In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
Matplotlib is building the font cache; this may take a moment.
```

In [64]:

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

In [65]:

```
sns.set(style="whitegrid")
```

In [66]:

```
train_df = pd.read_csv("train.csv")   # Titanic dataset
test_df = pd.read_csv("test.csv")
```

In [67]:

```
train_df.head() # First few rows
```

Out[67]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500

In [68]:

```
train_df.isnull().sum() # Null value count
```

Out[68]:

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [69]:

```
train_df.info()  # Data types and null values
train_df.describe()  # Statistical summary
```

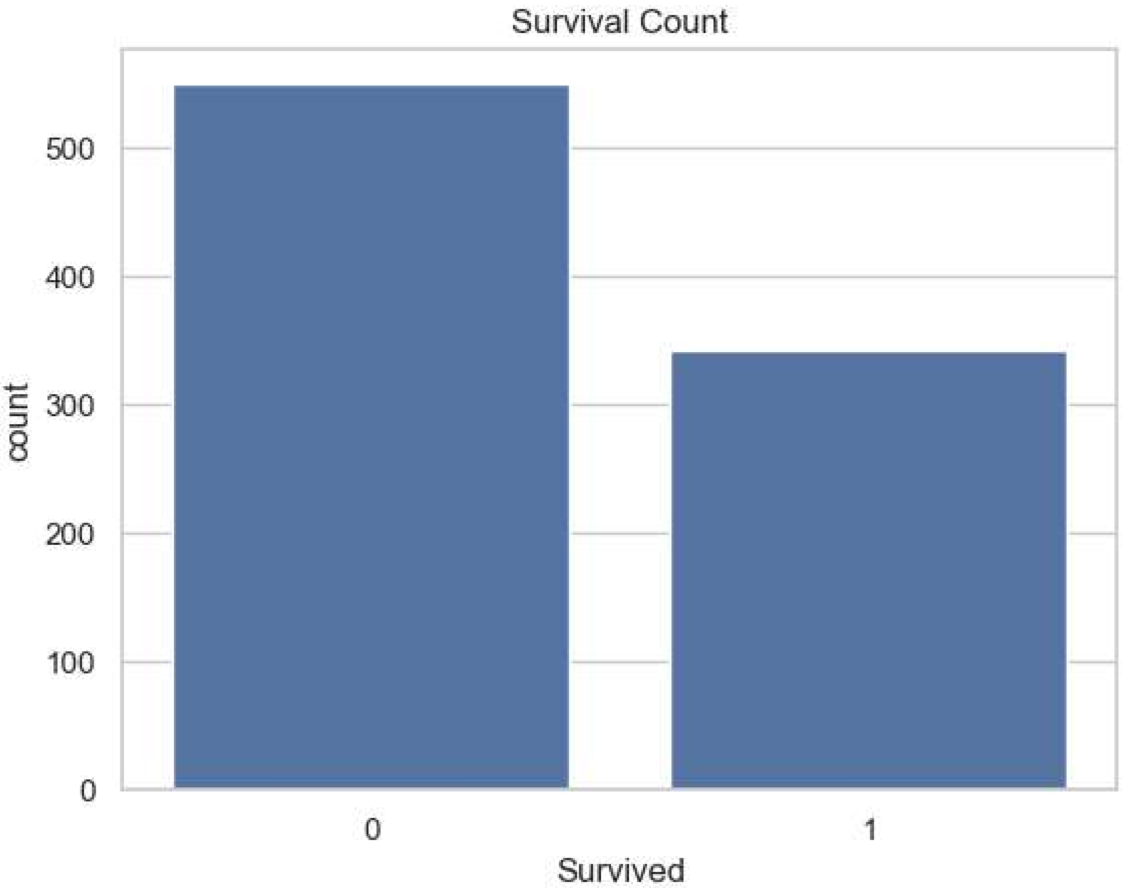
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

Out[69]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.00000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.20420
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.69342
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.00000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.91040
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.45420
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.00000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.32920

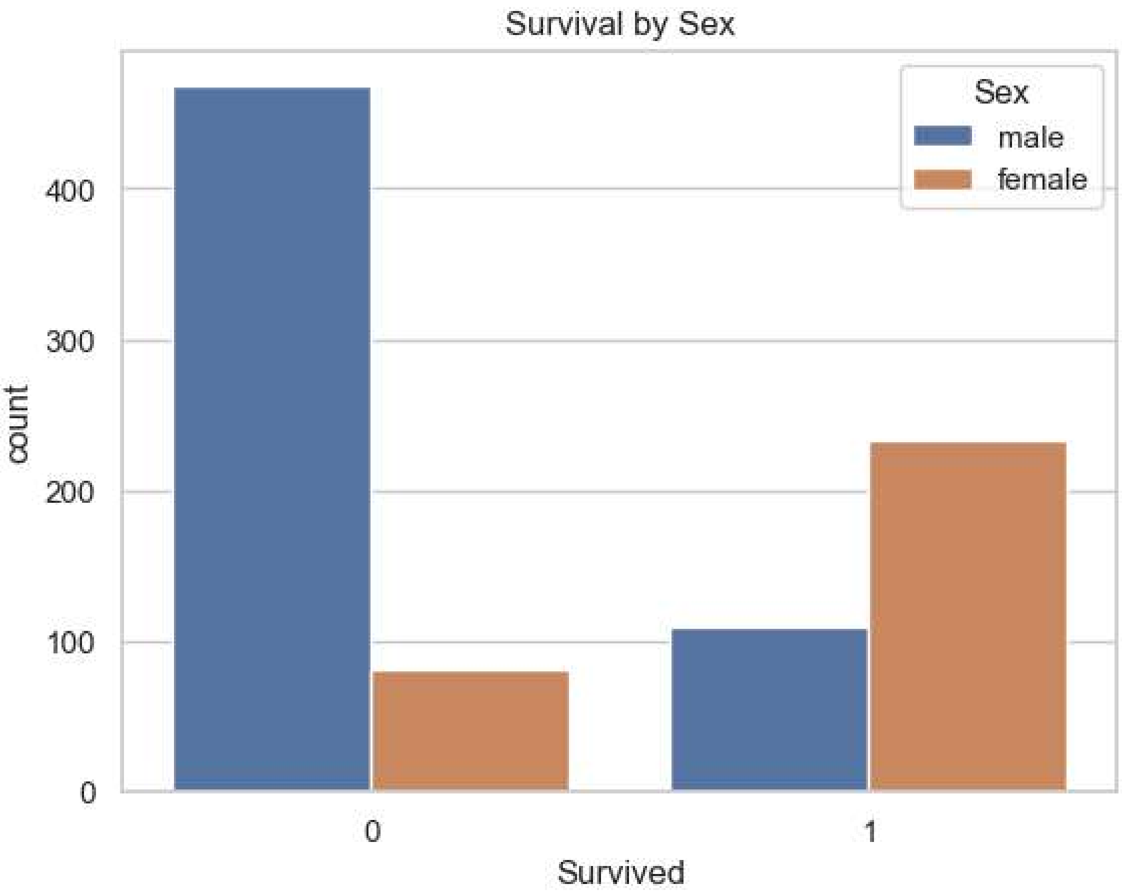
In [70]:

```
sns.countplot(data=train_df, x='Survived')
plt.title("Survival Count")
plt.show()
```



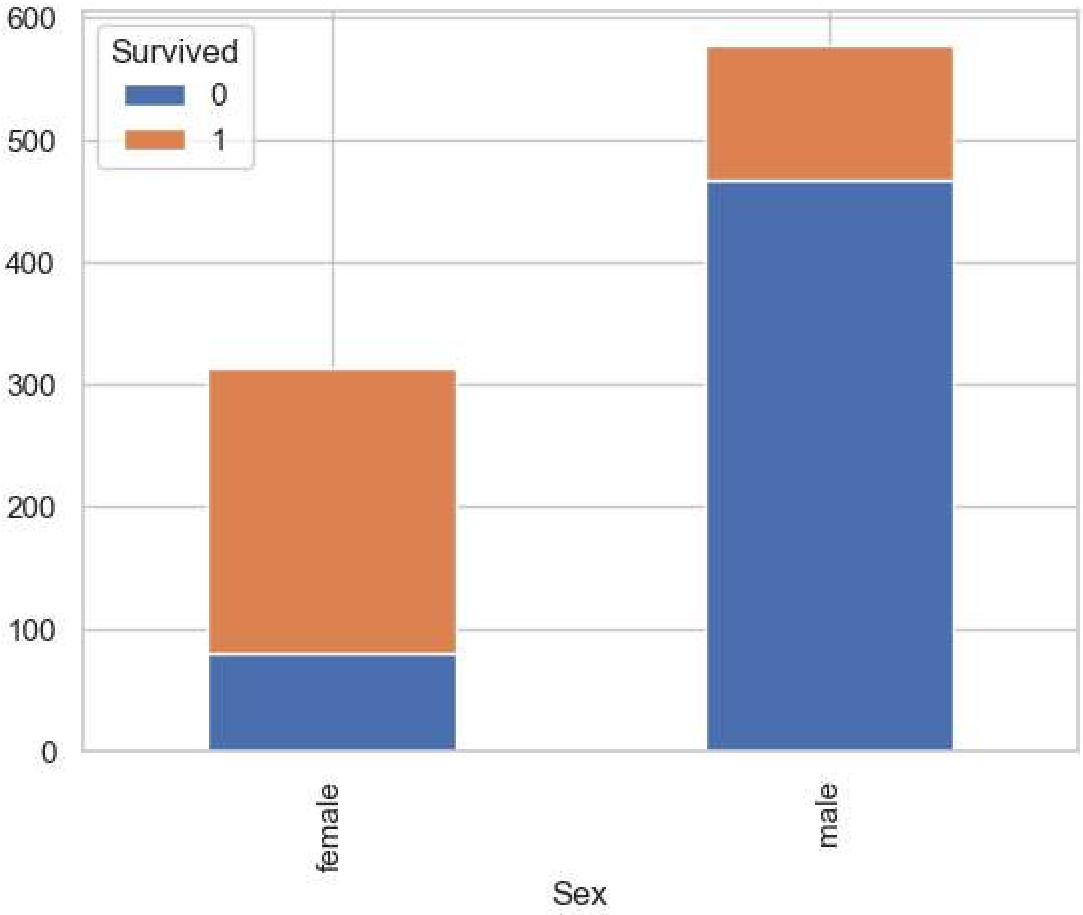
In [71]:

```
sns.countplot(data=train_df, x='Survived', hue='Sex')
plt.title("Survival by Sex")
plt.show()
```



```
In [75]: pd.crosstab(train_df['Sex'], train_df['Survived']).plot(kind='bar', stacked=True)

Out[75]: <Axes: xlabel='Sex'>
```

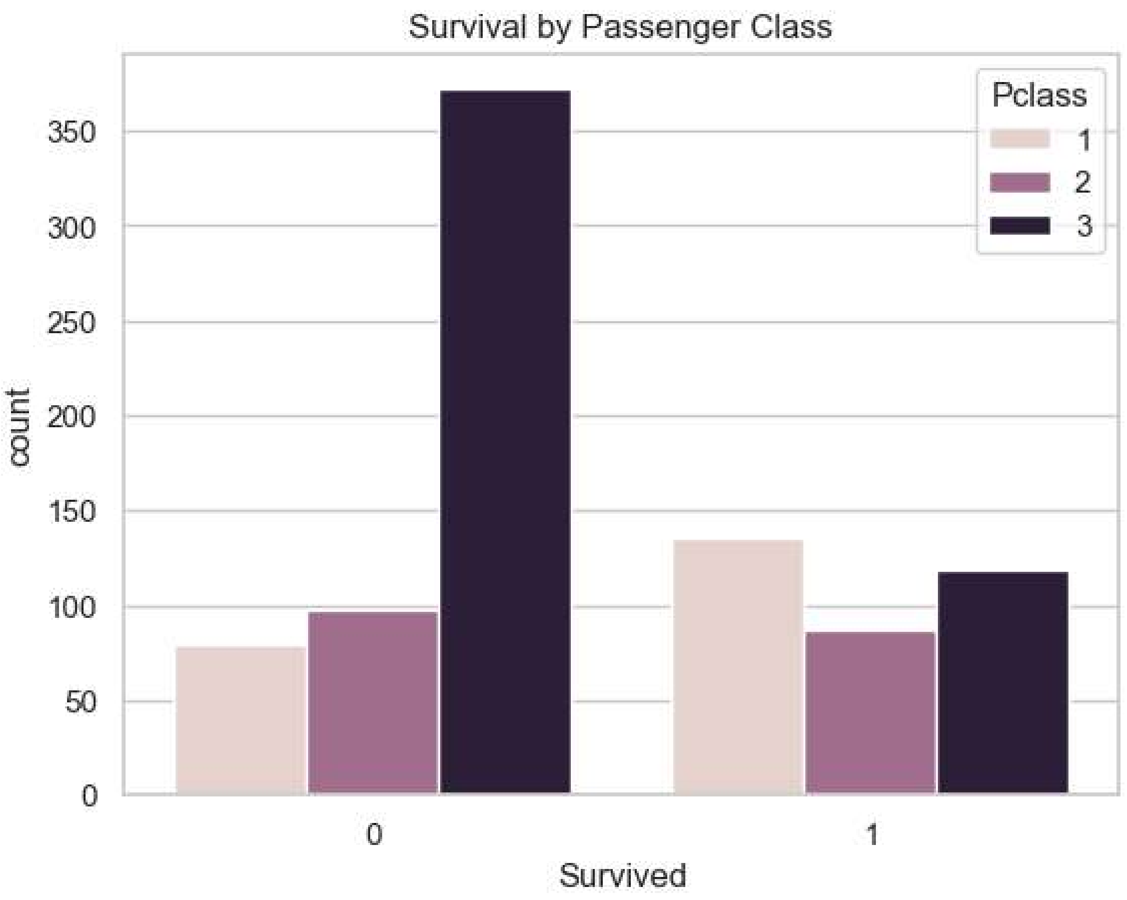


In [ ]:

```
Females had a higher survival rate than males.
```

In [76]:

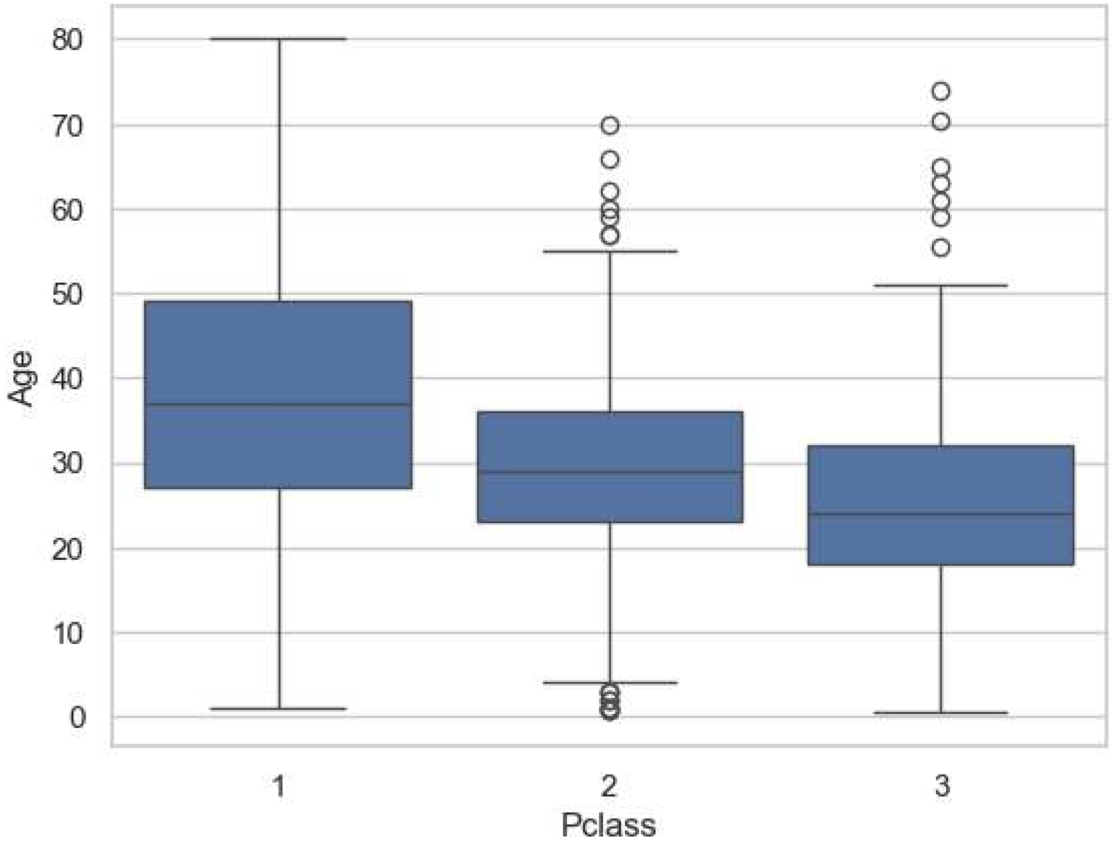
```
sns.countplot(x='Survived', hue='Pclass', data=train_df)
plt.title("Survival by Passenger Class")
plt.show()
```



Survival by Passenger Class

```
In [77]: sns.boxplot(x='Pclass', y='Age', data=train_df)
```

```
Out[77]: <Axes: xlabel='Pclass', ylabel='Age'>
```

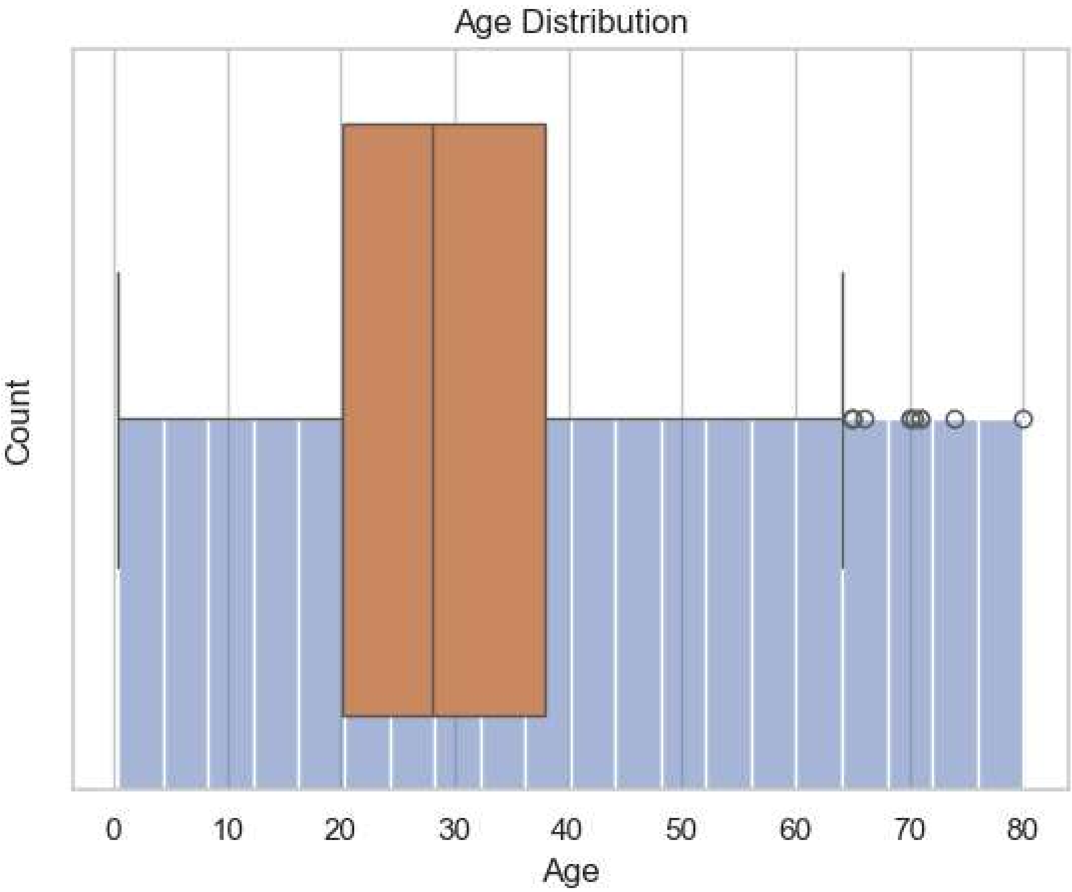


In [78]:

```
sns.histplot(data=train_df['Age'].dropna(), kde=True)
plt.title("Age Distribution")
sns.boxplot(x='Age', data=train_df)
```

Out[78]:

```
<Axes: title={'center': 'Age Distribution'}, xlabel='Age', ylabel='Count'>
```

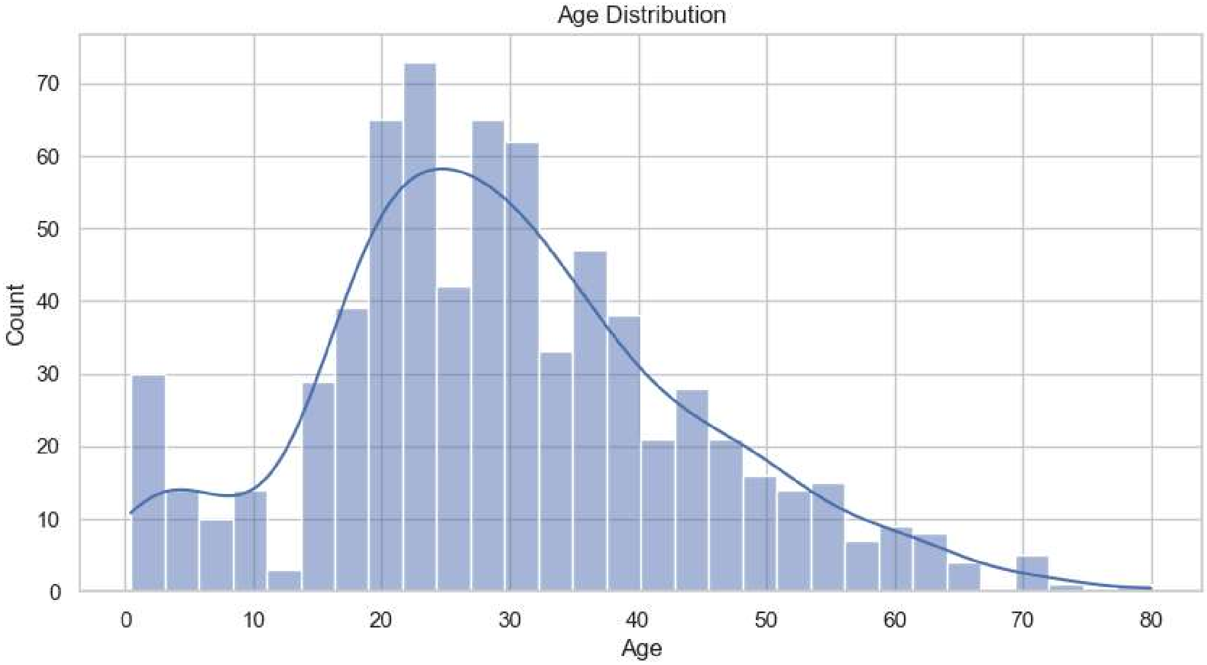


In [ ]:

```
Most passengers were between 20-40 years old. There are outliers present in the Age
```

In [80]:

```python
plt.figure(figsize=(10,5))
sns.histplot(train_df['Age'].dropna(), bins=30, kde=True)
plt.title("Age Distribution")
plt.show()
```



In [81]:

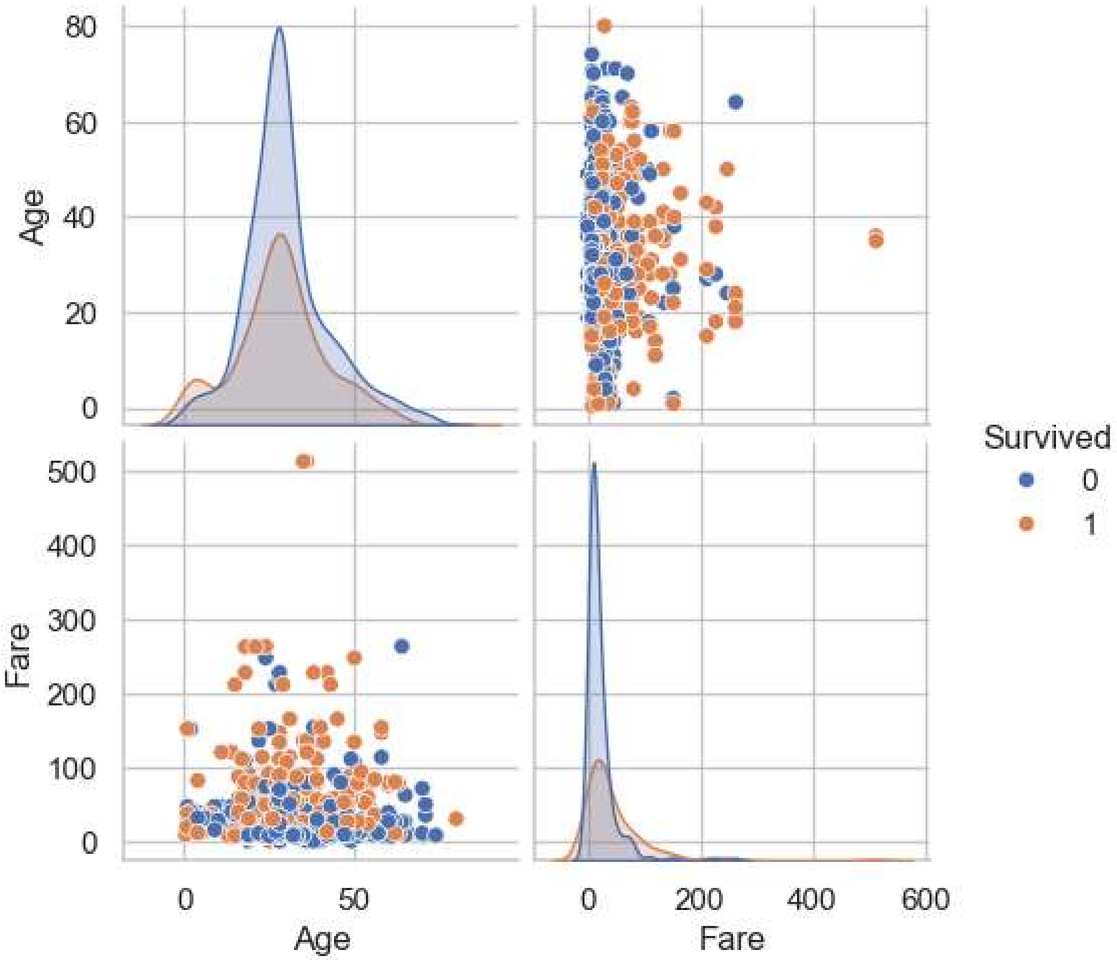
```
if 'Embarked' in train_df.columns:
    train_df['Embarked'] = train_df['Embarked'].fillna(train_df['Embarked'].mode()[
if 'Age' in train_df.columns:
    train_df['Age'] = train_df['Age'].fillna(train_df['Age'].median())
if 'Cabin' in train_df.columns:
    train_df.drop('Cabin', axis=1, inplace=True)
```

In [82]:

```
sns.pairplot(train_df[['Age', 'Fare', 'Survived']], hue='Survived')
```

Out[82]:

```
<seaborn.axisgrid.PairGrid at 0x22fa45e80b0>
```



In [84]:

```
non_numeric_cols = train_df.select_dtypes(include=['object']).columns
correlation_df = train_df.drop(columns=non_numeric_cols)
```

In [85]:

```
train_df['Sex'] = train_df['Sex'].map({'male': 0, 'female': 1}) # Convert 'Sex' to
```

In [86]:

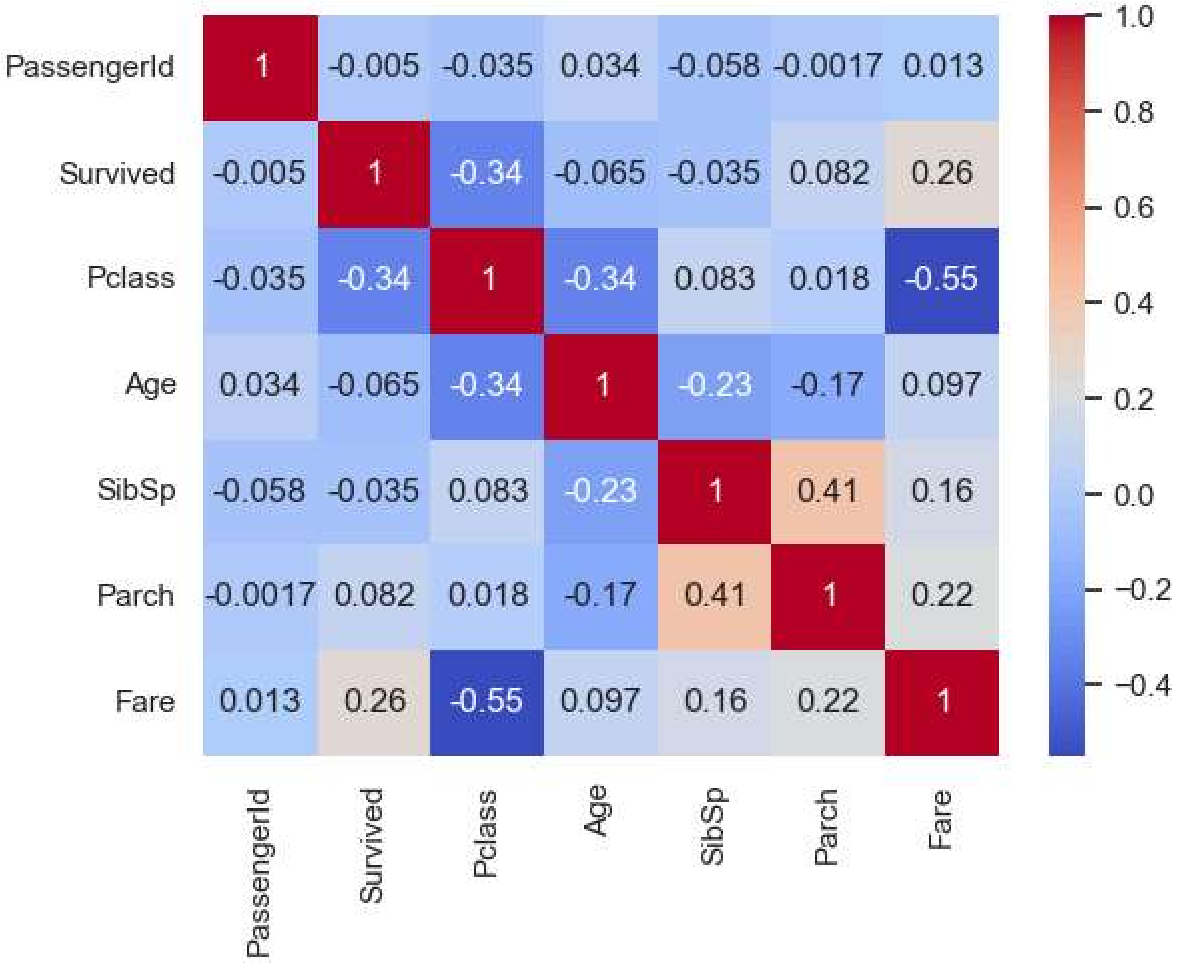
```
train_df = pd.get_dummies(train_df, columns=['Embarked'], drop_first=True) # One-ho
```

In [87]:

```
sns.heatmap(correlation_df.corr(), annot=True, cmap='coolwarm')
```

Out[87]:

```
<Axes: >
```



In [ ]:

```
Fare is positively correlated with survival, while Pclass is negatively correlated.
```

In [88]:

```
print("\n--- TEST CASES ---")
print("Test 1 - No missing Age values:", train_df['Age'].isnull().sum() == 0)
print("Test 2 - No missing Embarked values:", train_df['Embarked_Q'].isnull().sum()
print("Test 3 - Sex mapped correctly (0 and 1 only):", set(train_df['Sex'].unique()
print("Test 4 - Cabin column removed:", 'Cabin' not in train_df.columns)
print("Test 5 - Dummy variables created:", 'Embarked_Q' in train_df.columns and 'Em
```

```
--- TEST CASES ---
Test 1 - No missing Age values: True
Test 2 - No missing Embarked values: True
Test 3 - Sex mapped correctly (0 and 1 only): True
Test 4 - Cabin column removed: True
Test 5 - Dummy variables created: True
```

In [90]:

```
X = train_df[['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Embarked_Q', 'Emba
y = train_df['Survived']
```

In [91]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [92]:

```
model = LogisticRegression(max_iter=200)
model.fit(X_train, y_train)
predictions = model.predict(X_test)
```

In [93]:
```
print("\n--- Model Evaluation ---")
print("Accuracy:", accuracy_score(y_test, predictions))
print("\nConfusion Matrix:\n", confusion_matrix(y_test, predictions))
print("\nClassification Report:\n", classification_report(y_test, predictions))
```

```
--- Model Evaluation ---
Accuracy: 0.8100558659217877

Confusion Matrix:
 [[90 15]
 [19 55]]

Classification Report:
               precision    recall  f1-score   support

           0       0.83      0.86      0.84       105
           1       0.79      0.74      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
```

In [94]:
```
# 10. Summary of Findings
print("\n--- Summary of Findings ---")
print("\nPatterns Observed:")
print("- Majority of passengers were in 3rd class.")
print("- More males were on board than females.")
print("- Most survivors were women and children.")

print("\nImportant Relationships:")
print("- 'Sex' and 'Survived' are strongly related. Females had a higher survival r
print("- 'Pclass' and 'Survived' show that higher class passengers were more likely
print("- Higher 'Fare' values also corresponded with higher survival rates.")

print("\nAnomalies Detected:")
print("- Missing values were found in 'Age', 'Embarked', and 'Cabin'.")
print("- The 'Cabin' feature was dropped due to excessive missing data.")

print("\nFinal Thoughts:")
print("- Logistic Regression provides a decent baseline model for predicting surviv
print("- Further model improvement could involve feature engineering or ensemble mo
--- Summary of Findings ---

Patterns Observed:
- Majority of passengers were in 3rd class.
- More males were on board than females.
- Most survivors were women and children.

Important Relationships:
- 'Sex' and 'Survived' are strongly related. Females had a higher survival rate.
- 'Pclass' and 'Survived' show that higher class passengers were more likely to surv
ive.
- Higher 'Fare' values also corresponded with higher survival rates.

Anomalies Detected:
- Missing values were found in 'Age', 'Embarked', and 'Cabin'.
- The 'Cabin' feature was dropped due to excessive missing data.

Final Thoughts:
- Logistic Regression provides a decent baseline model for predicting survival.
- Further model improvement could involve feature engineering or ensemble models.
```

In [ ]: