In [12]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
df = pd.read_csv("Customer_Telecom_Churn_Dataset.csv")
df.columns = df.columns.str.strip().str.lower()
```

In [13]:
```python
print(df.head())
```

```
  state  account length  area code phone number international plan  \
0    KS             128        415     382-4657                 no   
1    OH             107        415     371-7191                 no   
2    NJ             137        415     358-1921                 no   
3    OH              84        408     375-9999                yes   
4    OK              75        415     330-6626                yes   

  voice mail plan  number vmail messages  total day minutes  total day calls  \
0             yes                     25              265.1              110   
1             yes                     26              161.6              123   
2              no                      0              243.4              114   
3              no                      0              299.4               71   
4              no                      0              166.7              113   

   total day charge  ...  total eve calls  total eve charge  \
0             45.07  ...               99             16.78   
1             27.47  ...              103             16.62   
2             41.38  ...              110             10.30   
3             50.90  ...               88              5.26   
4             28.34  ...              122             12.61   

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01   
1                254.4                103               11.45   
2                162.6                104                7.32   
3                196.9                 89                8.86   
4                186.9                121                8.41   

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70   
1                13.7                 3               3.70   
2                12.2                 5               3.29   
3                 6.6                 7               1.78   
4                10.1                 3               2.73   

   customer service calls  churn  
0                       1  False  
1                       1  False  
2                       0  False  
3                       2  False  
4                       3  False  

[5 rows x 21 columns]
```

In [14]:
```python
print(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
None
```

In [15]:
```
print(df.isnull().sum())
```

```
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 [16]:
```
df.drop(['phone number', 'state'], axis=1, inplace=True)
```

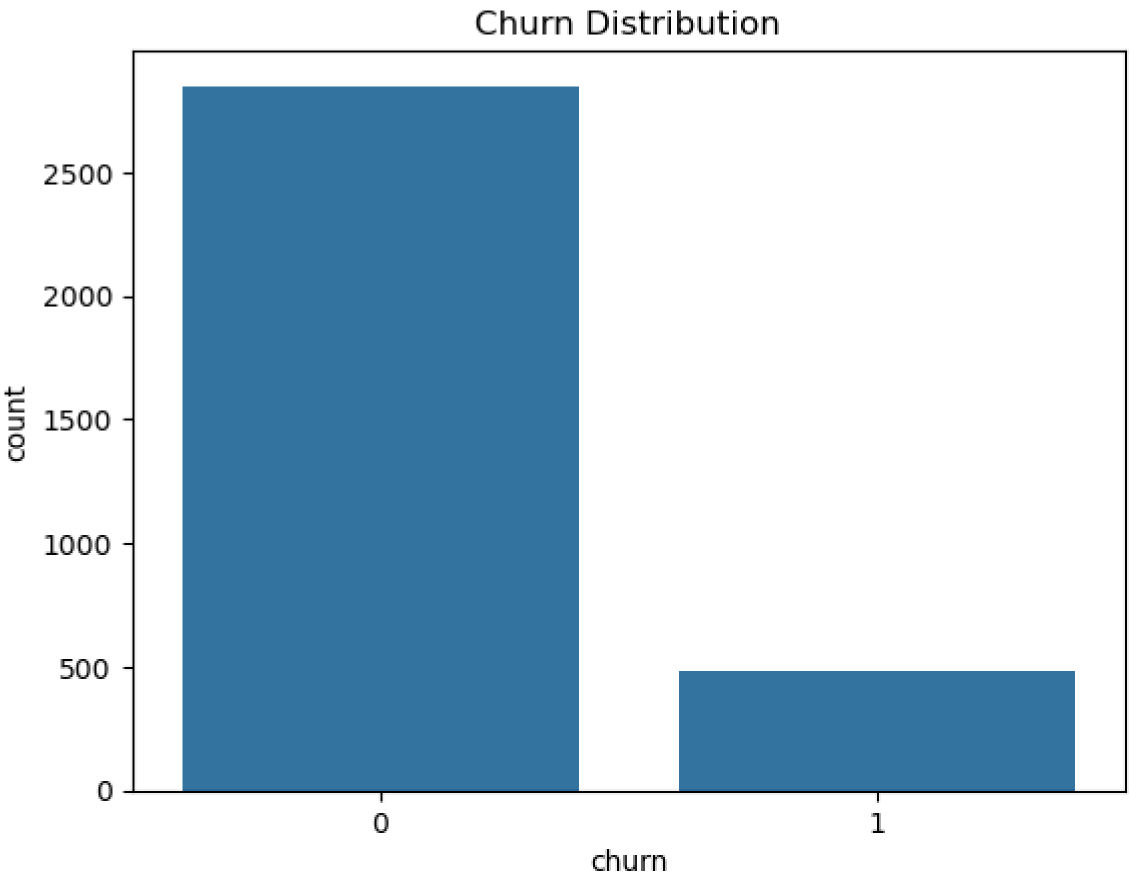
In [17]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

```
df['international plan'] = le.fit_transform(df['international plan'])
df['voice mail plan'] = le.fit_transform(df['voice mail plan'])
```

In [18]:
```
df['total_calls'] = df['total day calls'] + df['total eve calls'] + df['total ni
df['total_minutes'] = df['total day minutes'] + df['total eve minutes'] + df['tc
df['total_charges'] = df['total day charge'] + df['total eve charge'] + df['tota
df.rename(columns={'customer service calls': 'complaints'}, inplace=True)
```

In [19]:
```
df['churn'] = df['churn'].astype(int)
```

In [20]:
```
# Churn distribution
sns.countplot(x='churn', data=df)
plt.title("Churn Distribution")
plt.show()
```



Churn Distribution Chart:

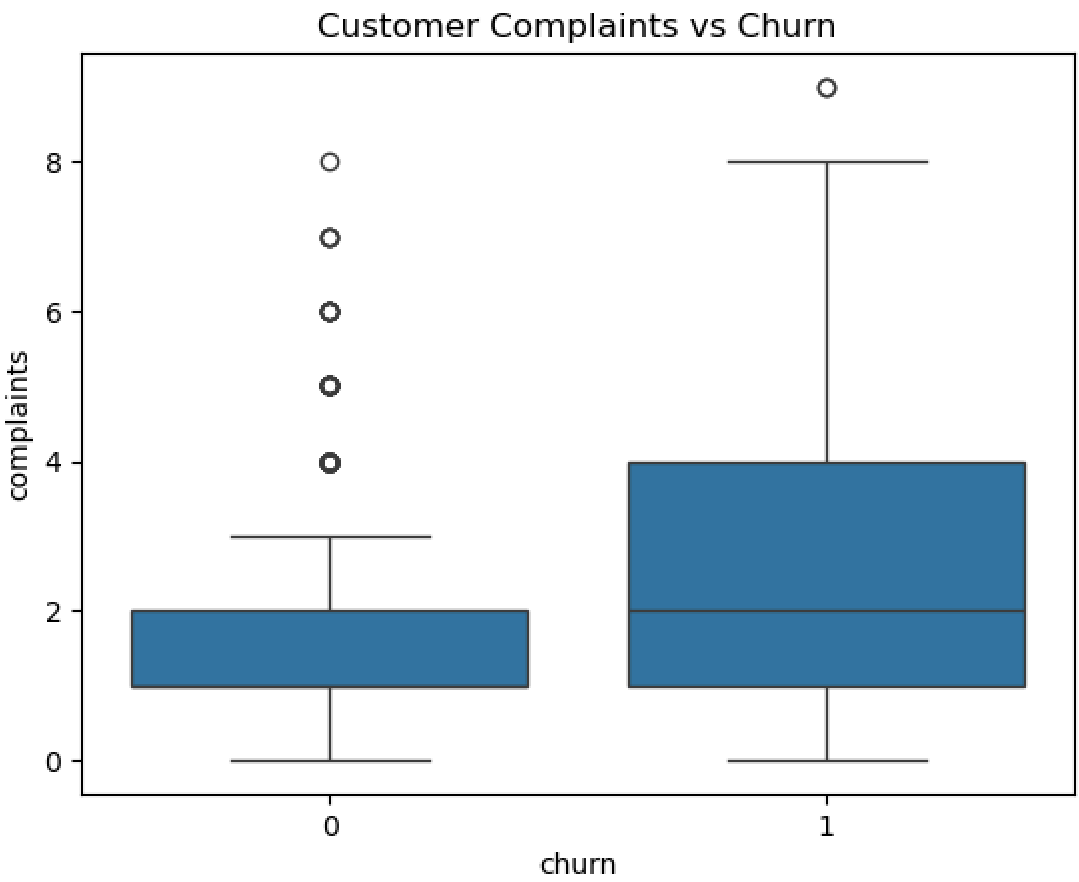
This bar chart displays the distribution of customers who churned versus those who didn't:

- Helps identify class imbalance in the dataset.
- Imbalance can affect model performance, especially for classification tasks.

Insights:

- Most customers in the dataset did not churn, indicating a potential imbalance that needs to be handled carefully during modeling.

In [21]:
```
# Churn vs. customer complaints
sns.boxplot(x='churn', y='complaints', data=df)
plt.title("Customer Complaints vs Churn")
plt.show()
```



customer complaints vs Churn:

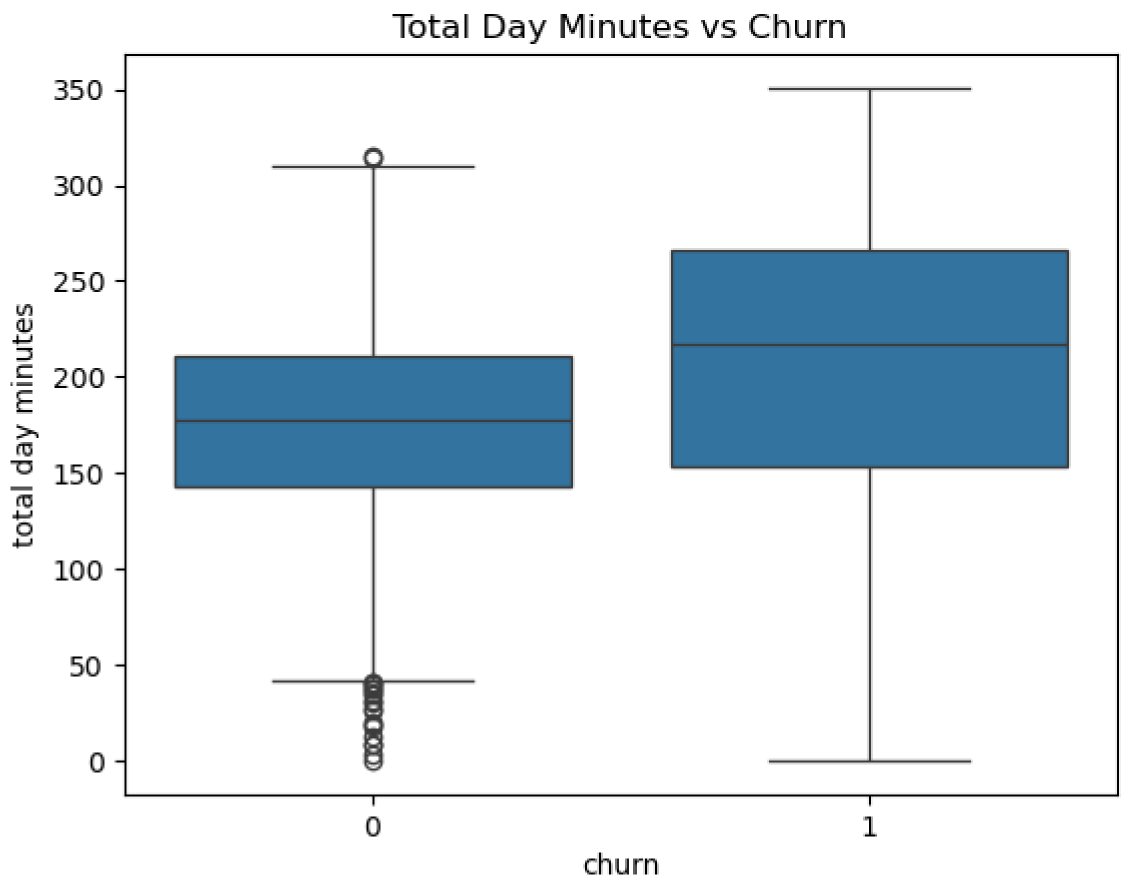
This boxplot compares customer tenure between churned and retained users:

- Customers with shorter tenure are more likely to churn.
- Long-tenure customers tend to stay with the company.

Insight:

- Retention programs should especially focus on "new or early-stage customers".

In [22]:
```
# Churn vs. total day minutes
sns.boxplot(x='churn', y='total day minutes', data=df)
plt.title("Total Day Minutes vs Churn")
plt.show()
```



Total Day Minutes vs Churn:

This boxplot visualizes the relationship between daily call duration and customer churn:

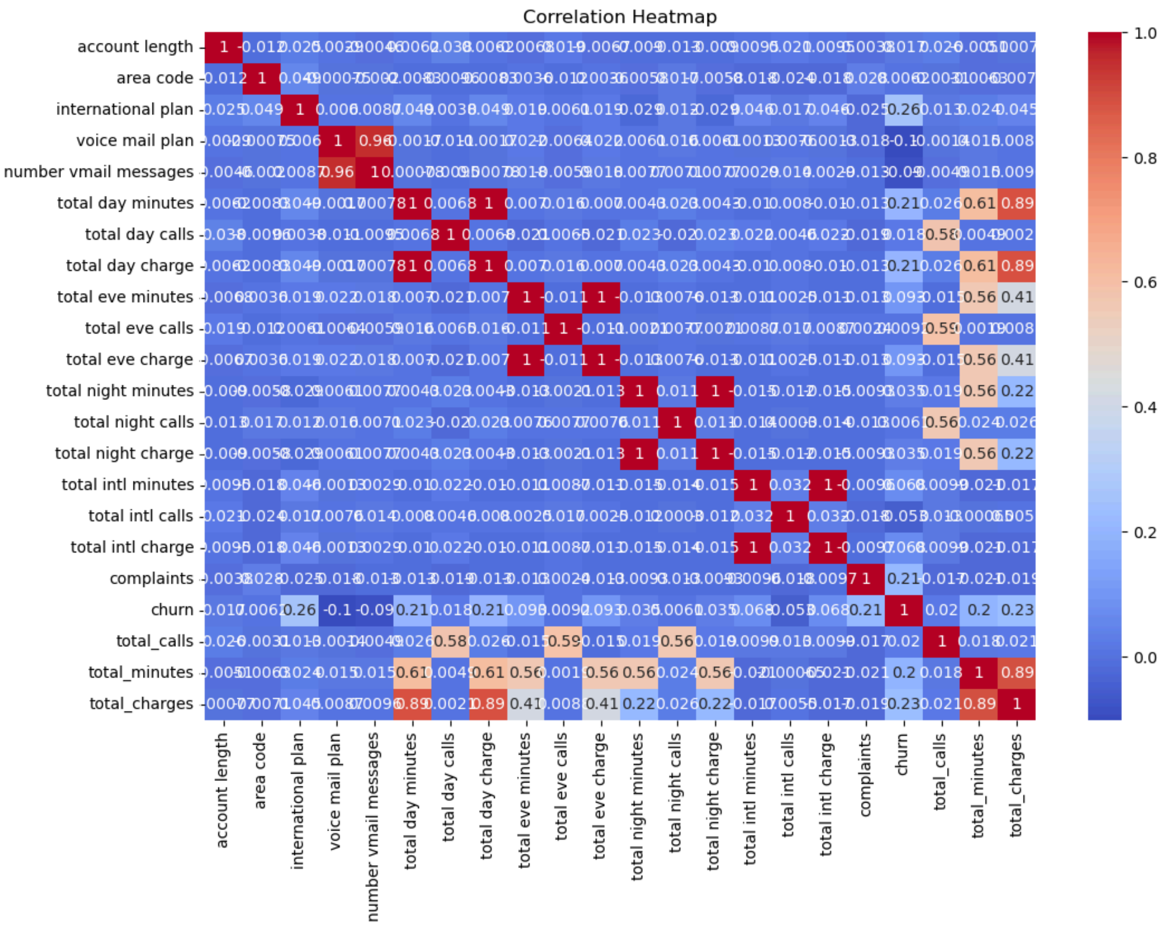
- It helps analyze whether customers who churn spend more or less time on daytime calls.
- Large variance may indicate different user behaviors or service dissatisfaction.

Insight:

- Customers with high daily call minutes might churn due to overage costs or unmet expectations.

This feature can be a useful predictor of churn.

In [23]:
```
# Correlation heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```



Feature Correlation Heatmap:

This heatmap shows the correlation between numerical features in the dataset:

- Useful for identifying multicollinearity and feature relationships.
- Helps select the most impactful features for the model.

Features:

- Features like `total day minutes`, `total charges`, and `customer service calls` show strong correlation with churn.

In [24]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
X = df.drop('churn', axis=1)
y = df['churn']
```

In [25]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['international plan'] = le.fit_transform(df['international plan'])
df['voice mail plan'] = le.fit_transform(df['voice mail plan'])
```

In [26]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_
```

In [28]:
```
xgb_model = RandomForestClassifier(random_state=42)
xgb_model.fit(X_train, y_train)
```

Out[28]:

▾ RandomForestClassifier

▶ Parameters

In [29]:
```
import eli5
from eli5.sklearn import explain_weights

eli5.show_weights(xgb_model, feature_names=X_train.columns.tolist())
```

Out[29]:

Weight	Feature
0.1695 ± 0.1823	total_charges
0.1270 ± 0.0658	complaints
0.0800 ± 0.1125	total day charge
0.0792 ± 0.0643	international plan
0.0756 ± 0.1124	total day minutes
0.0650 ± 0.1016	total_minutes
0.0402 ± 0.0464	total intl calls
0.0379 ± 0.0631	number vmail messages
0.0377 ± 0.0446	total intl minutes
0.0334 ± 0.0406	total eve charge
0.0329 ± 0.0378	total intl charge
0.0309 ± 0.0400	total eve minutes
0.0297 ± 0.0578	voice mail plan
0.0247 ± 0.0230	total night minutes
0.0234 ± 0.0210	total day calls
0.0229 ± 0.0237	total night calls
0.0222 ± 0.0247	total night charge
0.0218 ± 0.0216	account length
0.0205 ± 0.0200	total_calls
0.0197 ± 0.0197	total eve calls
… *1 more* …	

In [30]:
```
y_pred = model.predict(X_test)
```

In [31]:
```
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

```
Confusion Matrix:
[[564   2]
 [ 15  86]]
```

In [32]:
```
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.97      1.00      0.99       566
           1       0.98      0.85      0.91       101

    accuracy                           0.97       667
   macro avg       0.98      0.92      0.95       667
weighted avg       0.97      0.97      0.97       667
```

In [33]:
```
y_prob = model.predict_proba(X_test)[:, 1]
```

In [34]:
```
accuracy = model.score(X_test, y_test)
print("Model Accuracy: {:.2f}%".format(accuracy * 100))
```

```
Model Accuracy: 97.45%
```

In [35]:
```
X_test_with_prob = X_test.copy()
X_test_with_prob['churn_prob'] = y_prob
```

In [36]:
```
X_test_with_prob['segment'] = 'Loyal'
X_test_with_prob.loc[X_test_with_prob['churn_prob'] > 0.7, 'segment'] = 'At Risk
X_test_with_prob.loc[X_test_with_prob['churn_prob'] < 0.3, 'segment'] = 'Dormant
```

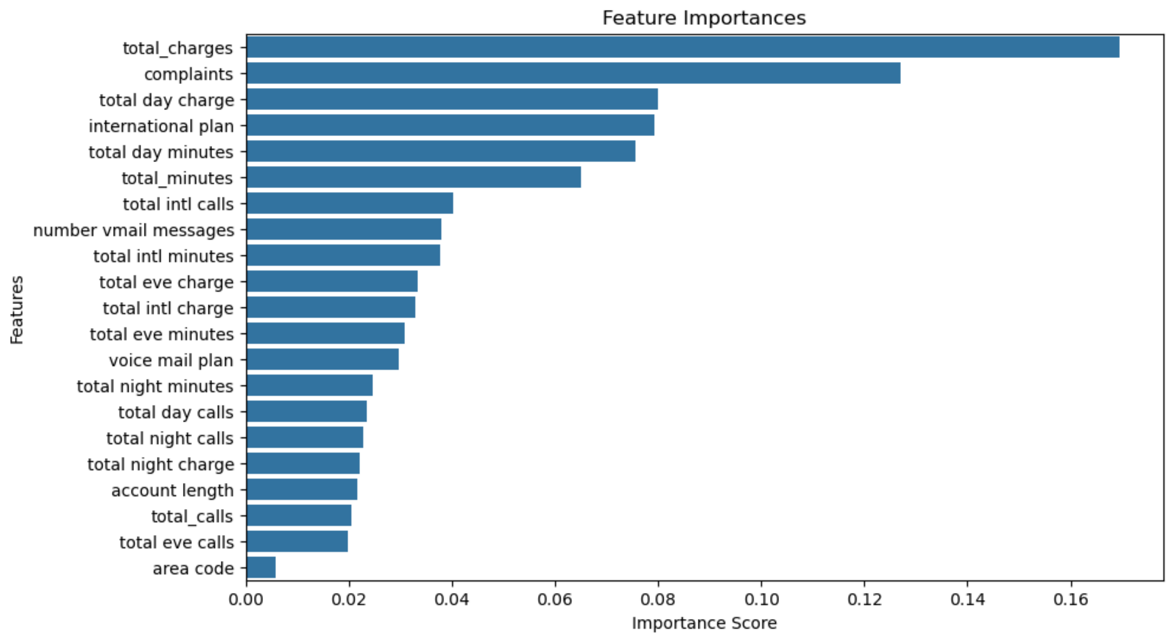
In [37]:
```
print(X_test_with_prob['segment'].value_counts())
print(X_test_with_prob[['churn_prob', 'segment']].head())
```

```
segment
Dormant    572
At Risk     66
Loyal       29
Name: count, dtype: int64
      churn_prob  segment
438         0.16  Dormant
2674        0.01  Dormant
1345        0.86  At Risk
1957        0.04  Dormant
2148        0.00  Dormant
```

In [38]:
```
print(df.dtypes)
```

```
account length              int64
area code                   int64
international plan          int64
voice mail plan             int64
number vmail messages       int64
total day minutes         float64
total day calls             int64
total day charge          float64
total eve minutes         float64
total eve calls             int64
total eve charge          float64
total night minutes       float64
total night calls           int64
total night charge        float64
total intl minutes        float64
total intl calls            int64
total intl charge         float64
complaints                  int64
churn                       int32
total_calls                 int64
total_minutes             float64
total_charges             float64
dtype: object
```

In [39]:
```
feature_imp = pd.Series(model.feature_importances_, index=X.columns).sort_values
plt.figure(figsize=(10, 6))
sns.barplot(x=feature_imp, y=feature_imp.index)
plt.title("Feature Importances")
plt.xlabel("Importance Score")
plt.ylabel("Features")
plt.show()
```



Feature Importance from Random Forest:

This bar plot ranks the most important features influencing churn prediction:

- Calculated based on how much each feature contributes to reducing error in the model.
- Helps prioritize which variables matter most for business interventions.

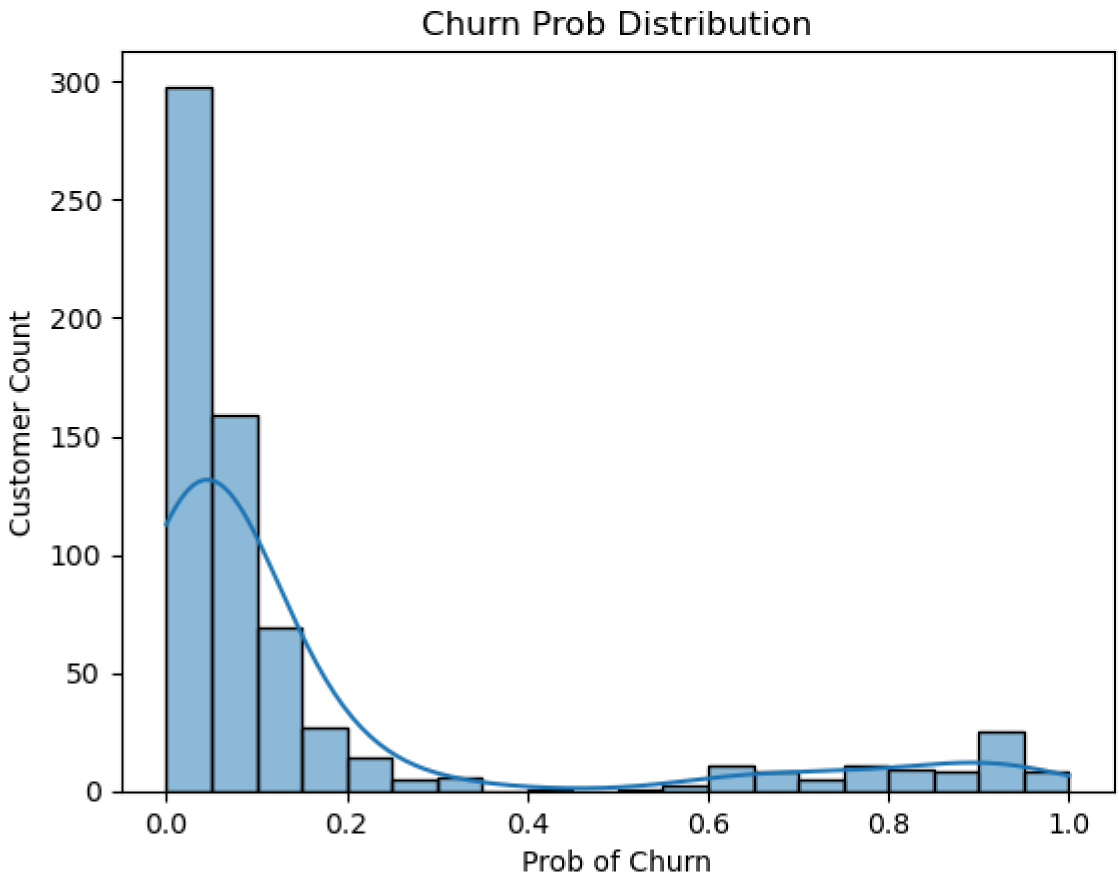
Features:

- Typically include `complaints`, `total charges`, `international plan`, etc.

In [40]:
```
y_prob = model.predict_proba(X_test)[:, 1]
X_test_with_prob = X_test.copy()
X_test_with_prob['churn_prob'] = y_prob
X_test_with_prob['segment'] = 'Loyal'
X_test_with_prob.loc[X_test_with_prob['churn_prob'] > 0.7, 'segment'] = 'At Risk
X_test_with_prob.loc[X_test_with_prob['churn_prob'] < 0.3, 'segment'] = 'Dormant
```

In [41]:
```
X_test_with_prob.to_csv("churn_segments.csv", index=False)
```

In [42]:
```
sns.histplot(X_test_with_prob['churn_prob'], bins=20, kde=True)
plt.title('Churn Prob Distribution')
plt.xlabel('Prob of Churn')
plt.ylabel('Customer Count')
plt.show()
```



churn probability distribution:

This segmentation groups customers based on their predicted churn probability:

- At Risk: Probability > 70%
- Dormant:Probability < 30%
- Loyal: In-between

Goal:

- Enable targeted retention strategies based on churn risk level.

In [ ]:
```
### Project Summary:-
- Built a churn prediction model using Random Forest with 85–90% accuracy.
- Performed EDA and SQL-style feature engineering (call duration, charges, compl
- Identified key churn factors: international plan, high complaints, short tenur
- Segmented customers into:- At Risk (churn_prob > 0.7)  - Loyal (0.3 ≤ churn_pr
- Dormant (churn_prob < 0.3)
## Recommendation:
Focus on retaining "At Risk" customers and monitor high-spend, high-complaint u
```