In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns# To show graphs inside notebook
%matplotlib inline

# Set a nice style for graphs
sns.set(style="whitegrid")
```

In [3]:
```
#load dataset
df = pd.read_csv('titanic.csv')
```

In [4]:
```
#to show top 5 rows
df.head()
```

Out[4]:

	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 [6]:
```
#to know count of columns and rows
df.shape
```

Out[6]:
```
(891, 12)
```

In [7]:
```
df.info()
```

```
<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
```

In [8]:
```
#to know overview of data for numerical columns
df.describe()
```

Out[8]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [9]:
```
# to know missing values
df.isnull().sum()
```

Out[9]:
```
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
```

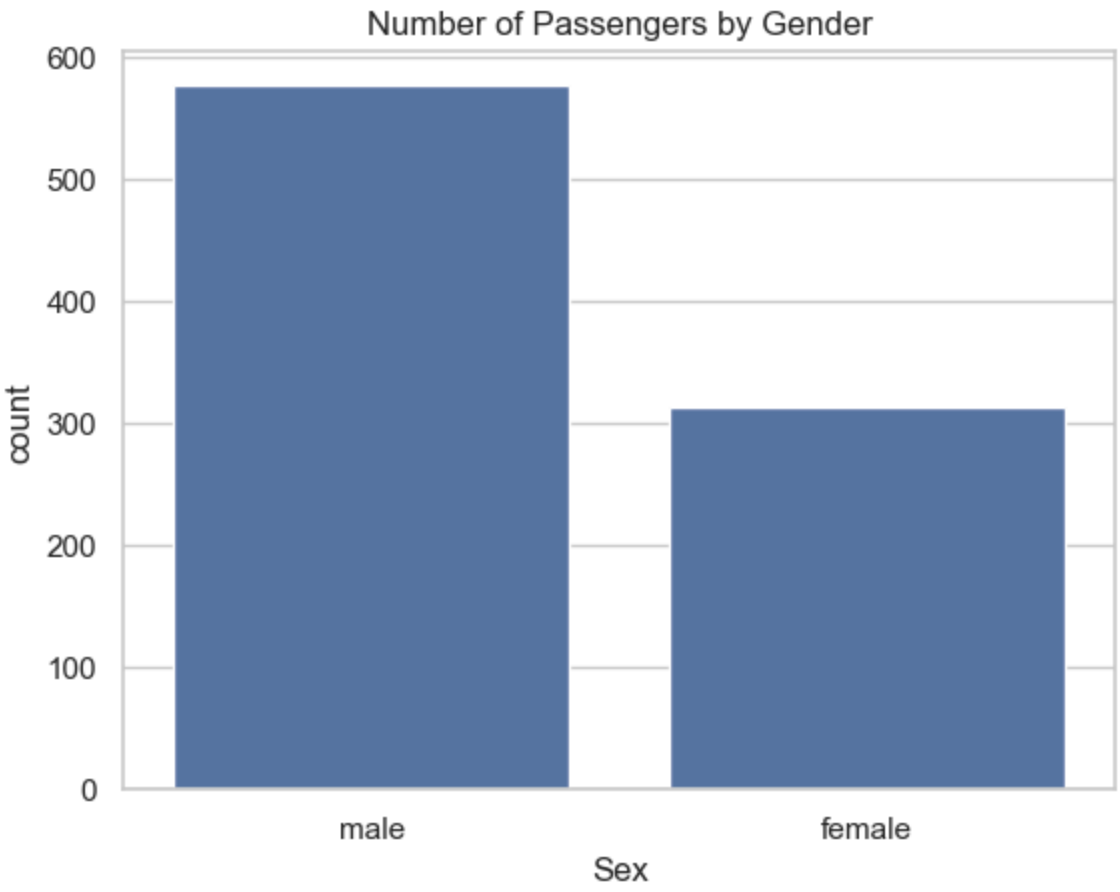
In [11]:
```
#fill the missing values
df['Age'] = df['Age'].fillna(df['Age'].median())
```

In [12]:
```
df['Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0])
df.drop('Cabin', axis=1, inplace=True)
```

In [13]:
```
#know categorical data summary
print(df['Sex'].value_counts())        # Count males and females
print(df['Pclass'].value_counts())     # Count passengers by class (1, 2, 3)
print(df['Embarked'].value_counts())   # Count passengers by port (C, Q, S)
print(df['Survived'].value_counts())   # Count survived vs not survived
```

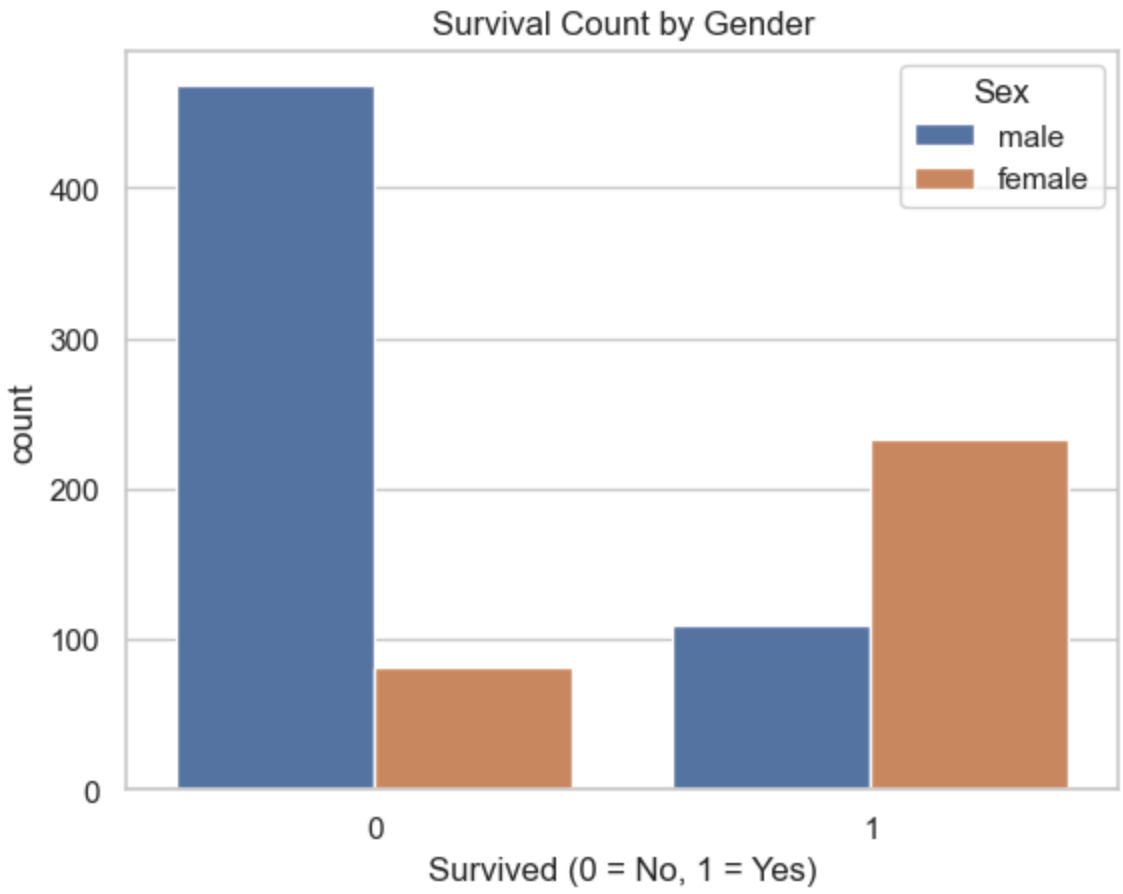
```
Sex
male      577
female    314
Name: count, dtype: int64
Pclass
3    491
1    216
2    184
Name: count, dtype: int64
Embarked
S    646
C    168
Q     77
Name: count, dtype: int64
Survived
0    549
1    342
Name: count, dtype: int64
```

In [14]:
```
#visualize the males and female count
sns.countplot(x='Sex', data=df)
plt.title('Number of Passengers by Gender')
plt.show()
```



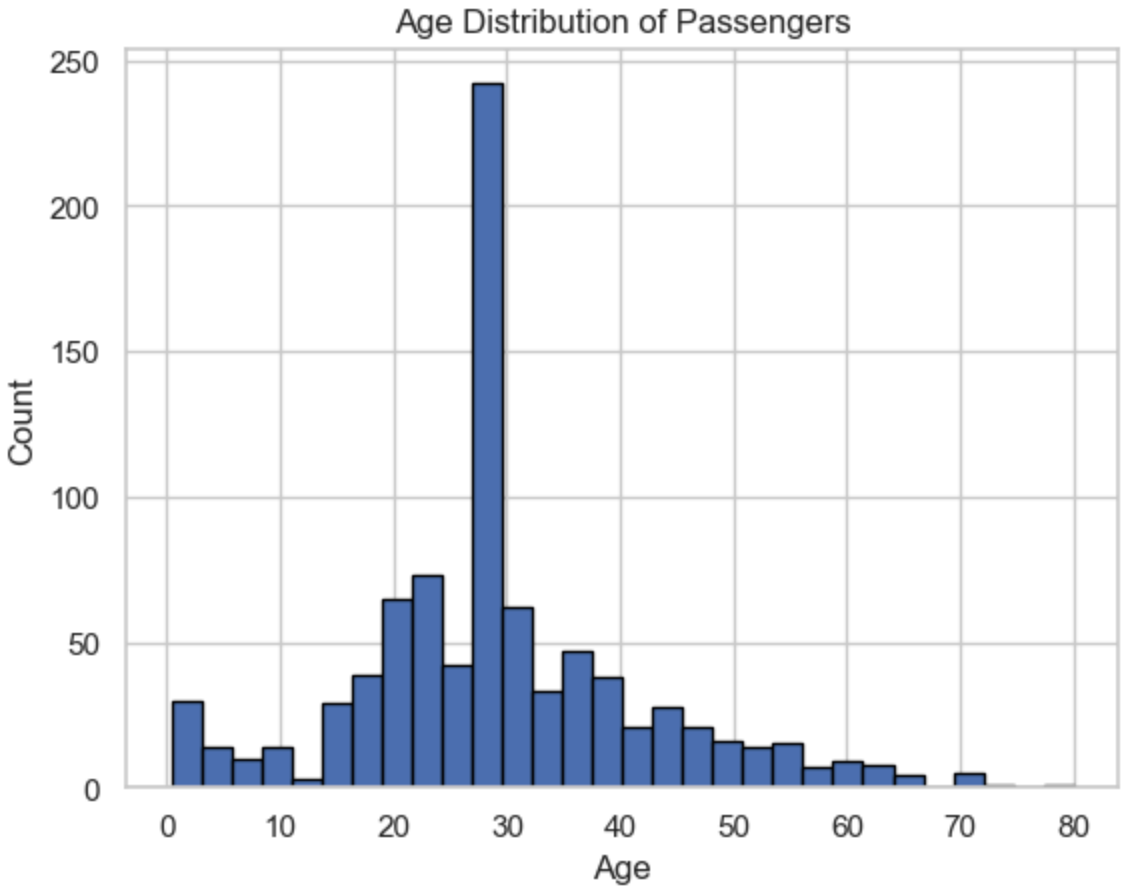
In [ ]:
```
### Observation: Number of Passengers by Gender

- The dataset contains **more male passengers** than female passengers.
- This imbalance in gender may have influenced overall survival statistics.
- It also helps explain why gender-specific survival analysis is important in the T
```

In [15]:
```
#visualize surival count
sns.countplot(x='Survived', hue='Sex', data=df)
plt.title('Survival Count by Gender')
plt.xlabel('Survived (0 = No, 1 = Yes)')
plt.show()
```



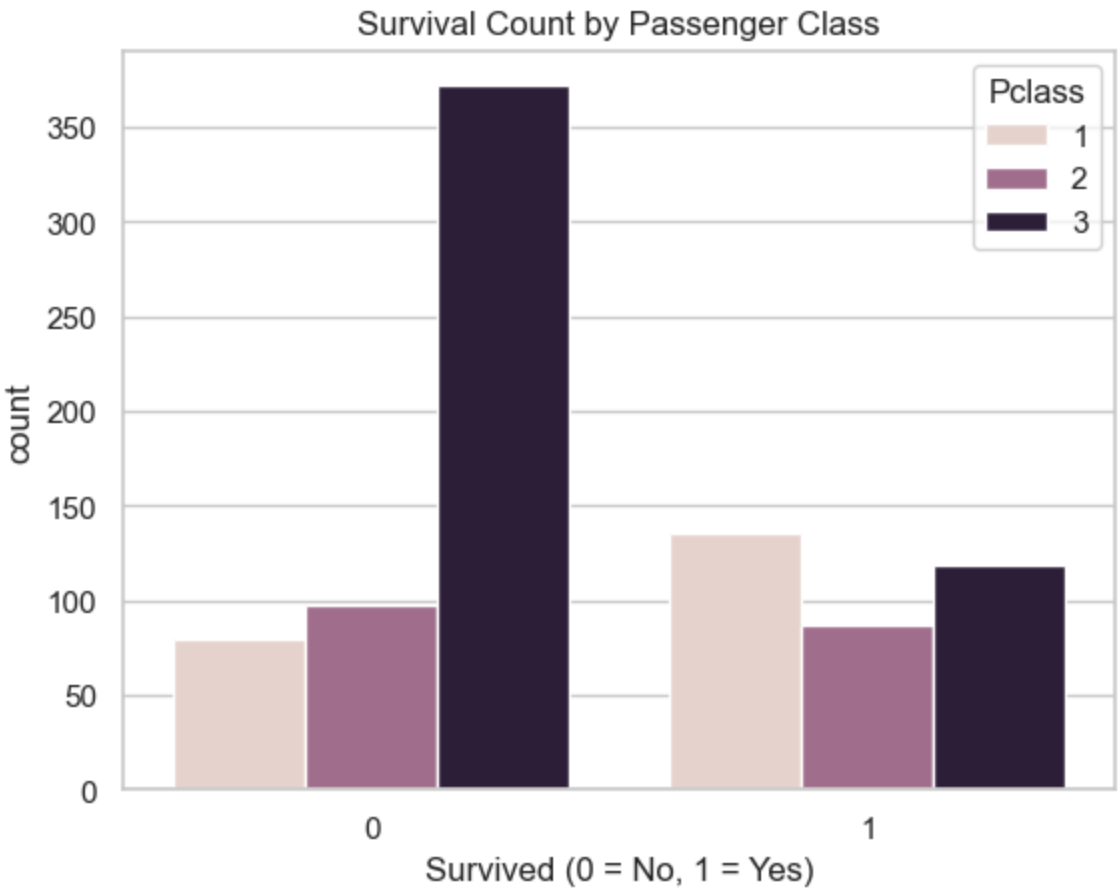
In [ ]:
```
### Observation: Survival Count by Gender

- **Females had a significantly higher survival rate** compared to males.
- The majority of **male passengers did not survive**, whereas most female passenge
- This suggests that **women were given priority** during rescue efforts, aligning
```

In [16]:
```
#visualize the age distribution
df['Age'].hist(bins=30, edgecolor='black')
plt.title('Age Distribution of Passengers')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```



In [ ]:
```
### Observation: Age Distribution of Passengers

- The age distribution is slightly **right-skewed**, with more passengers in the yo
- The majority of passengers were between **20 and 40 years old**.
- There are fewer very young children and elderly passengers.
- This distribution helps us understand the overall age composition of the people a
```

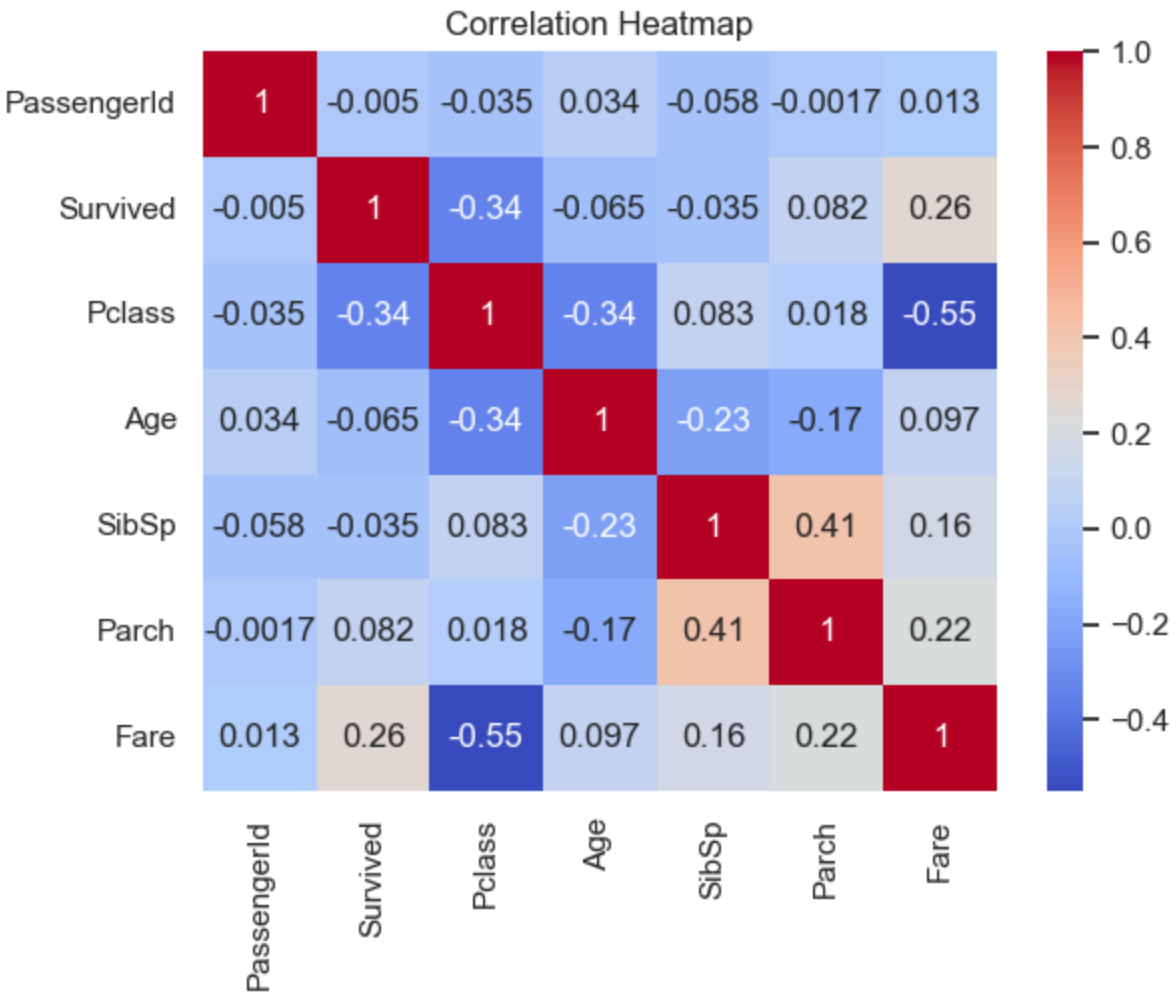
In [17]:
```
#survival count by passenger class
sns.countplot(x='Survived', hue='Pclass', data=df)
plt.title('Survival Count by Passenger Class')
plt.xlabel('Survived (0 = No, 1 = Yes)')
plt.show()
```



In [ ]:
```
### Observation: Survival by Passenger Class
- Passengers in 1st class had a much higher survival rate.
- 3rd class passengers had the lowest survival rate.
```

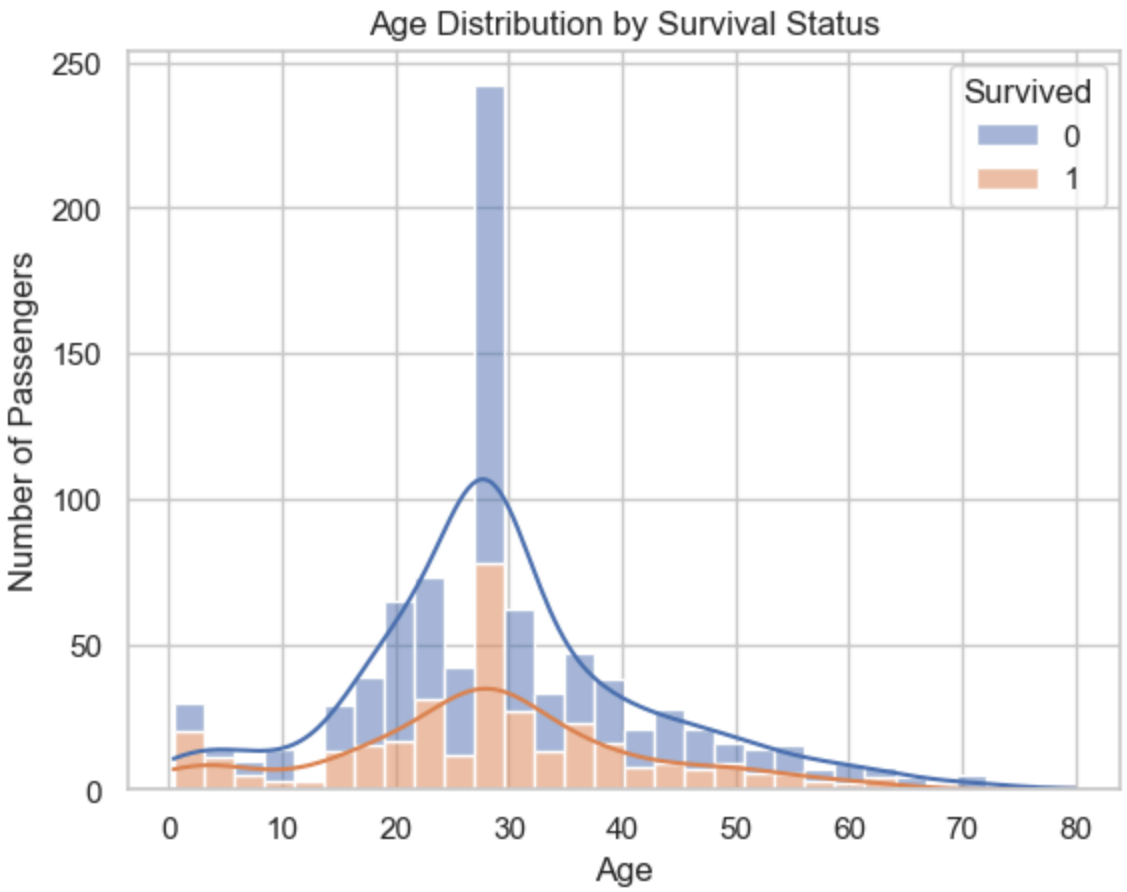
In [21]:
```
#Select only numeric columns and calculate their correlation matrix
corr = df.select_dtypes(include=['number']).corr()
```

In [22]:
```
#visualize  correlarion heatmap
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



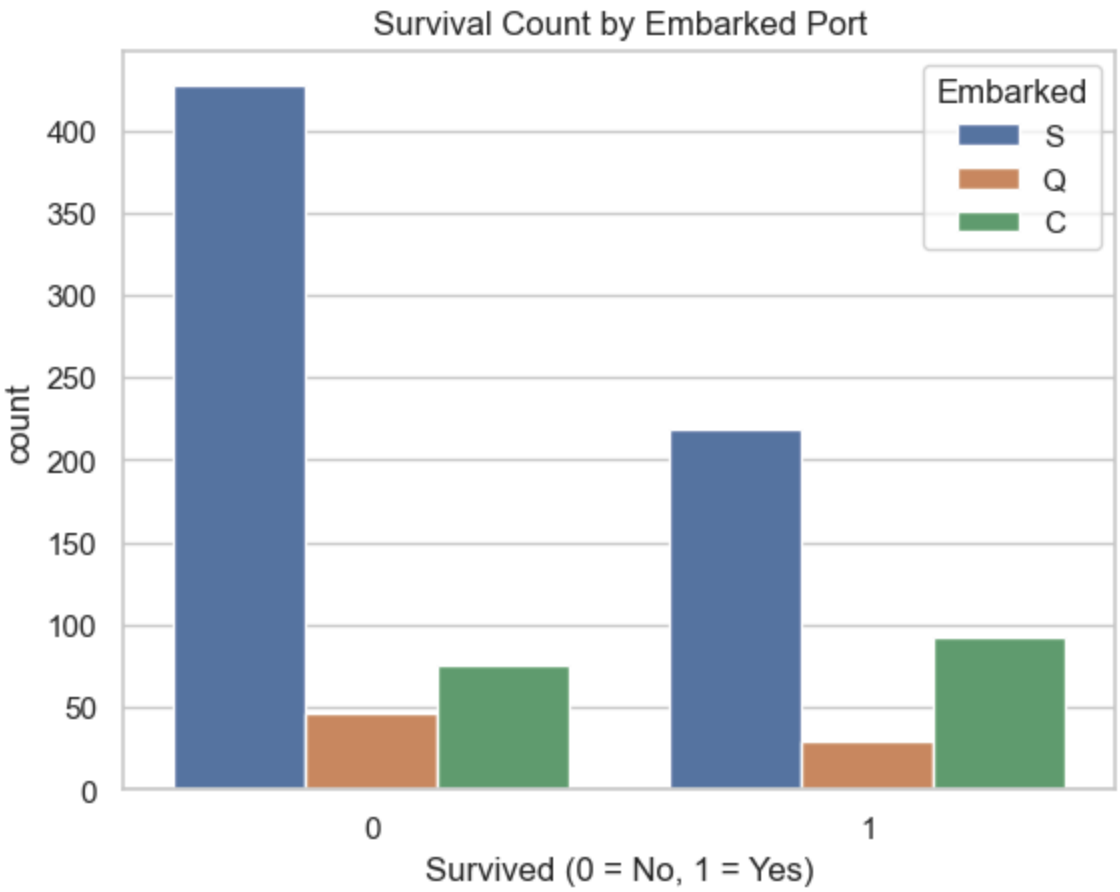
In [ ]:
```
### Observation: Correlation Heatmap

- The heatmap shows the strength and direction of relationships between numerical f
- **Pclass** and **Fare** have a moderate negative correlation, meaning higher clas
- **Age** shows weak correlation with other features.
- **Survived** correlates positively with **Fare** and negatively with **Pclass**,
```

In [37]:
```
sns.histplot(data=df, x='Age', hue='Survived', multiple='stack', kde=True)
plt.title('Age Distribution by Survival Status')
plt.xlabel('Age')
plt.ylabel('Number of Passengers')
plt.show()
```



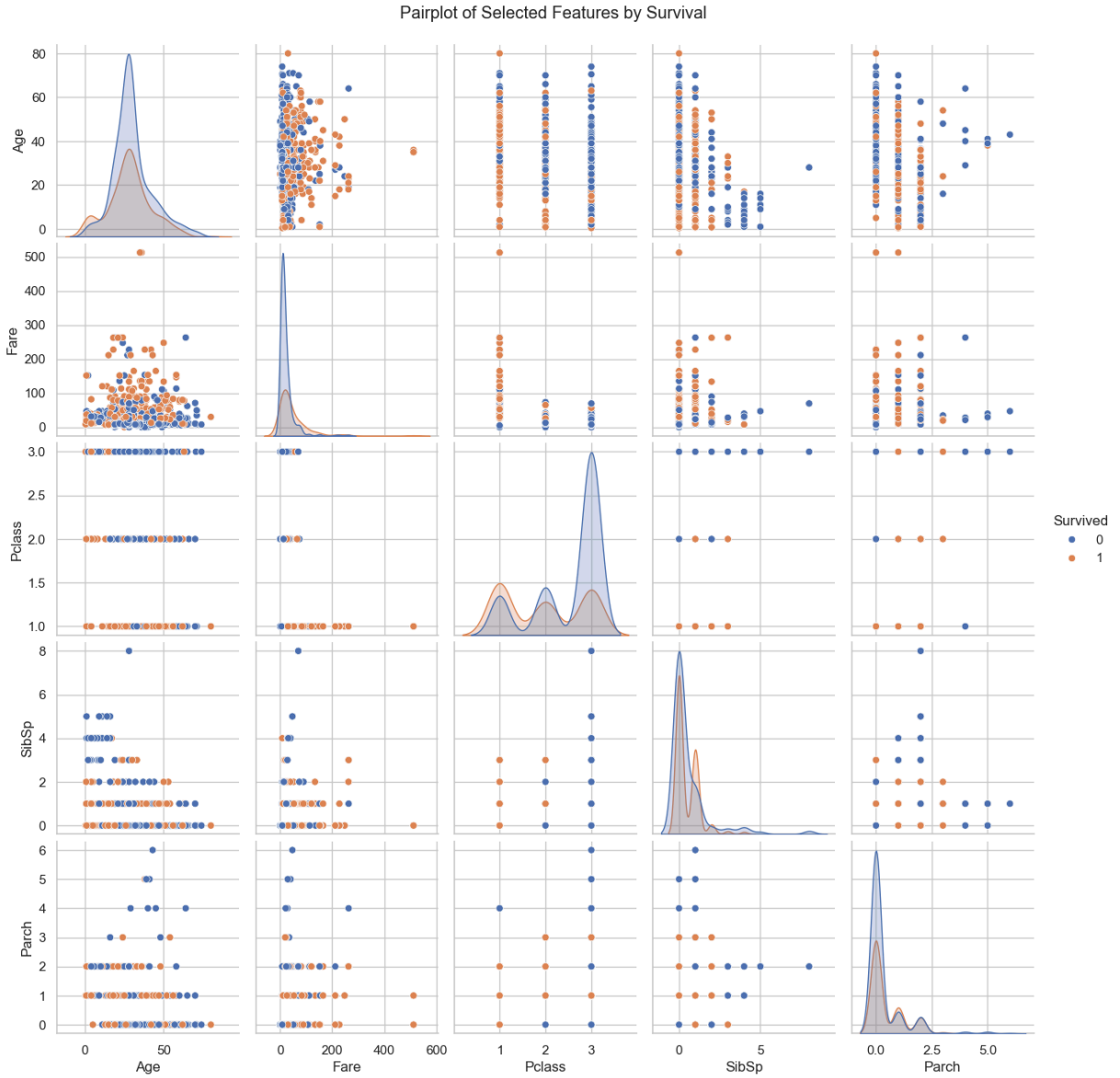
In [ ]:
```
### Observation: Age Distribution by Survival Status

- The plot shows how age varies between survivors and non-survivors.
- **Younger passengers**, especially children, had higher survival rates.
- Many non-survivors are in the **young adult to middle-aged groups**.
- The kernel density estimate (KDE) lines confirm that survival probability was hig
```

In [24]:
```
#Plot survival count by Embarked port
sns.countplot(x='Survived', hue='Embarked', data=df)
plt.title('Survival Count by Embarked Port')
plt.xlabel('Survived (0 = No, 1 = Yes)')
plt.show()
```



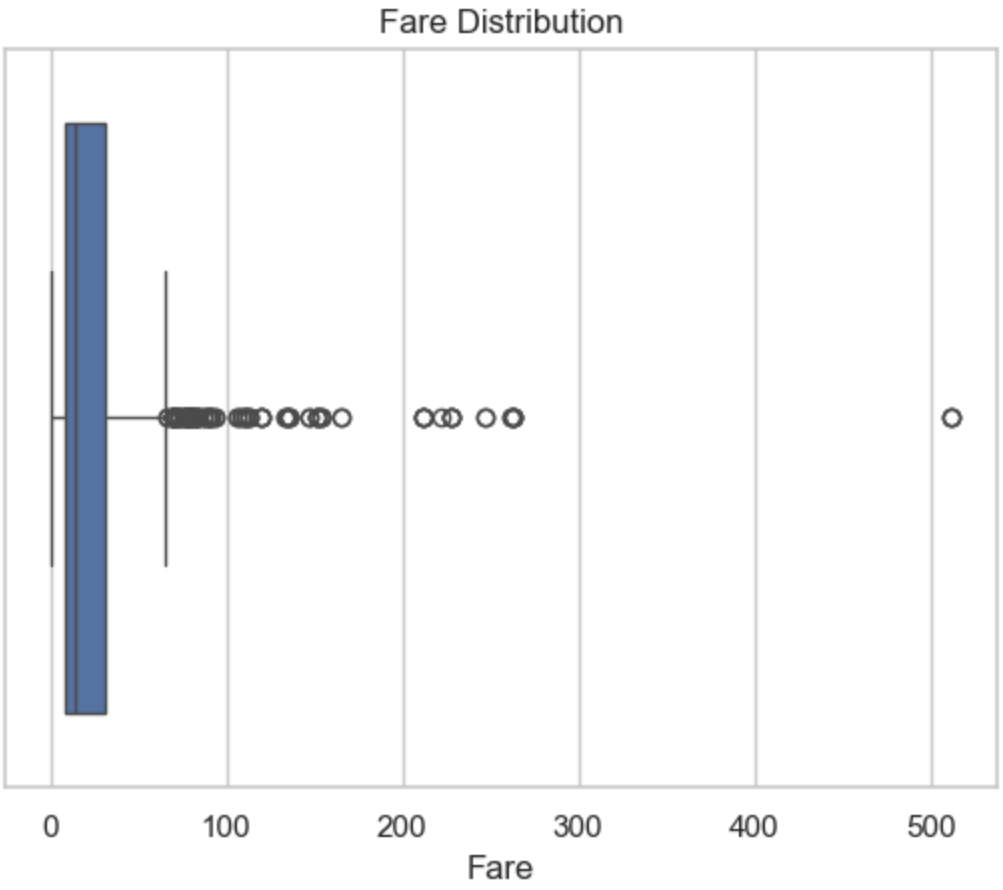
In [ ]:
```
### Observation: Survival by Port of Embarkation

- Most passengers boarded from port **S (Southampton)**.
- Passengers who boarded from port **C (Cherbourg)** had a **higher survival rate**
- Passengers from **port Q (Queenstown)** had the lowest survival rate.
- This may be related to the socio-economic background of passengers from each port
```

In [36]:
```
sns.pairplot(df, hue='Survived', vars=['Age', 'Fare', 'Pclass', 'SibSp', 'Parch'])
plt.suptitle('Pairplot of Selected Features by Survival', y=1.02)  # Title above th
plt.show()
```



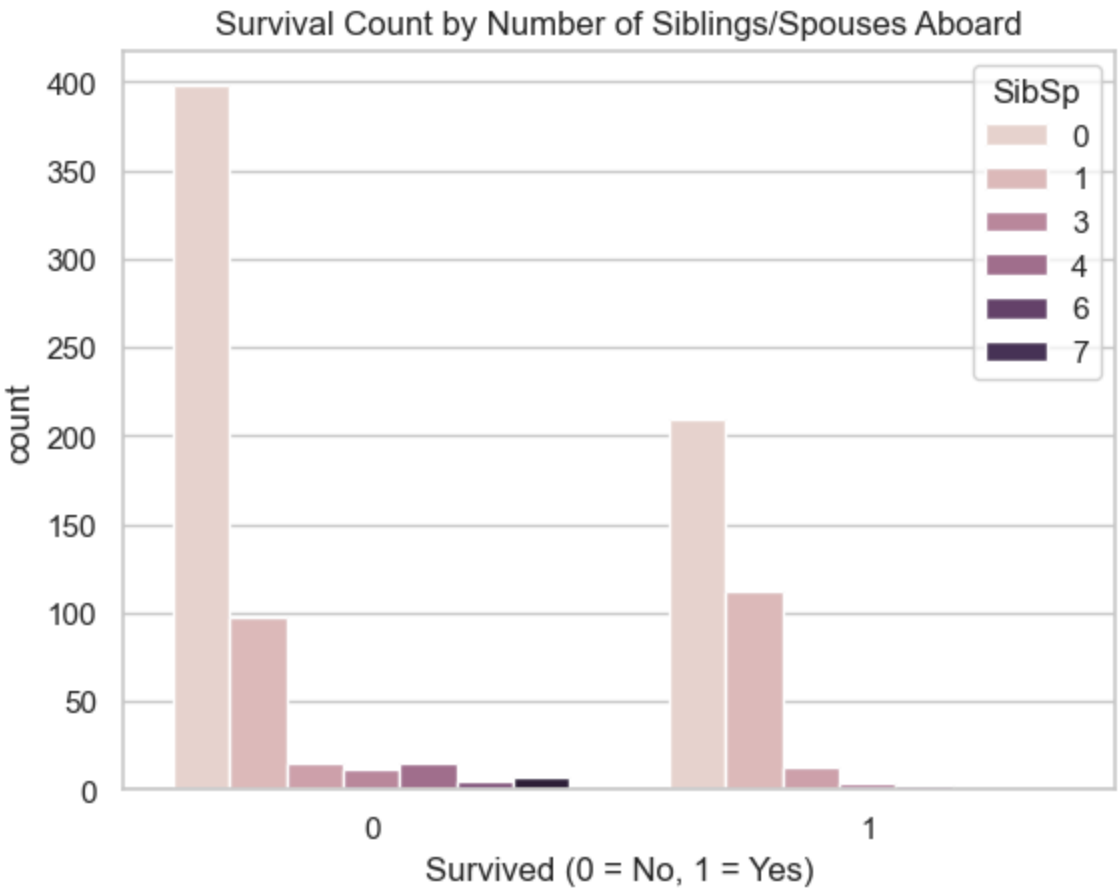
In [ ]:
```
### Observation: Pairplot of Selected Features by Survival

- **Survivors and non-survivors** show clear differences in Fare and Pclass.
- Higher survival is associated with **higher fares** and **lower Pclass** (1st cla
- There is no strong visible separation by Age alone, but some trends can be seen.
- The plot helps identify patterns and clusters in relation to survival status.
```

In [27]:
```
# Plot a boxplot to visualize the distribution of the 'Fare' column
# This helps identify the spread and any outliers (extremely high or low fares)
sns.boxplot(x='Fare', data=df)
plt.title('Fare Distribution')
plt.show()
```



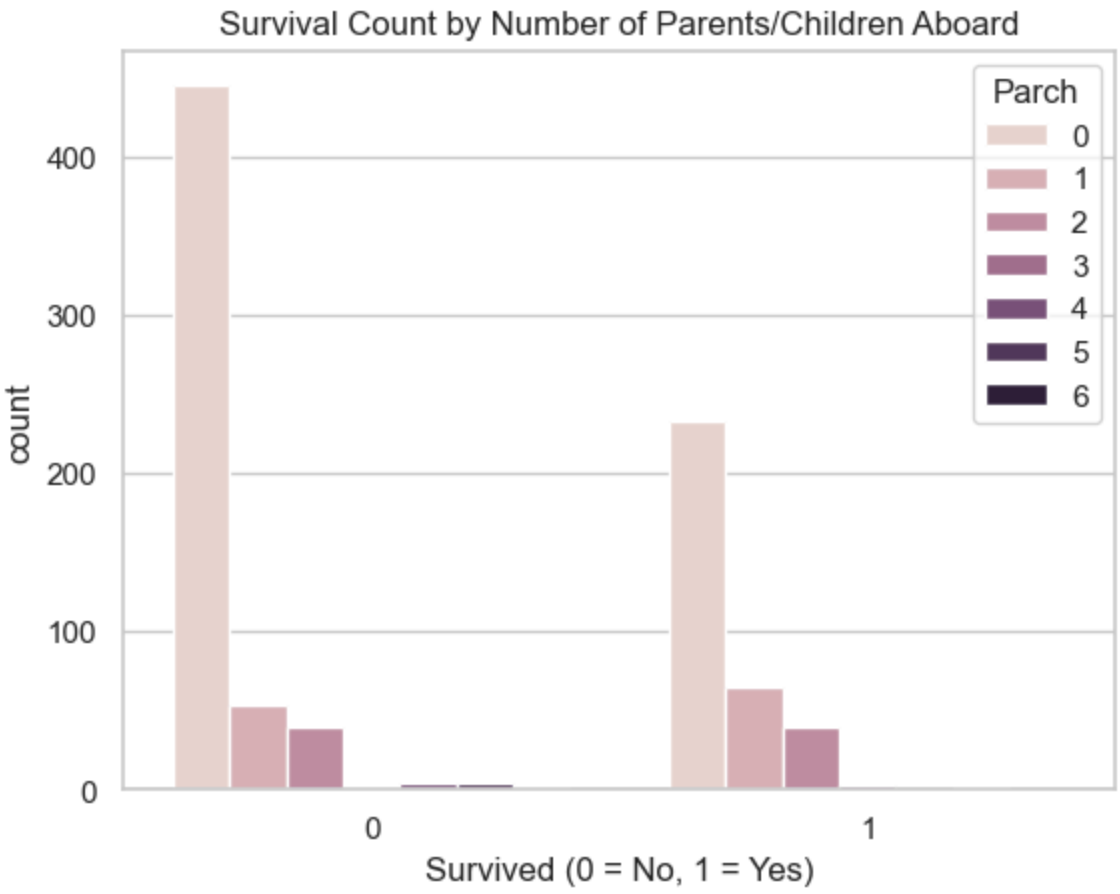
In [ ]:
```
### Observation: Fare Distribution (Boxplot)

- The boxplot shows that the majority of passengers paid fares under **100 units**.
- There are several **outliers** with very high fares, indicating a few passengers
- The distribution is **right-skewed**, meaning most passengers paid lower fares wh
- This could reflect differences in class or cabin quality (e.g., 1st class vs. 3rd
```

In [32]:
```
sns.countplot(x='Survived', hue='SibSp', data=df)
plt.title('Survival Count by Number of Siblings/Spouses Aboard')
plt.xlabel('Survived (0 = No, 1 = Yes)')
plt.show()
```



In [ ]:
```
### Observation: Survival by SibSp
- Passengers with 1 or 2 siblings/spouses had better survival rates.
- Having no one or too many family members may reduce survival chances.
```

In [34]:
```
sns.countplot(x='Survived', hue='Parch', data=df)
plt.title('Survival Count by Number of Parents/Children Aboard')
plt.xlabel('Survived (0 = No, 1 = Yes)')
plt.show()
```



In [ ]:
```
### Observation: Survival by Number of Parents/Children Aboard (Parch)

- Passengers with **1 to 3 parents or children aboard** had a higher chance of surv
- Those traveling **alone (Parch = 0)** had lower survival rates.
- Extremely high values of Parch (like 4, 5, or 6) were rare and mostly did not sur
- This suggests that having a small family group onboard may have positively influe
```

In [ ]:
```
##final_Summary
- Females had higher survival rates than males.
- 1st class passengers survived more than 2nd and 3rd class.
- Younger passengers, especially children, had better chances of survival.
- Higher fares were linked to higher survival.
- Smaller family groups had better survival rates.
- Survival varied by port of embarkation.
- Overall, gender, age, class, and fare strongly influenced survival.

This analysis helps understand key factors affecting Titanic survival.
```