paez_ramirez_jean_carlos_KNN

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[1]:
```python
# Librerías básicas
import pandas as pd
import numpy as np

# Librerías de visualización
import matplotlib.pyplot as plt
import seaborn as sns

# Librerías de scikit-learn
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.model_selection import (
    train_test_split,
    GridSearchCV,
    cross_val_score,
    StratifiedKFold
)
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import (
    accuracy_score,
    classification_report,
    confusion_matrix,
    roc_curve,
    auc,
    precision_recall_curve,
    f1_score
)
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectFromModel

# Librería para manejo de desbalance de clases
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline
from imblearn.metrics import classification_report_imbalanced

# Configuración de warnings
import warnings
warnings.filterwarnings('ignore')
```

```python
# Configuración de visualización
plt.style.use('default')
sns.set_theme()

# Configuración adicional de matplotlib
plt.rcParams.update({
    'figure.figsize': (12, 8),
    'axes.grid': True,
    'figure.autolayout': True,
    'font.size': 10,
    'axes.labelsize': 12,
    'axes.titlesize': 14
})

# Configuración para reproducibilidad
RANDOM_STATE = 42
np.random.seed(RANDOM_STATE)
```

0.1 Cargar los Datos

[2]:
```python
def load_and_check_data(file_paths):
    """
    Carga y realiza verificaciones iniciales de los datos
    """
    for path in file_paths:
        try:
            df = pd.read_csv(path)
            print(f"Dataset cargado exitosamente desde: {path}")

            # Verificación inicial de datos
            print("\nInformación básica del dataset:")
            print(df.info())

            # Verificar valores faltantes
            missing_values = df.isnull().sum()
            print("\nValores faltantes por columna:")
            print(missing_values[missing_values > 0])

            # Verificar tipos de datos
            print("\nTipos de datos:")
            print(df.dtypes)

            return df
        except FileNotFoundError:
            continue
```

```
    raise FileNotFoundError("No se pudo encontrar el archivo en ninguna de las␣
↪rutas especificadas")

# Uso de la función
file_paths = [
    "../data/WA_Fn-UseC_-Telco-Customer-Churn.csv",
    "data/WA_Fn-UseC_-Telco-Customer-Churn.csv"
]
df = load_and_check_data(file_paths)
```

```
Dataset cargado exitosamente desde: ../data/WA_Fn-UseC_-Telco-Customer-Churn.csv

Información básica del dataset:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
None

Valores faltantes por columna:
Series([], dtype: int64)

Tipos de datos:
```

```
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
```

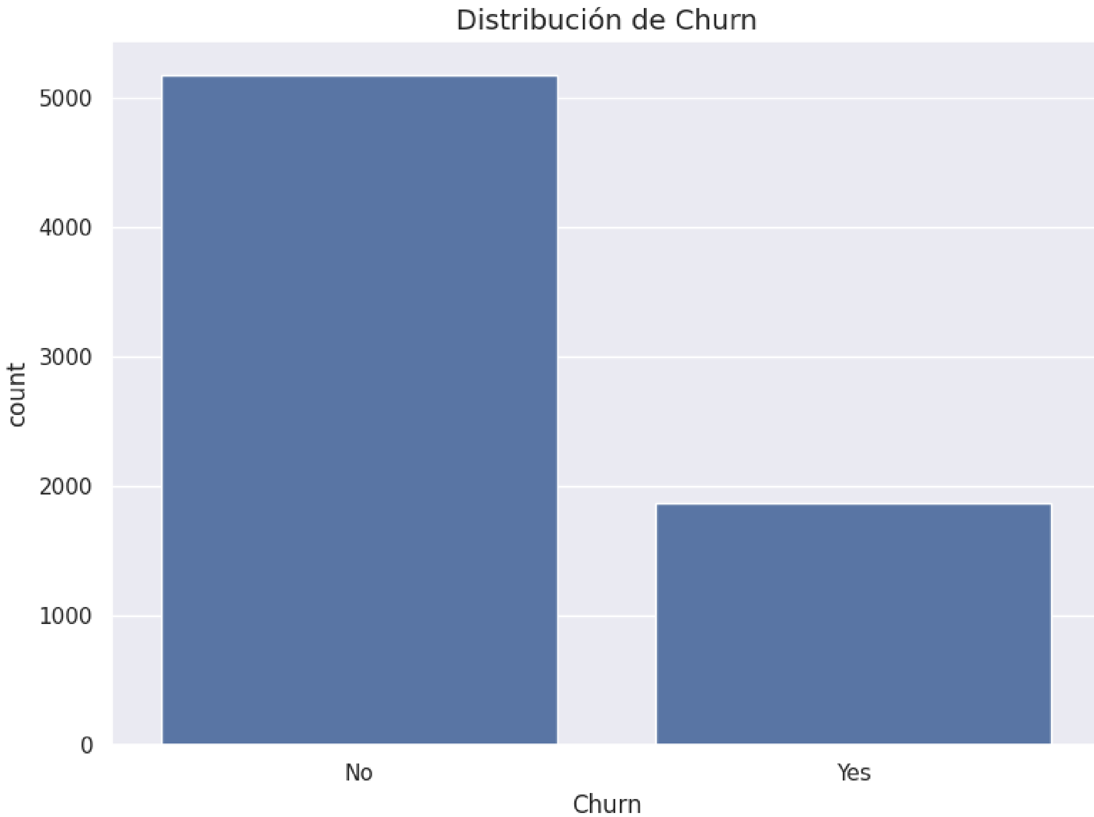
0.2 Análisis Exploratorio de Dato

[3]:
```python
# Resumen Estadístico:
print("Resumen Estadístico:")
print(df.describe())
print("\n")
```

```
Resumen Estadístico:
       SeniorCitizen       tenure  MonthlyCharges
count    7043.000000  7043.000000     7043.000000
mean        0.162147    32.371149       64.761692
std         0.368612    24.559481       30.090047
min         0.000000     0.000000       18.250000
25%         0.000000     9.000000       35.500000
50%         0.000000    29.000000       70.350000
75%         0.000000    55.000000       89.850000
max         1.000000    72.000000      118.750000
```

[4]:
```python
# Distribución de Clases:
plt.figure(figsize=(8, 6))
sns.countplot(data=df, x='Churn')
plt.title('Distribución de Churn')
```

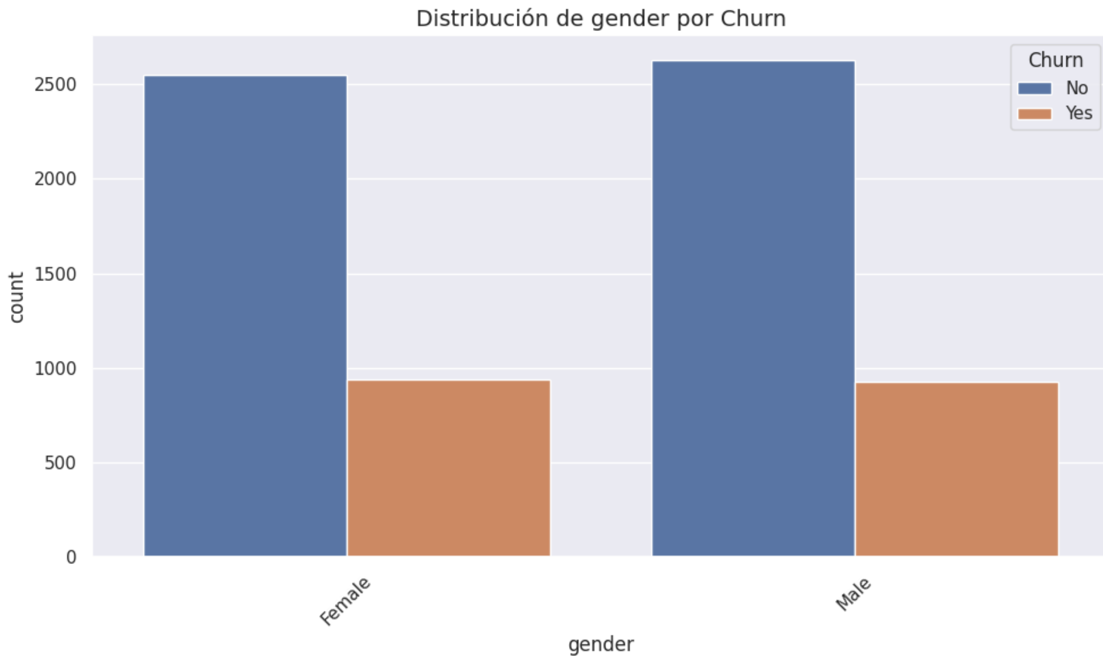
```
plt.show()
```



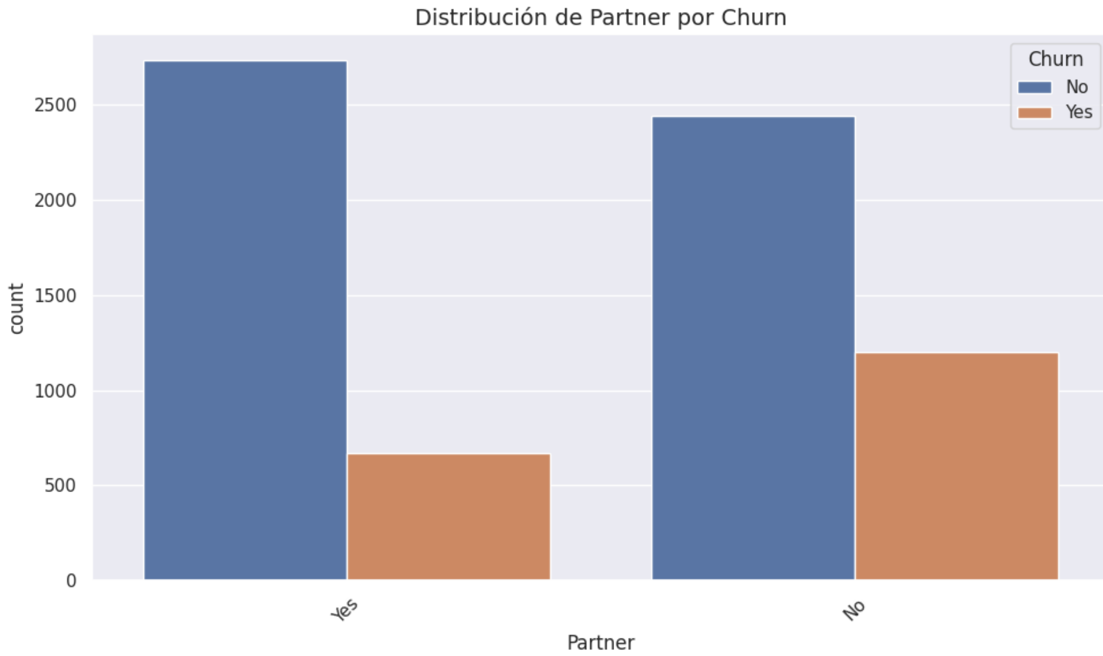

```
[5]: # Análisis de Variables Categóricas:
categorical_columns = df.select_dtypes(include=['object']).columns
print("\nVariables Categóricas:")
for col in categorical_columns:
    if col != 'customerID':  # Excluimos el ID del cliente
        print(f"\nDistribución de {col}:")
        print(df[col].value_counts())

        # Visualización
        plt.figure(figsize=(10, 6))
        sns.countplot(data=df, x=col, hue='Churn')
        plt.title(f'Distribución de {col} por Churn')
        plt.xticks(rotation=45)
        plt.tight_layout()
        plt.show()
```

```
Variables Categóricas:
```

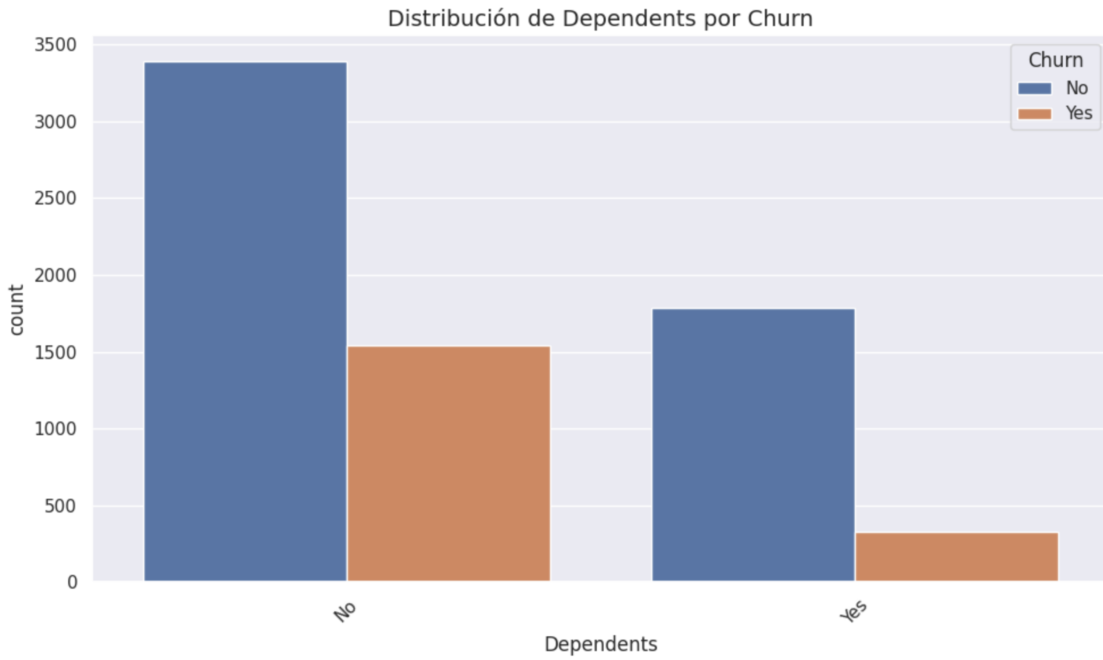
```
Distribución de gender:
gender
Male      3555
Female    3488
Name: count, dtype: int64
```



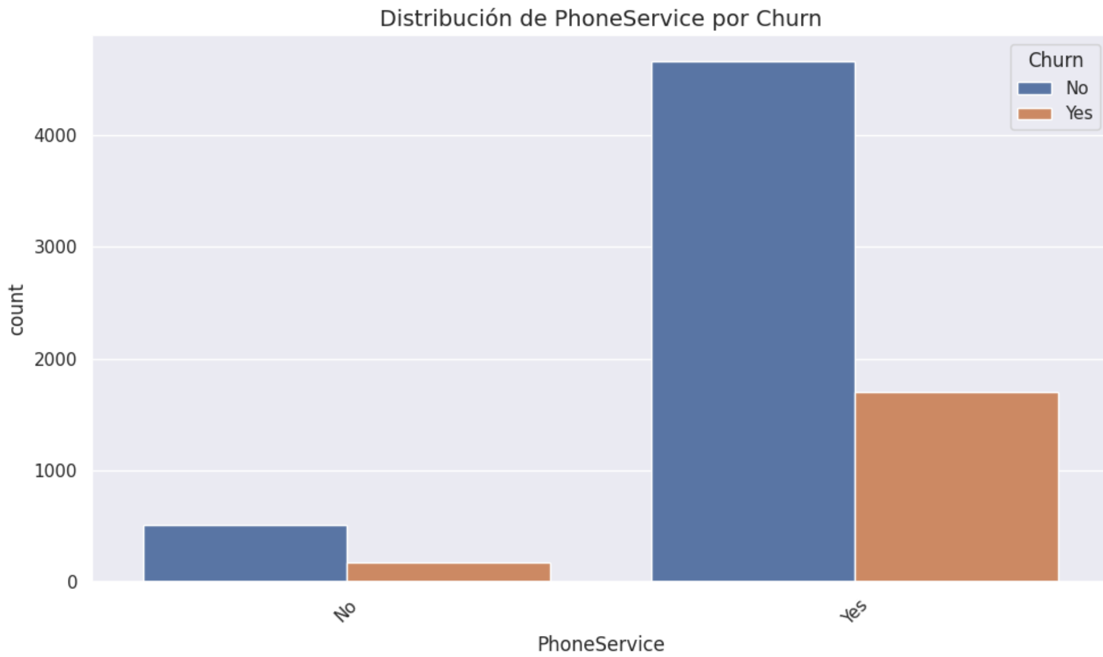

```
Distribución de Partner:
Partner
No     3641
Yes    3402
Name: count, dtype: int64
```



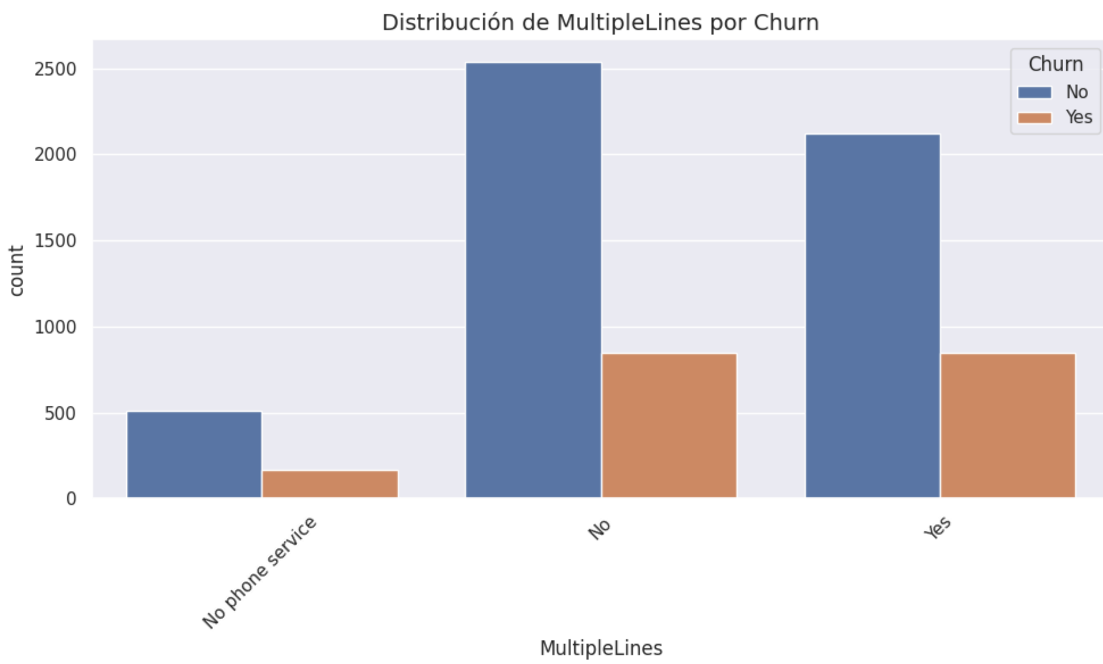

```
Distribución de Dependents:
Dependents
No     4933
Yes    2110
Name: count, dtype: int64
```



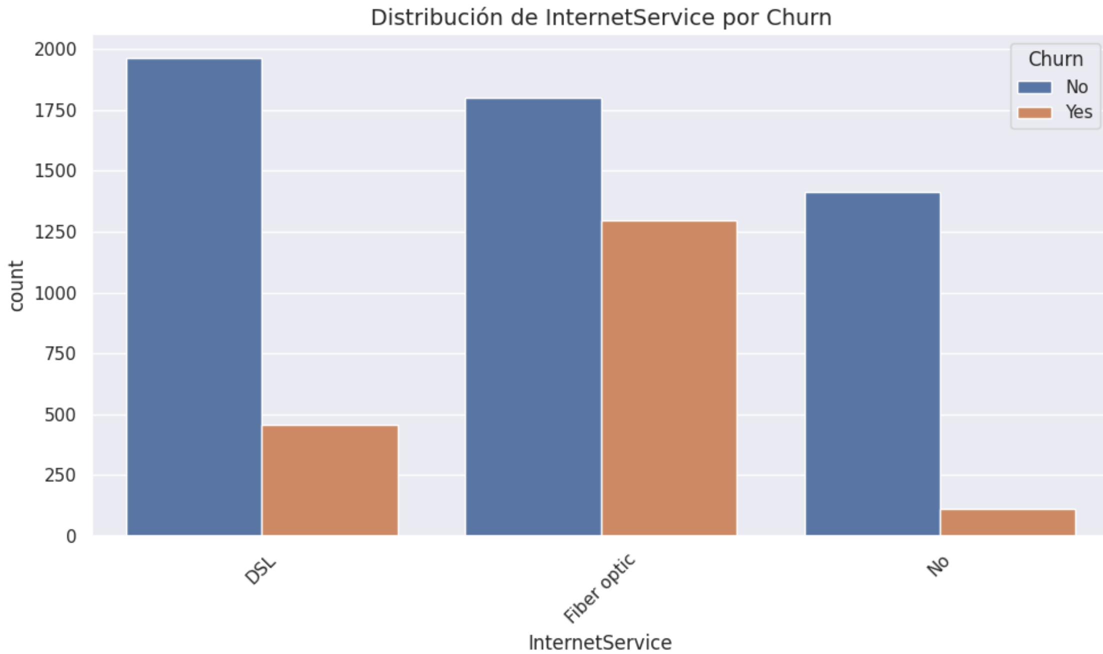
```
Distribución de PhoneService:
PhoneService
Yes    6361
No      682
Name: count, dtype: int64
```



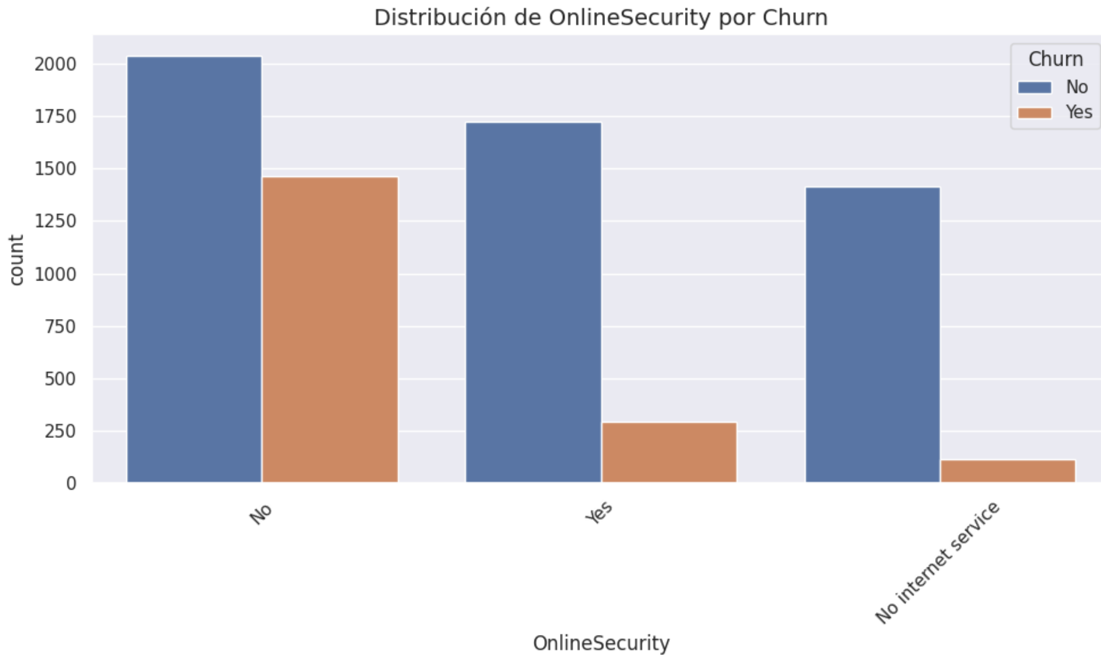

```
Distribución de MultipleLines:
MultipleLines
No                  3390
Yes                 2971
No phone service     682
Name: count, dtype: int64
```



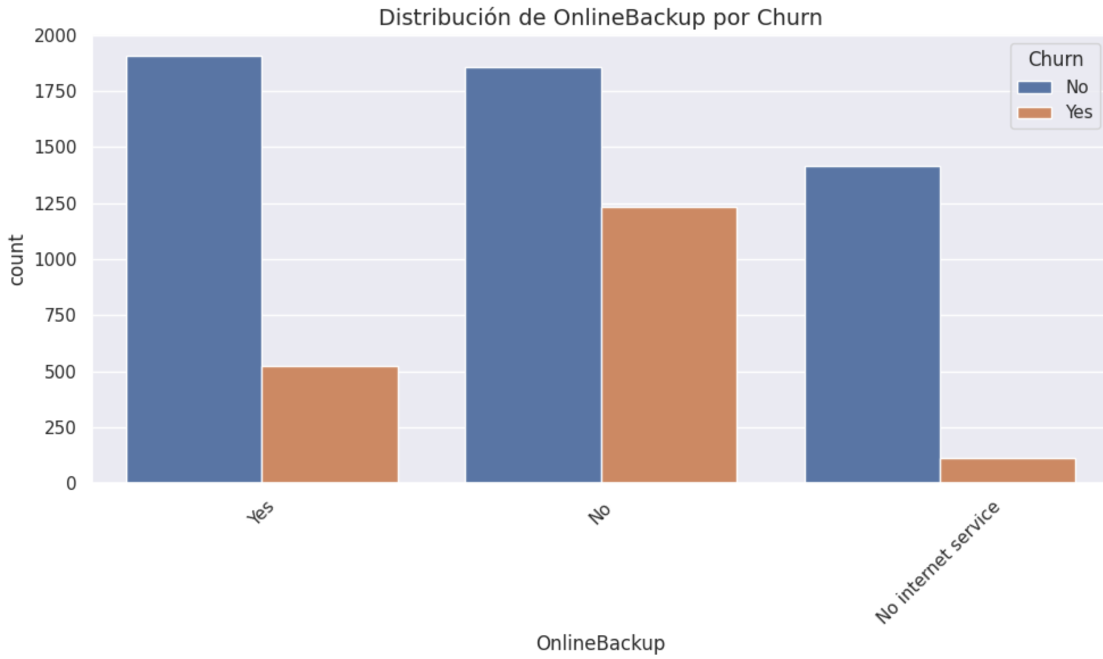

```
Distribución de InternetService:
InternetService
Fiber optic    3096
DSL            2421
No             1526
Name: count, dtype: int64
```



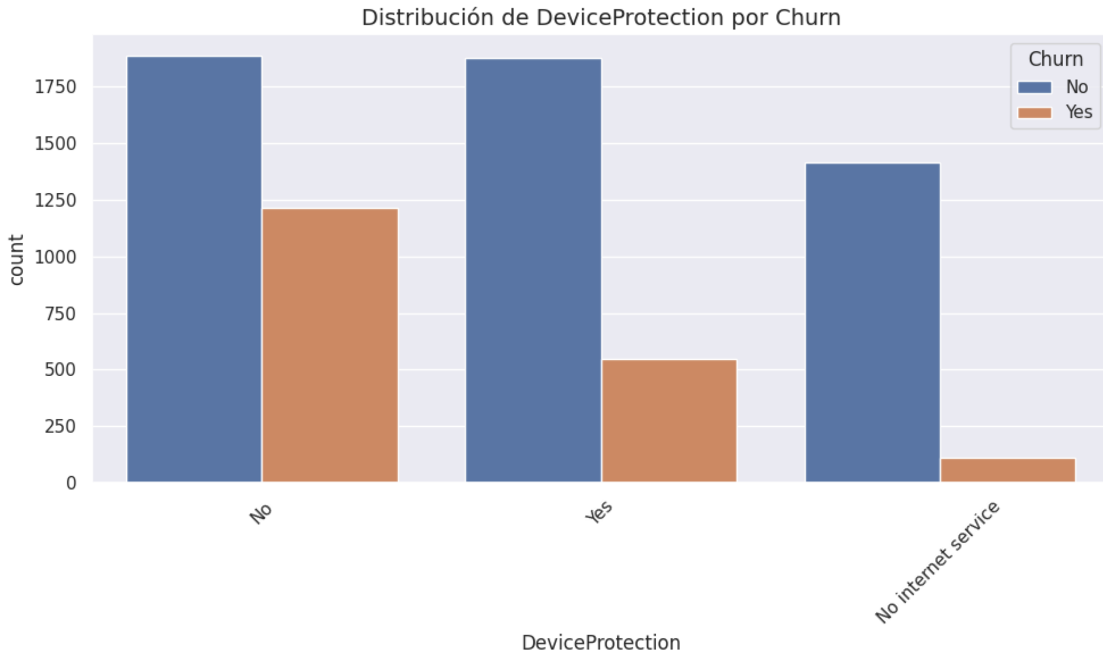

```
Distribución de OnlineSecurity:
OnlineSecurity
No                      3498
Yes                     2019
No internet service     1526
Name: count, dtype: int64
```



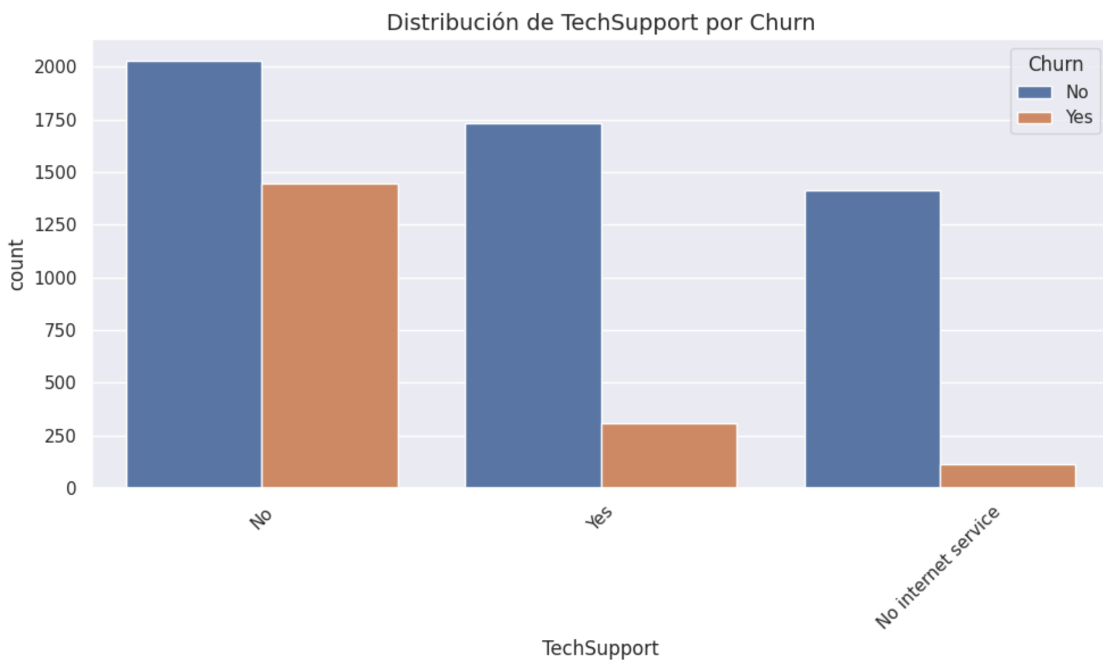

```
Distribución de OnlineBackup:
OnlineBackup
No                     3088
Yes                    2429
No internet service    1526
Name: count, dtype: int64
```



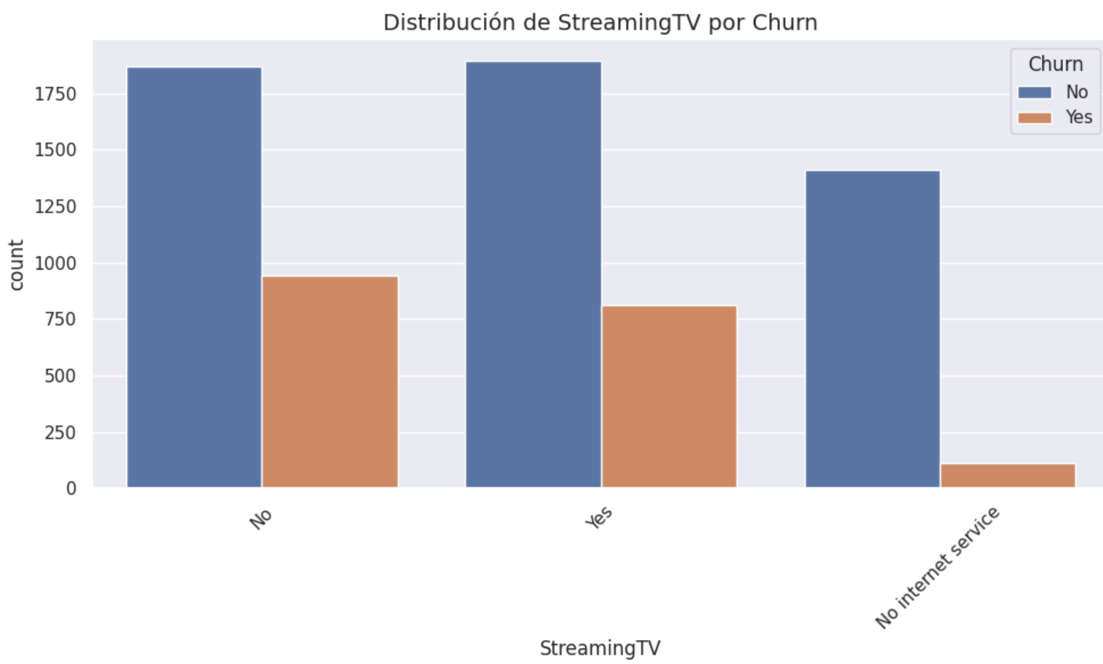

```
Distribución de DeviceProtection:
DeviceProtection
No                     3095
Yes                    2422
No internet service    1526
Name: count, dtype: int64
```



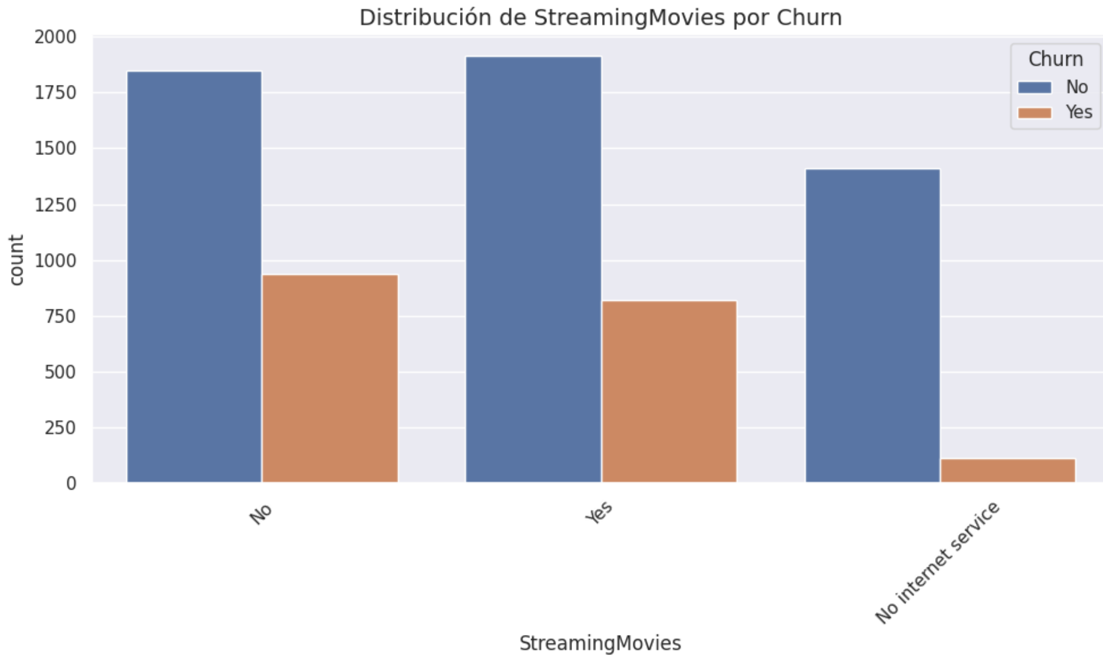

```
Distribución de TechSupport:
TechSupport
No                     3473
Yes                    2044
No internet service    1526
Name: count, dtype: int64
```



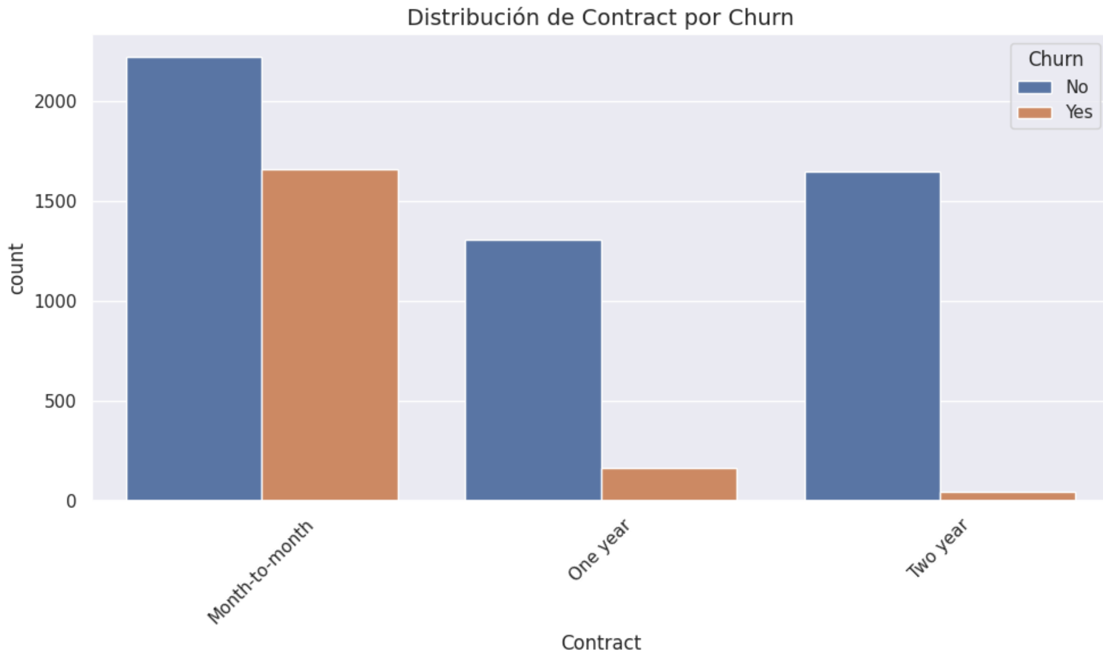

```
Distribución de StreamingTV:
StreamingTV
No                     2810
Yes                    2707
No internet service    1526
Name: count, dtype: int64
```




```
Distribución de StreamingMovies:
StreamingMovies
No                     2785
Yes                    2732
No internet service    1526
Name: count, dtype: int64
```

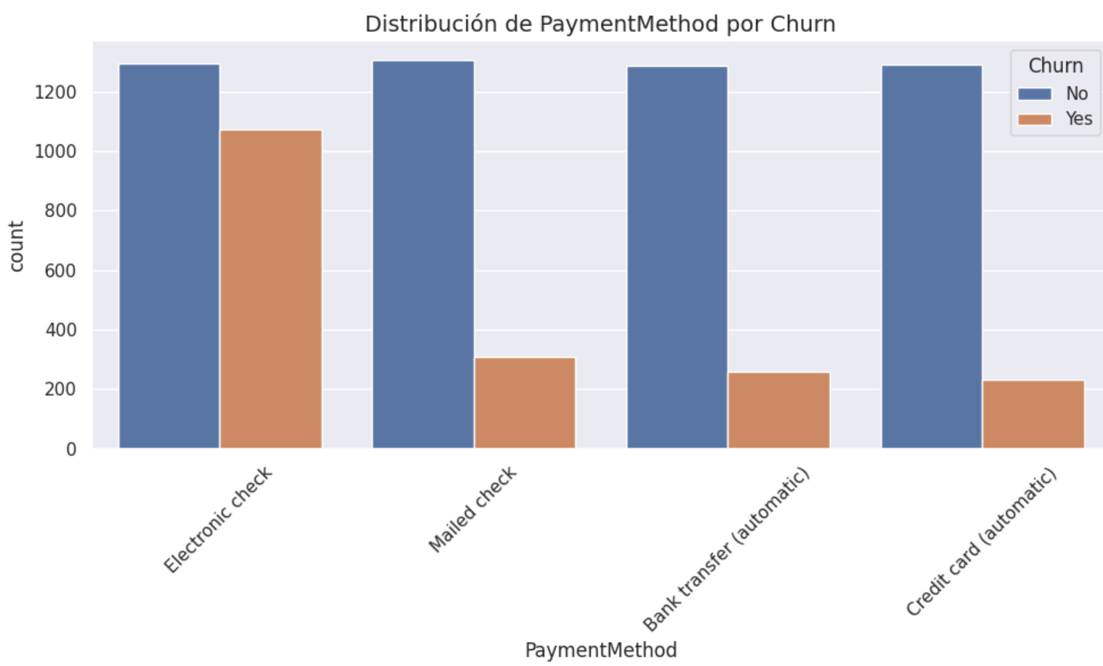



```
Distribución de Contract:
Contract
Month-to-month    3875
Two year          1695
One year          1473
Name: count, dtype: int64
```

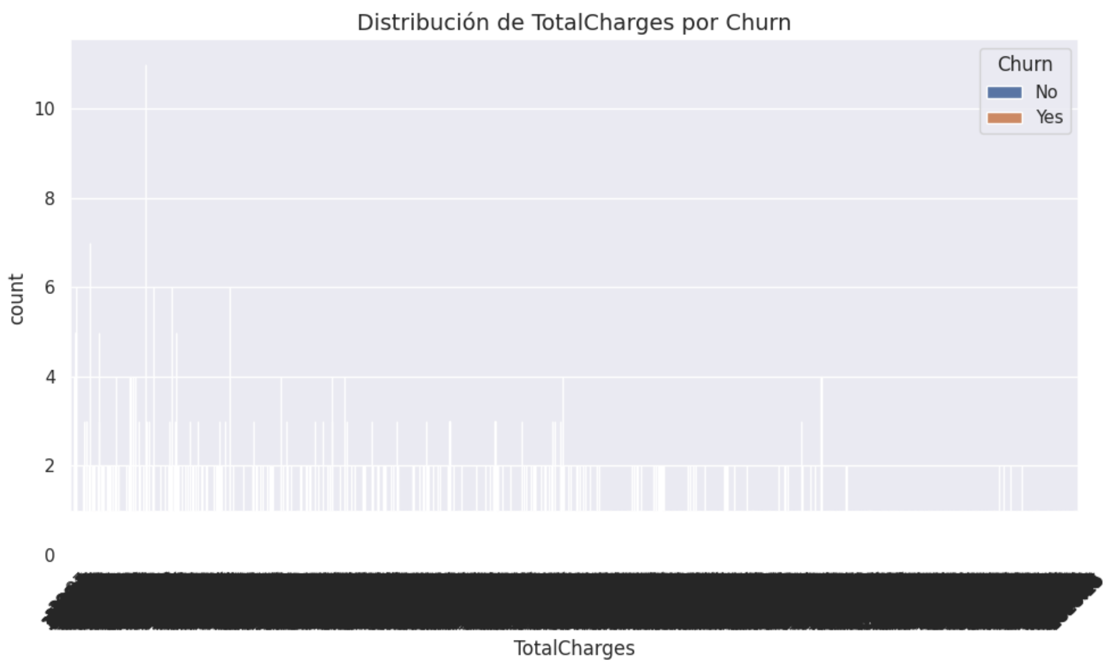



```
Distribución de PaperlessBilling:
PaperlessBilling
Yes    4171
No     2872
Name: count, dtype: int64
```

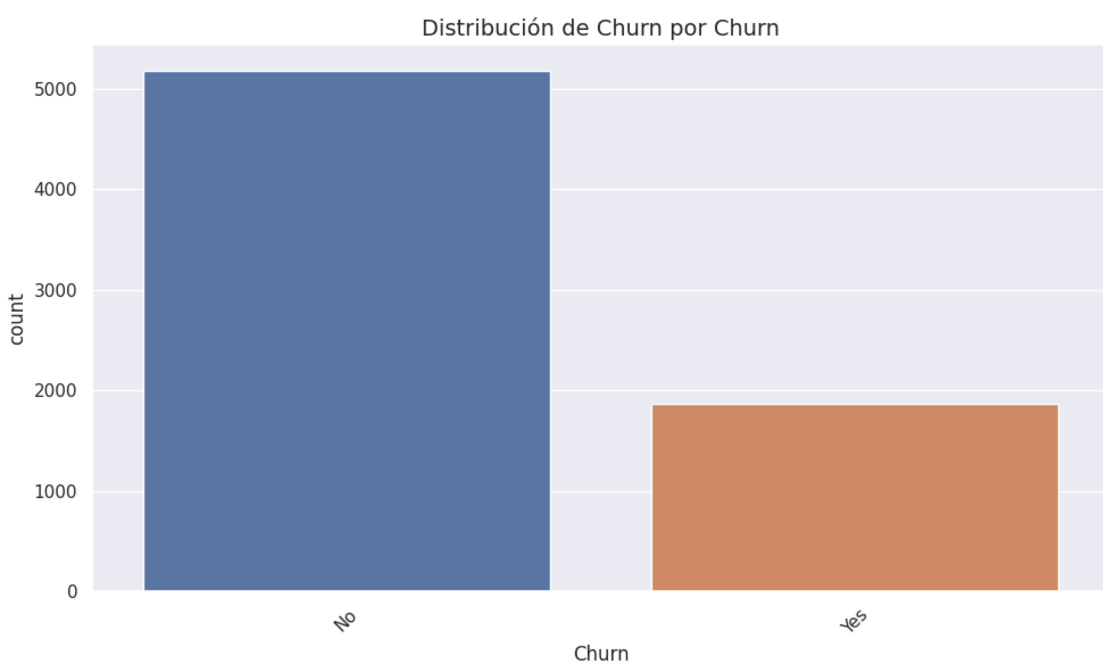
```
Distribución de PaymentMethod:
PaymentMethod
Electronic check             2365
Mailed check                 1612
Bank transfer (automatic)    1544
Credit card (automatic)      1522
Name: count, dtype: int64
```



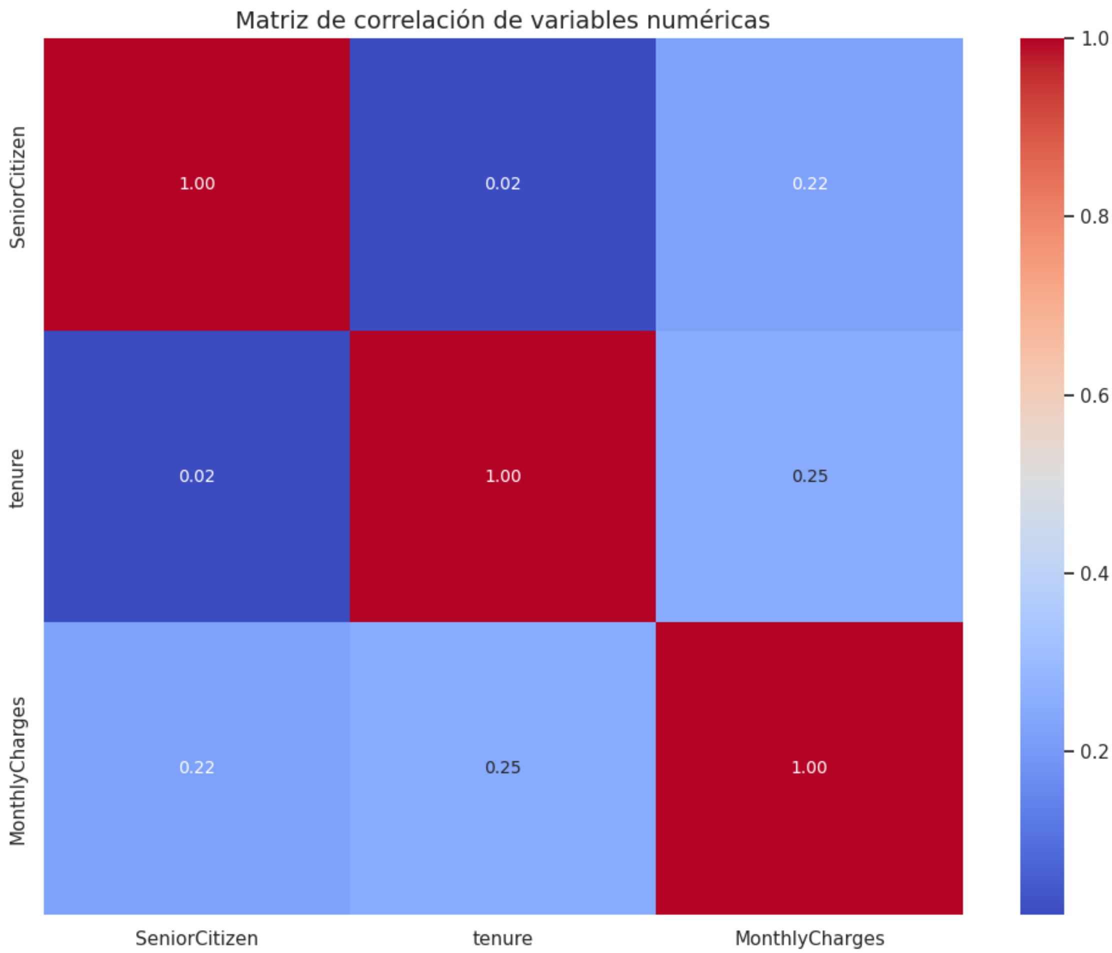

```
Distribución de TotalCharges:
TotalCharges
           11
20.2       11
19.75       9
20.05       8
19.9        8
           ..
130.15      1
3211.9      1
7843.55     1
2196.3      1
197.4       1
Name: count, Length: 6531, dtype: int64
```




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

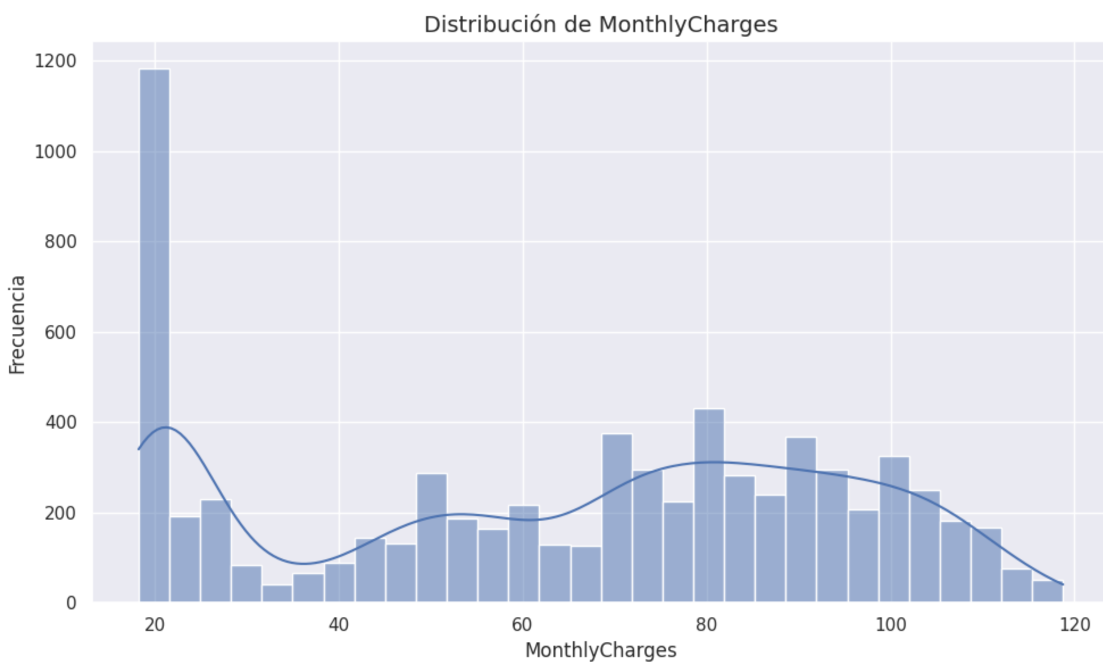


[6]:
```
# Correlación entre Variables Numéricas:
numeric_columns = df.select_dtypes(include=['float64', 'int64']).columns
corr_matrix = df[numeric_columns].corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", fmt='.2f')
plt.title("Matriz de correlación de variables numéricas")
plt.tight_layout()
plt.show()
```



[7]:
```
# Histograma de Ingresos:
plt.figure(figsize=(10, 6))
sns.histplot(data=df, x='MonthlyCharges', bins=30, kde=True)
plt.title('Distribución de MonthlyCharges')
plt.xlabel('MonthlyCharges')
```

```python
plt.ylabel('Frecuencia')
plt.show()

# Información adicional sobre el dataset
print("\nInformación del Dataset:")
print(df.info())

# Valores faltantes
print("\nValores faltantes por columna:")
print(df.isnull().sum())
```




```
Información del Dataset:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   customerID        7043 non-null   object
 1   gender            7043 non-null   object
 2   SeniorCitizen     7043 non-null   int64
 3   Partner           7043 non-null   object
 4   Dependents        7043 non-null   object
 5   tenure            7043 non-null   int64
 6   PhoneService      7043 non-null   object
 7   MultipleLines     7043 non-null   object
```

```
 8   InternetService   7043 non-null   object
 9   OnlineSecurity    7043 non-null   object
 10  OnlineBackup      7043 non-null   object
 11  DeviceProtection  7043 non-null   object
 12  TechSupport       7043 non-null   object
 13  StreamingTV       7043 non-null   object
 14  StreamingMovies   7043 non-null   object
 15  Contract          7043 non-null   object
 16  PaperlessBilling  7043 non-null   object
 17  PaymentMethod     7043 non-null   object
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object
 20  Churn             7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB
None

Valores faltantes por columna:
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
```

0.2.1 Función de evaluación del modelo

[8]:
```python
def evaluate_model(y_true, y_pred, y_prob=None):
    """
    Función para evaluar el modelo con múltiples métricas
    """
```

```python
    print("\n=== Métricas de Evaluación ===")

    # Métricas básicas
    print("\nInforme de clasificación detallado:")
    print(classification_report(y_true, y_pred))

    # Matriz de confusión
    plt.figure(figsize=(10, 8))
    cm = confusion_matrix(y_true, y_pred)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                xticklabels=['No Churn', 'Churn'],
                yticklabels=['No Churn', 'Churn'])
    plt.title("Matriz de Confusión")
    plt.xlabel("Predicción")
    plt.ylabel("Real")
    plt.show()

    if y_prob is not None:
        # Curva ROC
        fpr, tpr, _ = roc_curve(y_true, y_prob[:, 1])
        roc_auc = auc(fpr, tpr)

        plt.figure(figsize=(10, 8))
        plt.plot(fpr, tpr, color='darkorange', lw=2,
                 label=f'ROC curve (AUC = {roc_auc:.2f})')
        plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
        plt.xlim([0.0, 1.0])
        plt.ylim([0.0, 1.05])
        plt.xlabel('Tasa de Falsos Positivos')
        plt.ylabel('Tasa de Verdaderos Positivos')
        plt.title('Curva ROC')
        plt.legend(loc="lower right")
        plt.show()

        # Curva Precisión-Recall
        precision, recall, _ = precision_recall_curve(y_true, y_prob[:, 1])

        plt.figure(figsize=(10, 8))
        plt.plot(recall, precision, color='blue', lw=2)
        plt.xlabel('Recall')
        plt.ylabel('Precision')
        plt.title('Curva Precisión-Recall')
        plt.show()
```

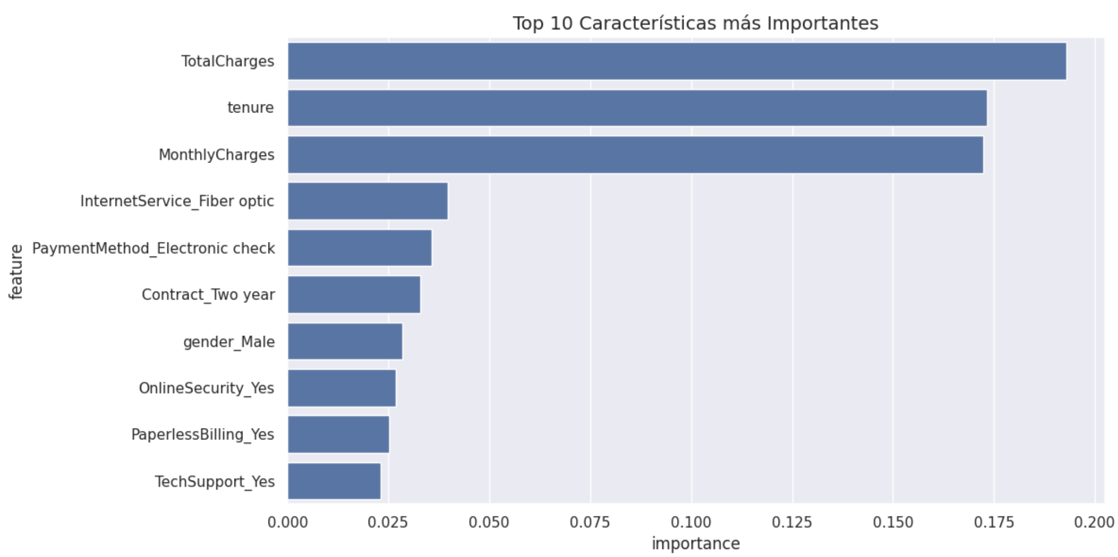
0.2.2 Selección de Características

[9]:
```python
def select_features(X, y):
    """
    Selección de características usando Random Forest
    """
    rf = RandomForestClassifier(n_estimators=100, random_state=RANDOM_STATE)
    selector = SelectFromModel(rf, prefit=False)
    selector.fit(X, y)

    # Obtener características importantes
    feature_importance = pd.DataFrame({
        'feature': X.columns,
        'importance': selector.estimator_.feature_importances_
    })
    feature_importance = feature_importance.sort_values('importance',␣
 ↪ascending=False)

    # Visualizar importancia de características
    plt.figure(figsize=(12, 6))
    sns.barplot(data=feature_importance.head(10), x='importance', y='feature')
    plt.title('Top 10 Características más Importantes')
    plt.show()

    return selector.get_support(), feature_importance
```

0.3 Preparación de Datos

[10]:
```python
# Convertir 'TotalCharges' a numérico
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')

# Rellenar valores faltantes en 'TotalCharges' con la mediana
df['TotalCharges'] = df['TotalCharges'].fillna(df['TotalCharges'].median())

# Codificar la columna objetivo 'Churn' como binaria
df['Churn'] = df['Churn'].map({'Yes': 1, 'No': 0})

# Eliminar columnas irrelevantes
df = df.drop(['customerID'], axis=1)

# Codificar variables categóricas
df_encoded = pd.get_dummies(df, drop_first=True)

# Separar características y variable objetivo
X = df_encoded.drop('Churn', axis=1)
y = df_encoded['Churn']
```

```python
# Selección de características
support_mask, feature_importance = select_features(X, y)
X_selected = X.loc[:, support_mask]

# División estratificada de datos
X_train, X_test, y_train, y_test = train_test_split(
    X_selected, y,
    test_size=0.2,
    random_state=RANDOM_STATE,
    stratify=y
)

# Normalización
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Aplicar SMOTE para balance de clases
smote = SMOTE(random_state=RANDOM_STATE)
X_train_balanced, y_train_balanced = smote.fit_resample(X_train_scaled, y_train)

print("Distribución original de clases en entrenamiento:")
print(pd.Series(y_train).value_counts(normalize=True))
print("\nDistribución después de SMOTE:")
print(pd.Series(y_train_balanced).value_counts(normalize=True))
```




```
Distribución original de clases en entrenamiento:
Churn
0    0.734647
```

```
1    0.265353
Name: proportion, dtype: float64

Distribución después de SMOTE:
Churn
0    0.5
1    0.5
Name: proportion, dtype: float64
```

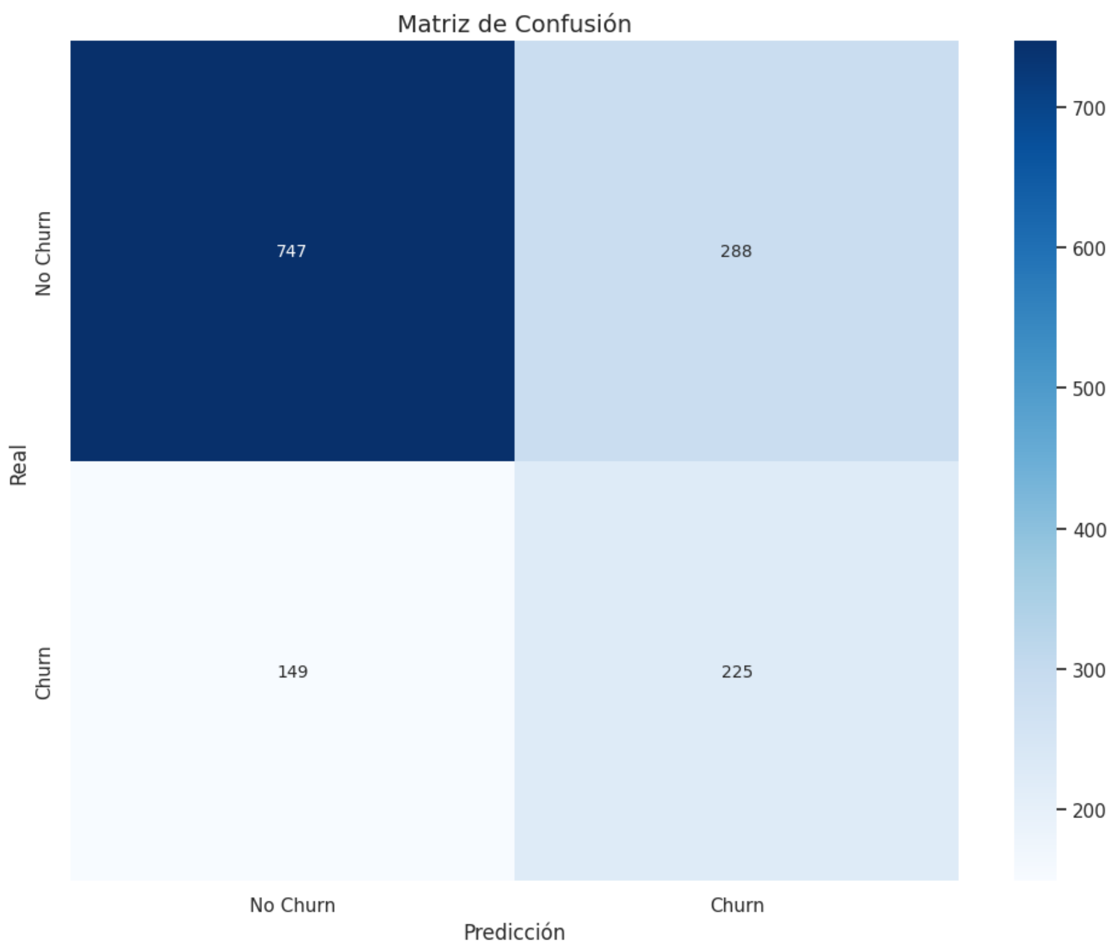
0.4 Implementación de KNN

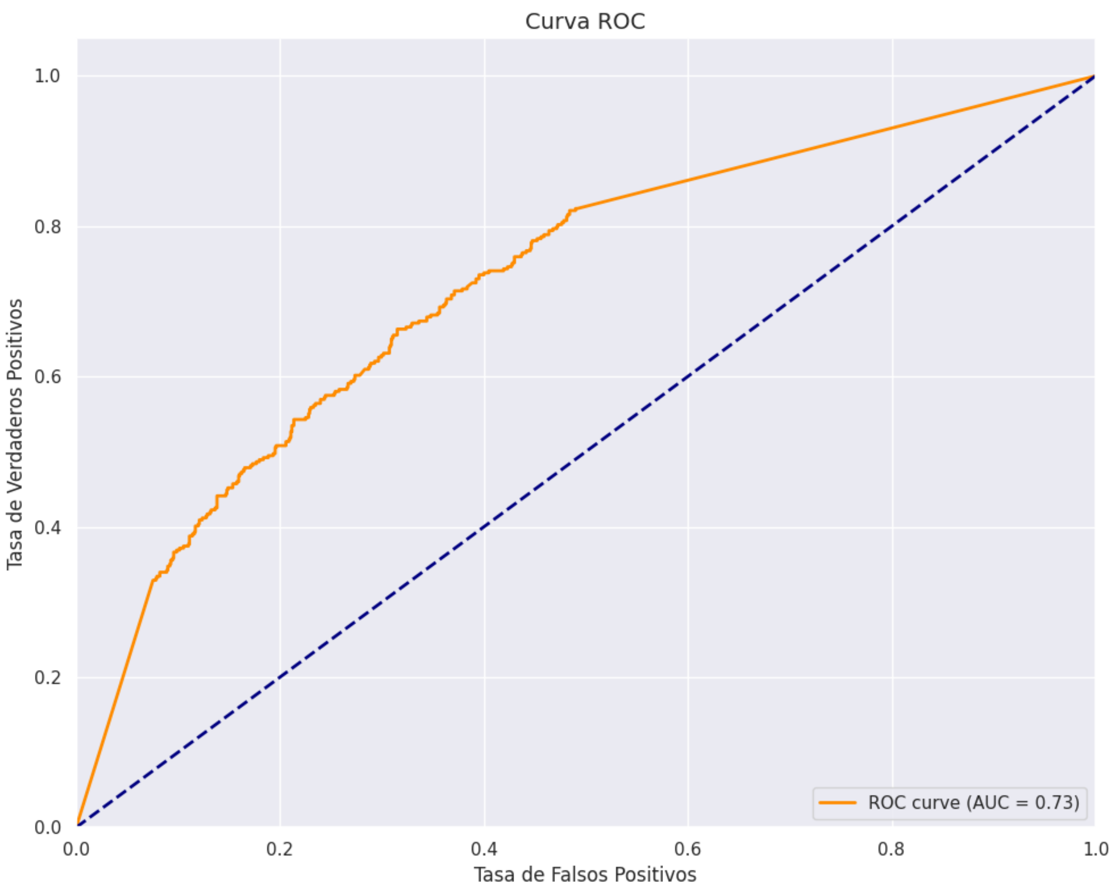
0.4.1 Entrenamiento del Modelo

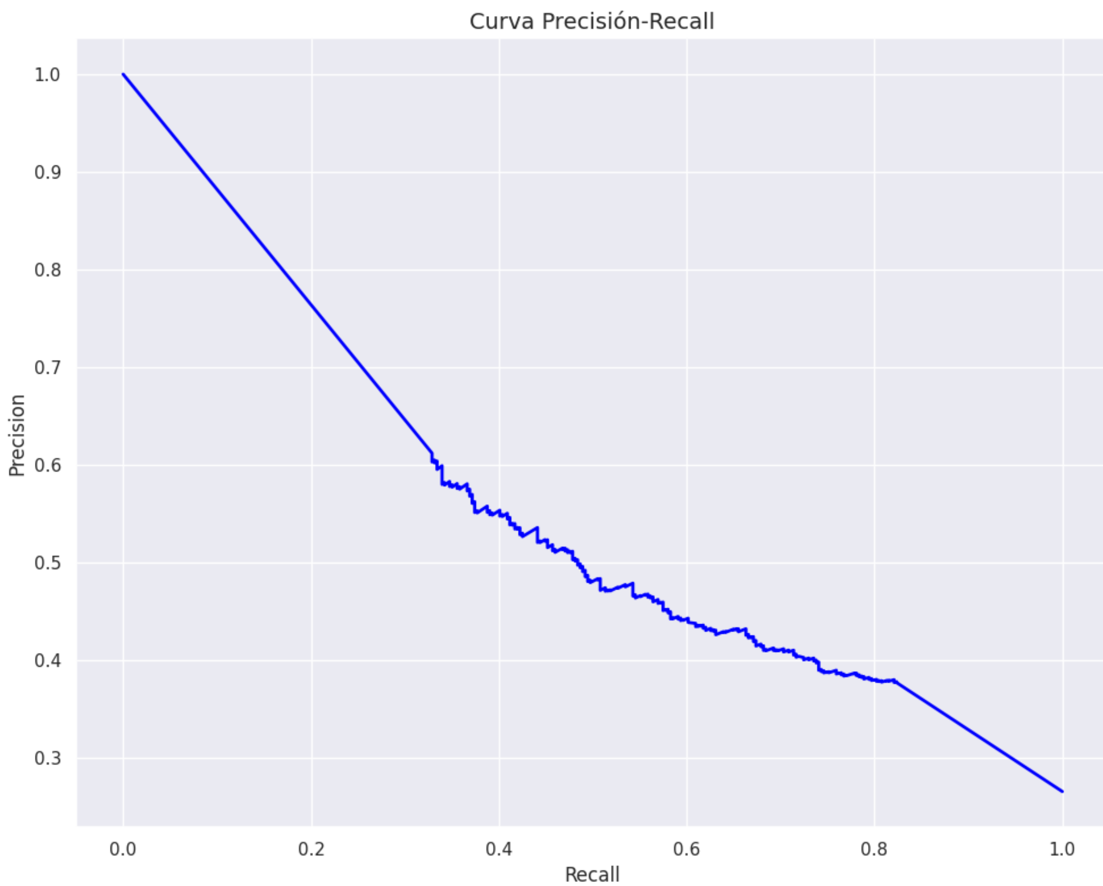
[11]:
```
# Definir parámetros para búsqueda
param_grid = {
    'n_neighbors': range(1, 21),
    'weights': ['uniform', 'distance'],
    'metric': ['euclidean', 'manhattan']
}

# Crear validación cruzada estratificada
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=RANDOM_STATE)

# Búsqueda de hiperparámetros
grid_search = GridSearchCV(
    KNeighborsClassifier(),
    param_grid,
    cv=cv,
    scoring='f1',
    n_jobs=-1
)

# Ajustar el modelo
grid_search.fit(X_train_balanced, y_train_balanced)

# Mostrar mejores parámetros
print("Mejores parámetros:", grid_search.best_params_)
print("Mejor puntuación F1:", grid_search.best_score_)

# Entrenar modelo final con mejores parámetros
best_knn = KNeighborsClassifier(**grid_search.best_params_)
best_knn.fit(X_train_balanced, y_train_balanced)

# Predicciones
y_pred = best_knn.predict(X_test_scaled)
y_prob = best_knn.predict_proba(X_test_scaled)

# Evaluación completa
```

```
evaluate_model(y_test, y_pred, y_prob)
```

```
Mejores parámetros: {'metric': 'euclidean', 'n_neighbors': 4, 'weights':
'distance'}
Mejor puntuación F1: 0.8136512367016442

=== Métricas de Evaluación ===

Informe de clasificación detallado:
              precision    recall  f1-score   support

           0       0.83      0.72      0.77      1035
           1       0.44      0.60      0.51       374

    accuracy                           0.69      1409
   macro avg       0.64      0.66      0.64      1409
weighted avg       0.73      0.69      0.70      1409
```




Curva ROC
1.0
0.8
0.6
0.4
0.2
0.0
Tasa de Verdaderos Positivos
0.0
0.2
0.4
0.6
0.8
1.0
Tasa de Falsos Positivos
ROC curve (AUC = 0.73)

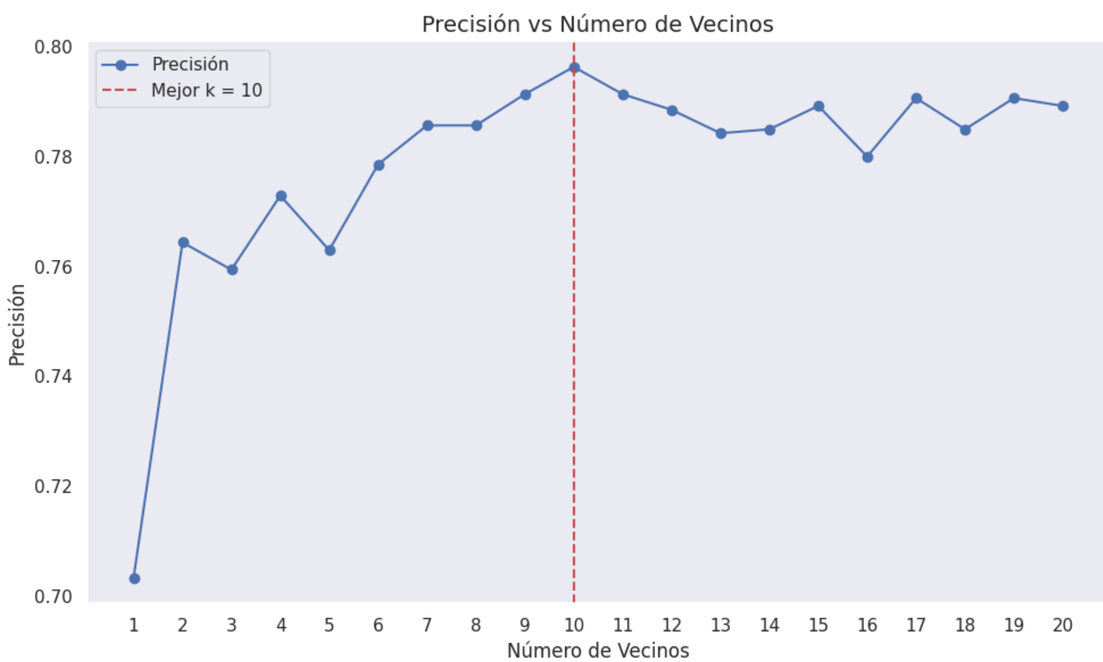


0.4.2 Visualización de Precisión para Diferentes Vecinos

[13]:
```
# Probar diferentes valores de n_neighbors y encontrar el mejor k
accuracies = []
best_accuracy = 0
best_k = 1

for k in range(1, 21):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    accuracies.append(accuracy)

    # Actualizar el mejor k si encontramos una mejor precisión
    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_k = k
```

```
print(f"Mejor número de vecinos (k): {best_k}")
print(f"Mejor precisión: {best_accuracy:.4f}")

# Visualizar los resultados
plt.figure(figsize=(10, 6))
plt.plot(range(1, 21), accuracies, marker='o', label='Precisión')
plt.axvline(x=best_k, color='r', linestyle='--', label=f'Mejor k = {best_k}')
plt.title("Precisión vs Número de Vecinos")
plt.xlabel("Número de Vecinos")
plt.ylabel("Precisión")
plt.xticks(range(1, 21))
plt.legend()
plt.grid()
plt.show()
```

```
Mejor número de vecinos (k): 10
Mejor precisión: 0.7963
```



0.4.3 Curvas de Aprendizaje

[15]:
```
def plot_learning_curve(estimator, X, y, cv=5):
    """
    Genera curvas de aprendizaje para evaluar el rendimiento del modelo
    """
    train_sizes = np.linspace(0.1, 1.0, 10)
```

```python
    # Cambiar el scoring a 'accuracy' en lugar de 'f1'
    train_sizes, train_scores, test_scores = learning_curve(
        estimator, X, y,
        cv=cv,
        n_jobs=-1,
        train_sizes=train_sizes,
        scoring='accuracy'  # Cambiado de 'f1' a 'accuracy'
    )

    train_mean = np.mean(train_scores, axis=1)
    train_std = np.std(train_scores, axis=1)
    test_mean = np.mean(test_scores, axis=1)
    test_std = np.std(test_scores, axis=1)

    plt.figure(figsize=(10, 6))
    plt.plot(train_sizes, train_mean, label='Training score')
    plt.plot(train_sizes, test_mean, label='Cross-validation score')
    plt.fill_between(train_sizes, train_mean - train_std,
                     train_mean + train_std, alpha=0.1)
    plt.fill_between(train_sizes, test_mean - test_std,
                     test_mean + test_std, alpha=0.1)
    plt.xlabel('Training Examples')
    plt.ylabel('Accuracy Score')  # Cambiado de 'F1 Score' a 'Accuracy Score'
    plt.title('Learning Curves')
    plt.legend(loc='best')
    plt.grid(True)
    plt.show()

# Aplicar SMOTE para balancear los datos
smote = SMOTE(random_state=42)
X_train_balanced, y_train_balanced = smote.fit_resample(X_train, y_train)

# Crear y entrenar el modelo KNN con los mejores parámetros
best_knn = KNeighborsClassifier(n_neighbors=18)
best_knn.fit(X_train_balanced, y_train_balanced)

# Generar las curvas de aprendizaje
plot_learning_curve(best_knn, X_train_balanced, y_train_balanced)
```


Learning Curves
Training score
Cross-validation score
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0.55
Accuracy Score
1000
2000
3000
4000
5000
6000
Training Examples