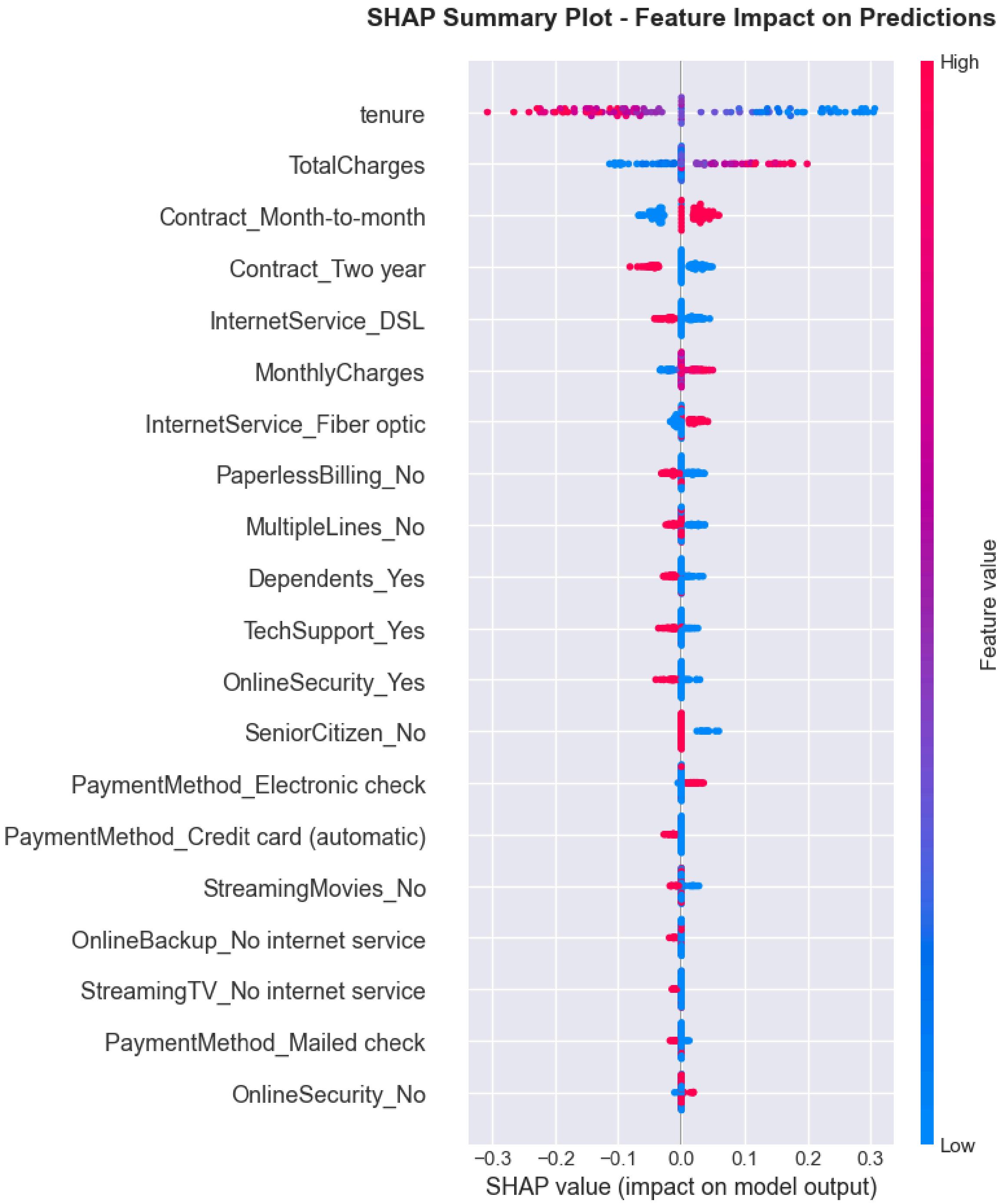
```
FEATURE IMPORTANCE ANALYSIS

 Permutation Importance

Top 10 Features (Permutation Importance):
                Feature  Importance       Std
                 tenure    0.111285 0.005902
           TotalCharges    0.020795 0.003743
      Contract_Two year    0.004471 0.004761
          gender_Female    0.003194 0.002205
       OnlineBackup_Yes    0.003052 0.002418
Contract_Month-to-month    0.003052 0.003675
    InternetService_DSL    0.002981 0.003074
   DeviceProtection_Yes    0.002342 0.002580
            Partner_Yes    0.002129 0.002311
    PaperlessBilling_No    0.001561 0.003202
```

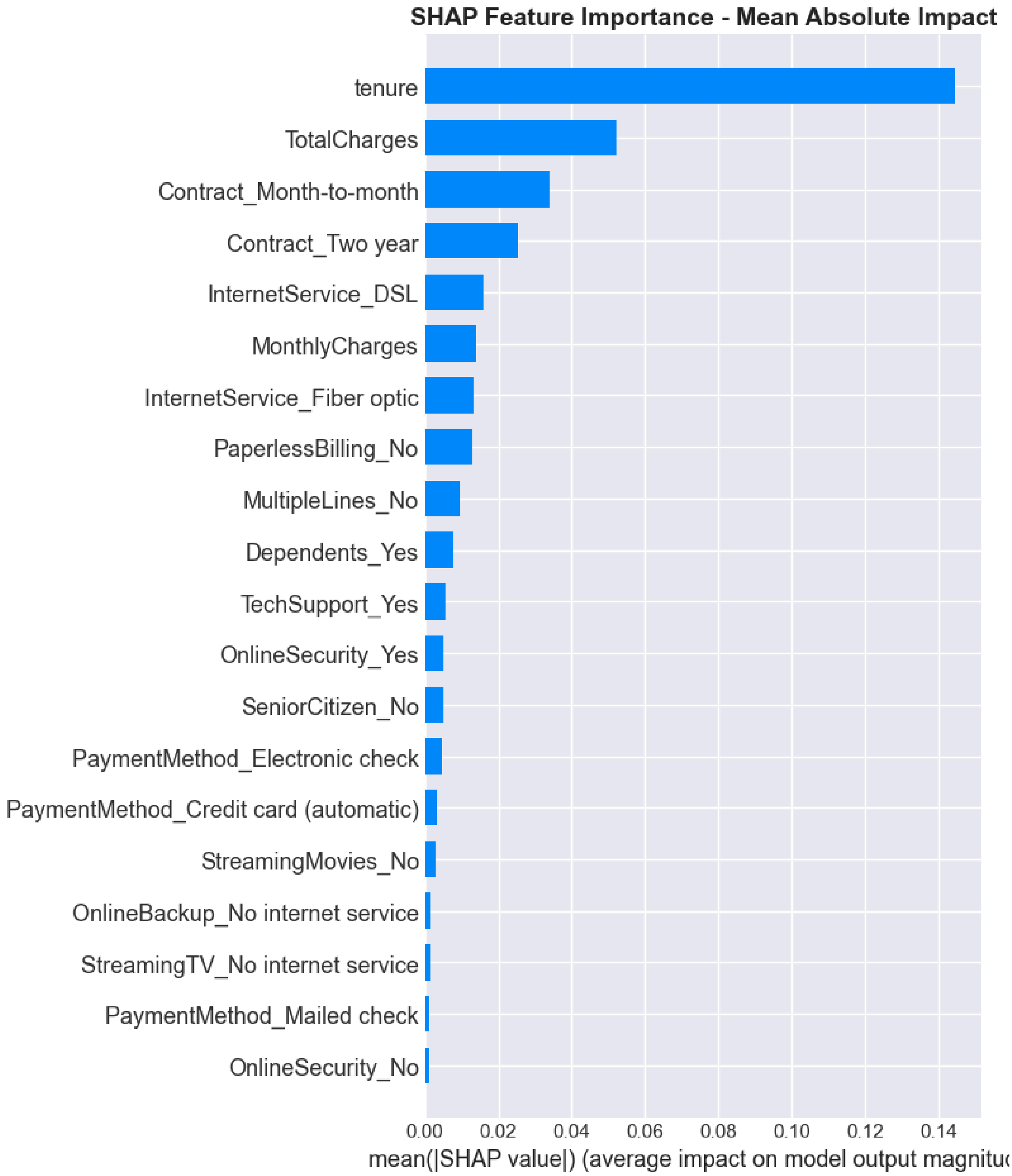


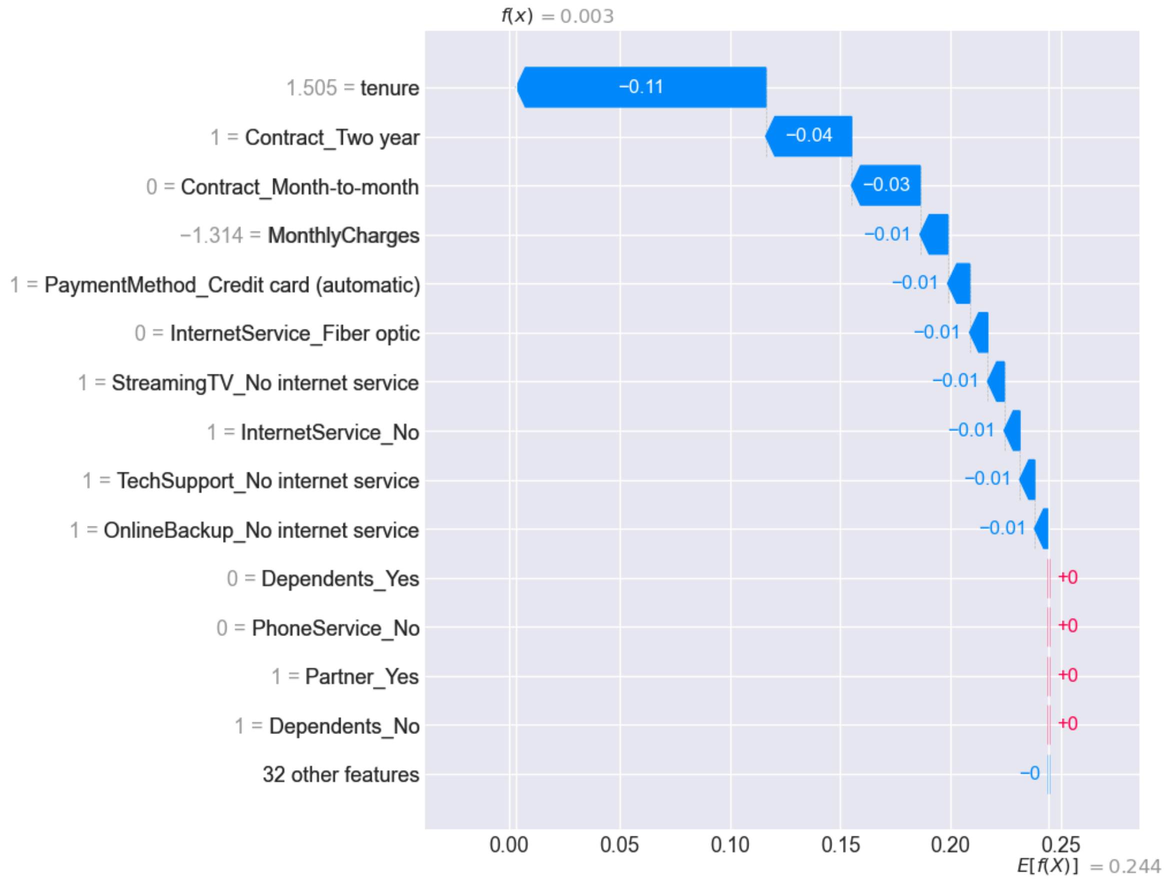

```
Top 10 Features (Coefficient Magnitude - Logistic Regression):
                Feature  Importance
                 tenure    1.415206
      Contract_Two year    0.771120
           TotalCharges    0.761122
Contract_Month-to-month    0.647923
    InternetService_DSL    0.374971
       PhoneService_Yes    0.327445
     OnlineSecurity_Yes    0.281240
    PaperlessBilling_No    0.272287
        TechSupport_Yes    0.270703
         Dependents_Yes    0.261183
```




```
SHAP ANALYSIS
  0%|          | 0/100 [00:00<?, ?it/s]
```


SHAP Summary Plot - Feature Impact on Predictions
tenure
TotalCharges
Contract_Month-to-month
Contract_Two year
InternetService_DSL
MonthlyCharges
InternetService_Fiber optic
PaperlessBilling_No
MultipleLines_No
Dependents_Yes
TechSupport_Yes
OnlineSecurity_Yes
SeniorCitizen_No
PaymentMethod_Electronic check
PaymentMethod_Credit card (automatic)
StreamingMovies_No
OnlineBackup_No internet service
StreamingTV_No internet service
PaymentMethod_Mailed check
OnlineSecurity_No
−0.3 −0.2 −0.1 0.0 0.1 0.2 0.3
SHAP value (impact on model output)
High
Low
Feature value


SHAP Feature Importance - Mean Absolute Impact
tenure
TotalCharges
Contract_Month-to-month
Contract_Two year
InternetService_DSL
MonthlyCharges
InternetService_Fiber optic
PaperlessBilling_No
MultipleLines_No
Dependents_Yes
TechSupport_Yes
OnlineSecurity_Yes
SeniorCitizen_No
PaymentMethod_Electronic check
PaymentMethod_Credit card (automatic)
StreamingMovies_No
OnlineBackup_No internet service
StreamingTV_No internet service
PaymentMethod_Mailed check
OnlineSecurity_No
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
mean(|SHAP value|) (average impact on model output magnitu




```
Key Findings:
1. Best Model: Logistic Regression
2. Test AUC: 0.8437
3. Performance is 0.14 std above baseline
4. Most important features identified through multiple methods
5. SHAP analysis provides local explanations for individual predictions
```

In [ ]: