In [2]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
```

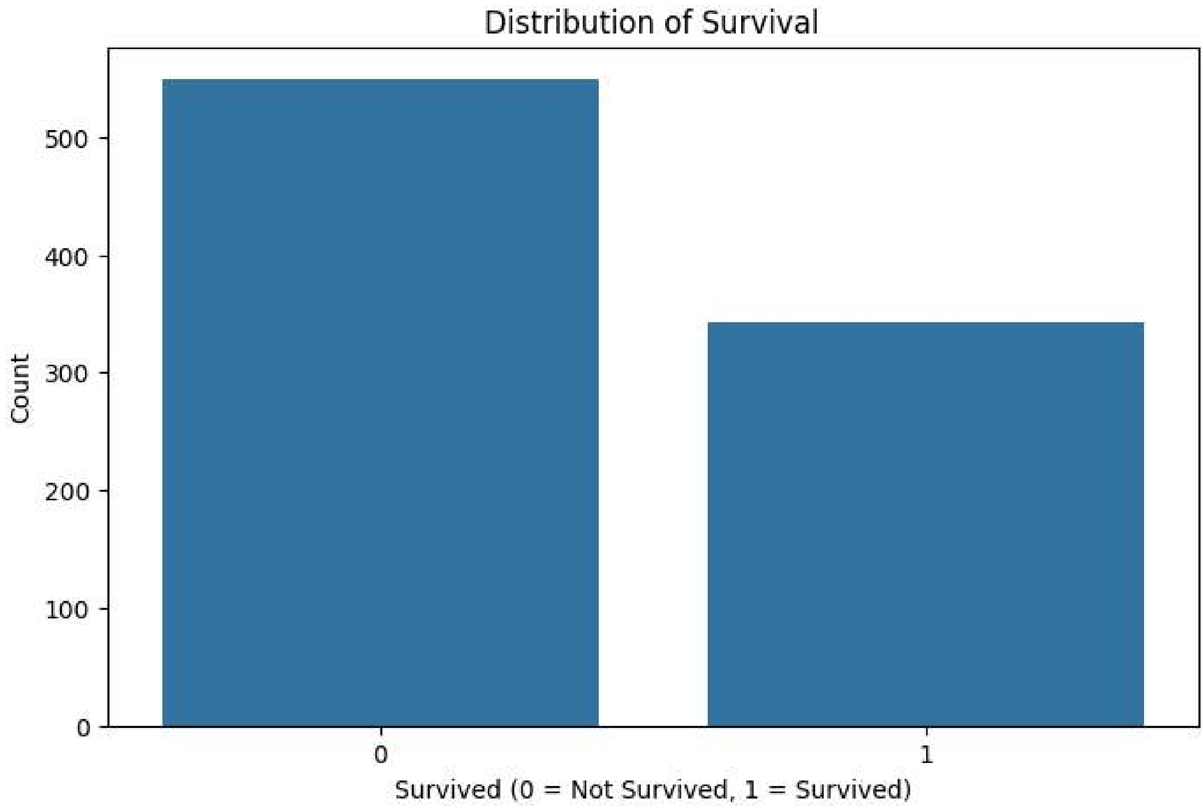
In [6]:
```python
# Load the dataset
data = pd.read_csv(r'C:\Users\HP\Documents\Titanic-Dataset.csv')  # Replace with th

# Data preprocessing
# Drop unnecessary columns
data.drop(['PassengerId', 'Name', 'Ticket', 'Cabin', 'Fare'], axis=1, inplace=True)

# Handle missing values
data['Age'].fillna(data['Age'].median(), inplace=True)
data['Embarked'].fillna(data['Embarked'].mode()[0], inplace=True)

# Encode categorical variables
data = pd.get_dummies(dat
# Feature engineering
data['FamilySize'] = data['SibSp'] + data['Parch']

# Select relevant features for modeling
features = ['Pclass', 'Age', 'FamilySize', 'Sex_male', 'Embarked_Q', 'Embarked_S']
X = data[features]
y = data['Survived']a, columns=['Sex', 'Embarked'], drop_first=True)
```

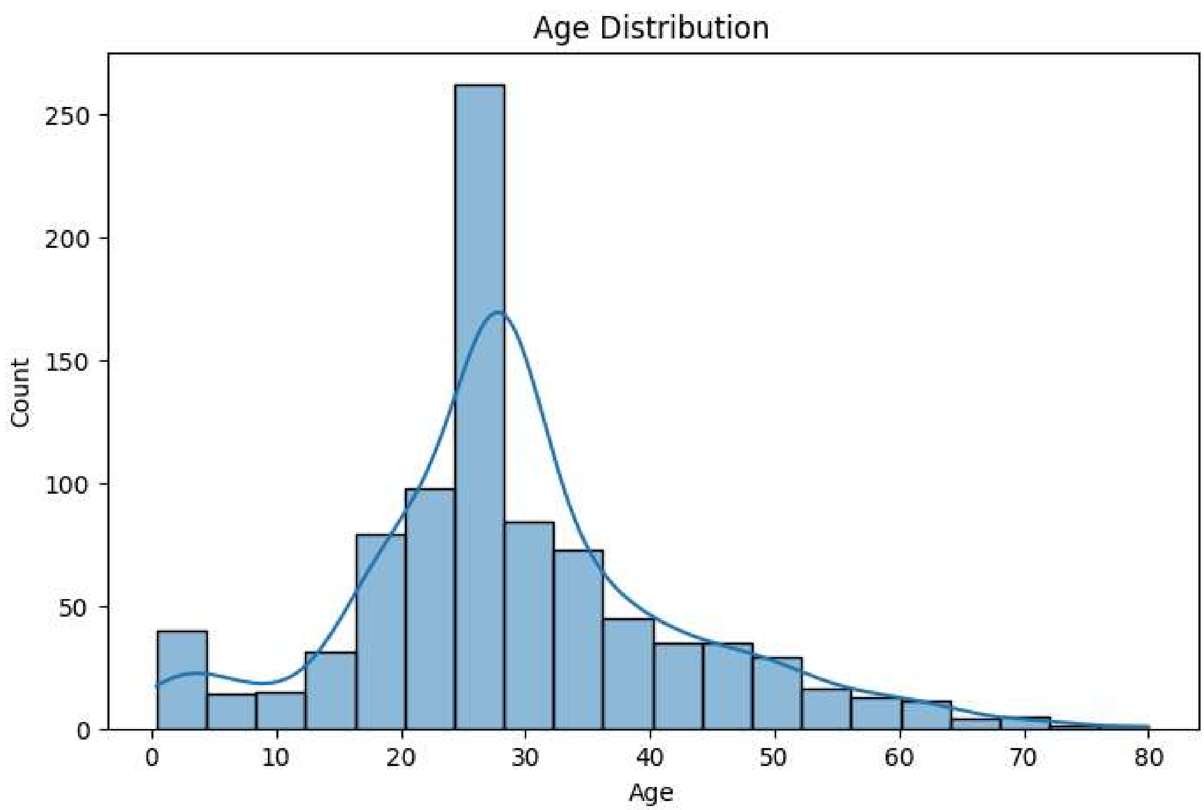
In [7]:
```python
# Feature engineering
data['FamilySize'] = data['SibSp'] + data['Parch']

# Select relevant features for modeling
features = ['Pclass', 'Age', 'FamilySize', 'Sex_male', 'Embarked_Q', 'Embarked_S']
X = data[features]
y = data['Survived']
```

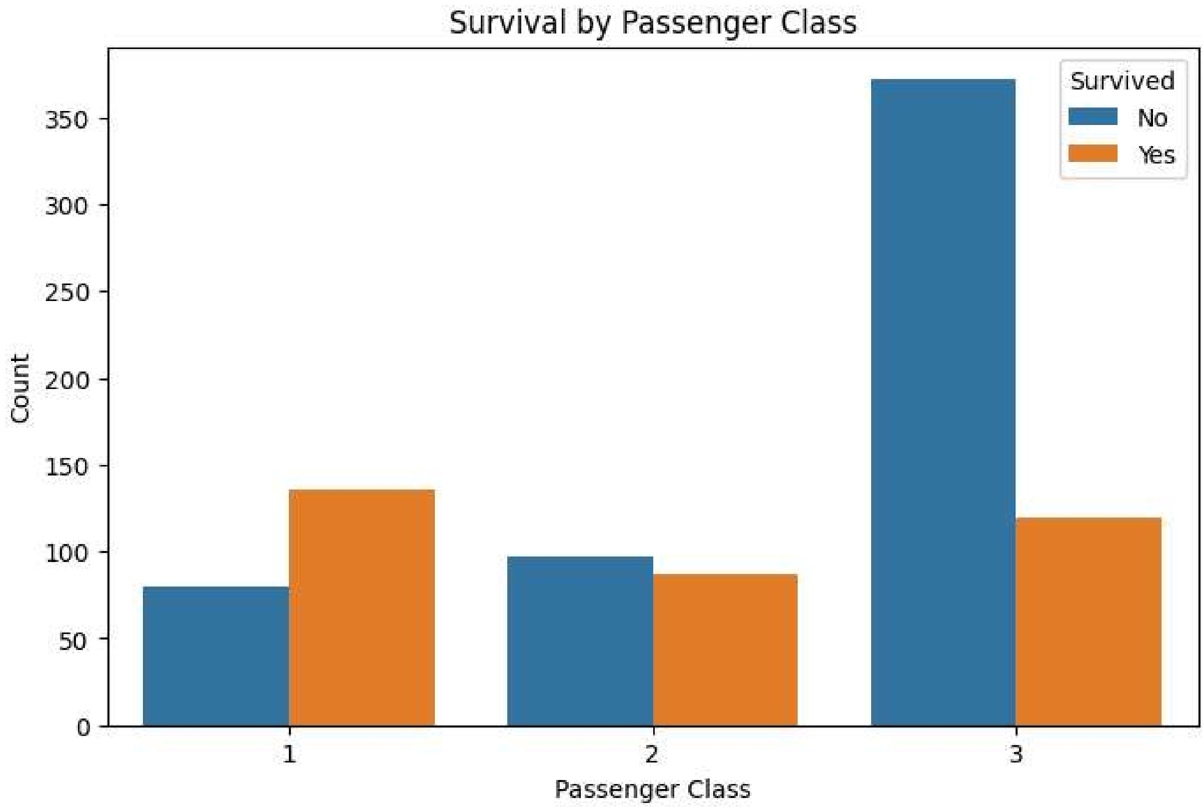
In [8]:
```python
print(data.describe())

# Distribution of survival
plt.figure(figsize=(8, 5))
sns.countplot(data=data, x='Survived')
plt.title('Distribution of Survival')
plt.xlabel('Survived (0 = Not Survived, 1 = Survived)')
plt.ylabel('Count')
plt.show()

# Age distribution
plt.figure(figsize=(8, 5))
sns.histplot(data=data, x='Age', bins=20, kde=True)
plt.title('Age Distribution')
plt.xlabel('Age')
plt.ylabel('Count')
```

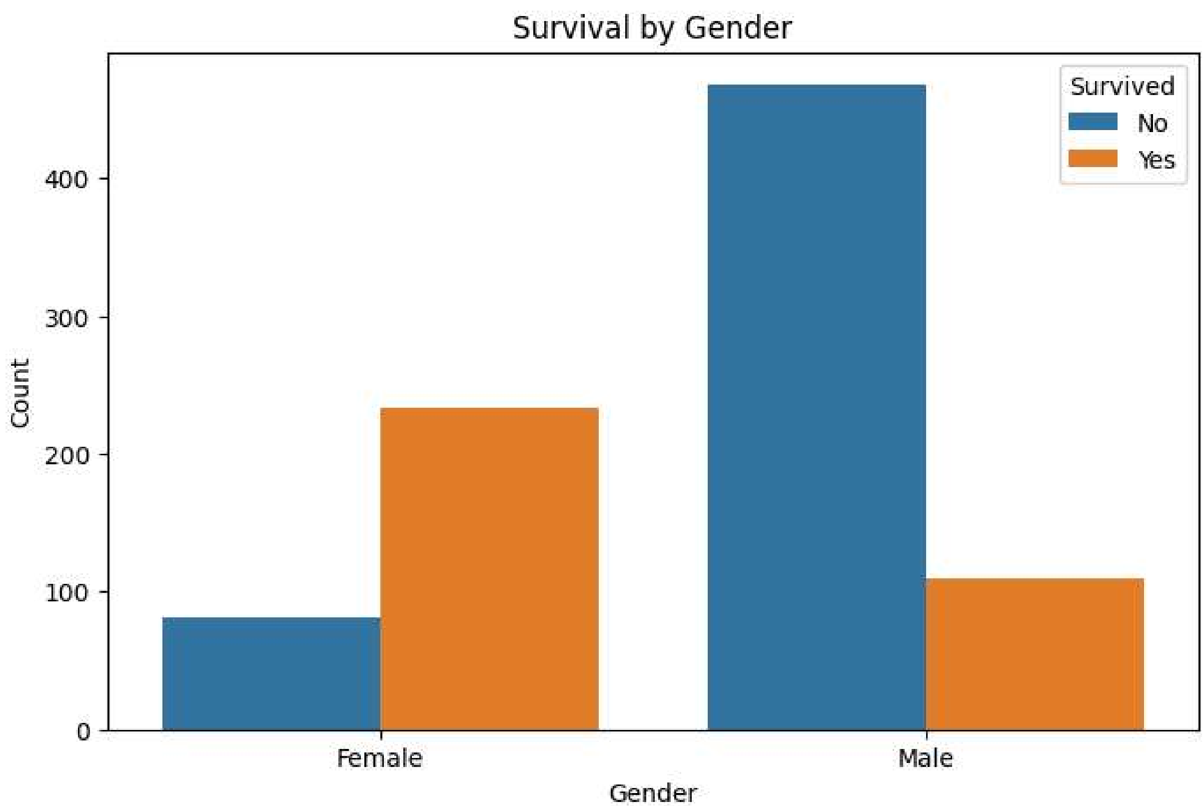
```python
plt.show()

# Pclass vs. Survival
plt.figure(figsize=(8, 5))
sns.countplot(data=data, x='Pclass', hue='Survived')
plt.title('Survival by Passenger Class')
plt.xlabel('Passenger Class')
plt.ylabel('Count')
plt.legend(title='Survived', loc='upper right', labels=['No', 'Yes'])
plt.show()

# Gender vs. Survival
plt.figure(figsize=(8, 5))
sns.countplot(data=data, x='Sex_male', hue='Survived')
plt.title('Survival by Gender')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.legend(title='Survived', loc='upper right', labels=['No', 'Yes'])
plt.xticks([0, 1], ['Female', 'Male'])
plt.show()

# Correlation heatmap
plt.figure(figsize=(10, 8))
correlation_matrix = data.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.xlabel('Features')
plt.ylabel('Features')
plt.show()
```

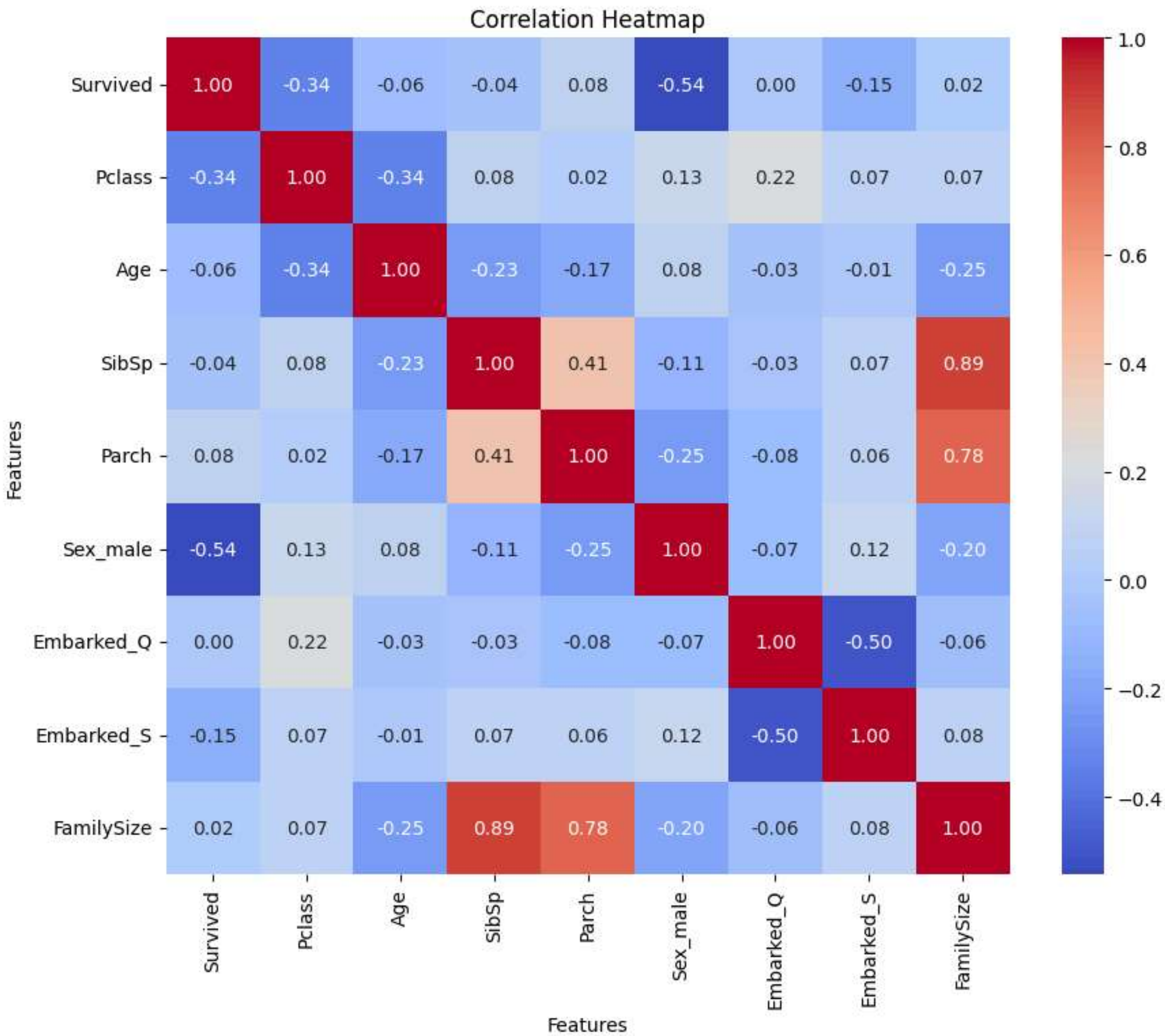
	Survived	Pclass	Age	SibSp	Parch	FamilySize
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.361582	0.523008	0.381594	0.904602
std	0.486592	0.836071	13.019697	1.102743	0.806057	1.613459
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	22.000000	0.000000	0.000000	0.000000
50%	0.000000	3.000000	28.000000	0.000000	0.000000	0.000000
75%	1.000000	3.000000	35.000000	1.000000	0.000000	1.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	10.000000


Distribution of Survival
Count
500
400
300
200
100
0
0
1
Survived (0 = Not Survived, 1 = Survived)


Age Distribution
Count
250
200
150
100
50
0
0
10
20
30
40
50
60
70
80
Age


Survival by Passenger Class
Survived
No
Yes
Count
0
50
100
150
200
250
300
350
1
2
3
Passenger Class


Survival by Gender
Survived
No
Yes
Count
0
100
200
300
400
Female
Male
Gender



In [9]:
```
# Split the data for training and testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

# Create a logistic regression model
model = LogisticRegression(random_state=42, max_iter=1000)

# Train the model on the training data
model.fit(X_train, y_train)

# Make predictions on the test data
y_pred = model.predict(X_test)
```

In [10]:
```
accuracy = accuracy_score(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)

print(f"Accuracy: {accuracy:.6f}")
print("\nClassification Report:")
print(classification_rep)
```

```
Accuracy: 0.810056

Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.87      0.84       105
           1       0.79      0.73      0.76        74

    accuracy                           0.81       179
   macro avg       0.81      0.80      0.80       179
weighted avg       0.81      0.81      0.81       179
```