In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
sns.set(style="whitegrid")
```

In [2]:
```
df = pd.read_csv('train.csv')
df.head()
```

Out[2]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

In [29]:
```
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          891 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     891 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

In [30]:
```
df.describe()
```

Out[30]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.361582	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	13.019697	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	22.000000	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	35.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [31]:
```
df.isnull().sum()
```

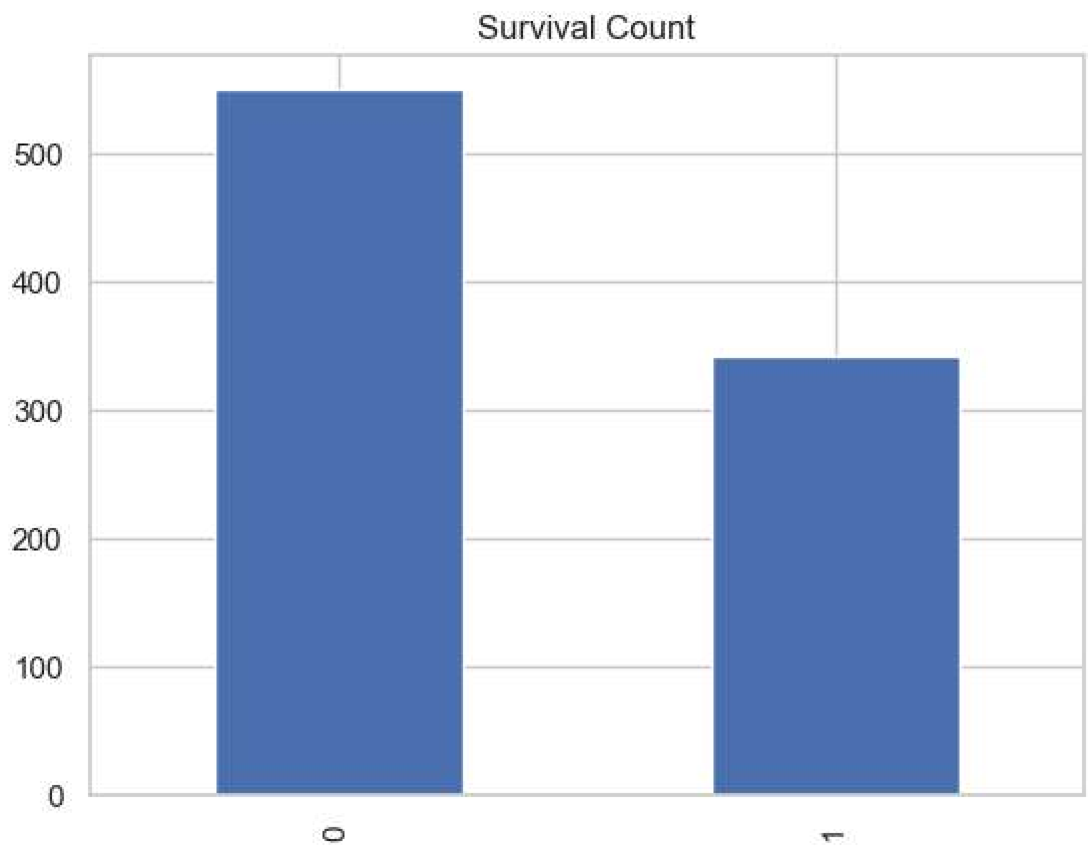
Out[31]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         0
dtype: int64
```

In [26]:
```
df['Survived'].value_counts().plot(kind='bar', title='Survival Count')

#Observation:

#The number of passengers who did not survive is higher than those who did. This indicates a survival rate of approxi
```

Out[26]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x211e27c2508>
```

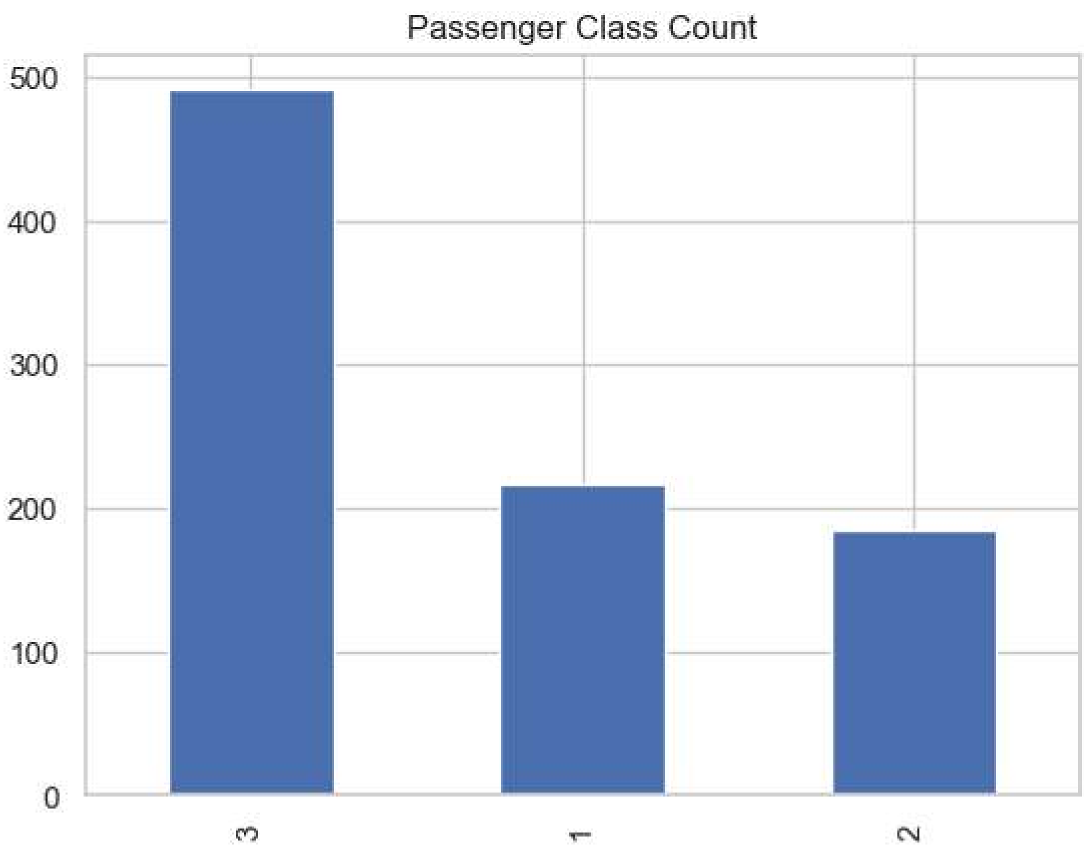


In [27]:
```
df['Pclass'].value_counts().plot(kind='bar', title='Passenger Class Count')

#Observation:

#Most passengers were in 3rd class, followed by 1st and 2nd class. This suggests that the Titanic carried more econon
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x211e282d3c8>

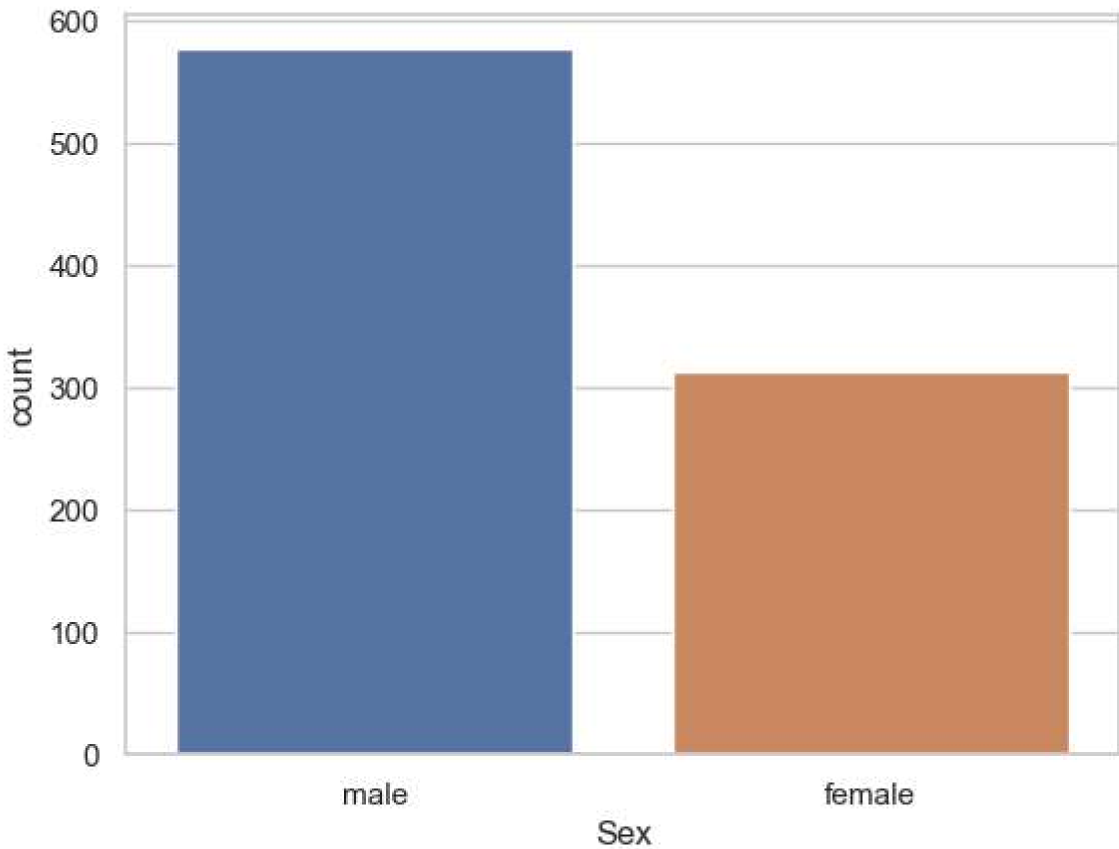


In [28]:
```
sns.countplot(data=df, x='Sex')

#Observation:

#There were more male passengers than female passengers on board.
```

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x211df8c7cc8>

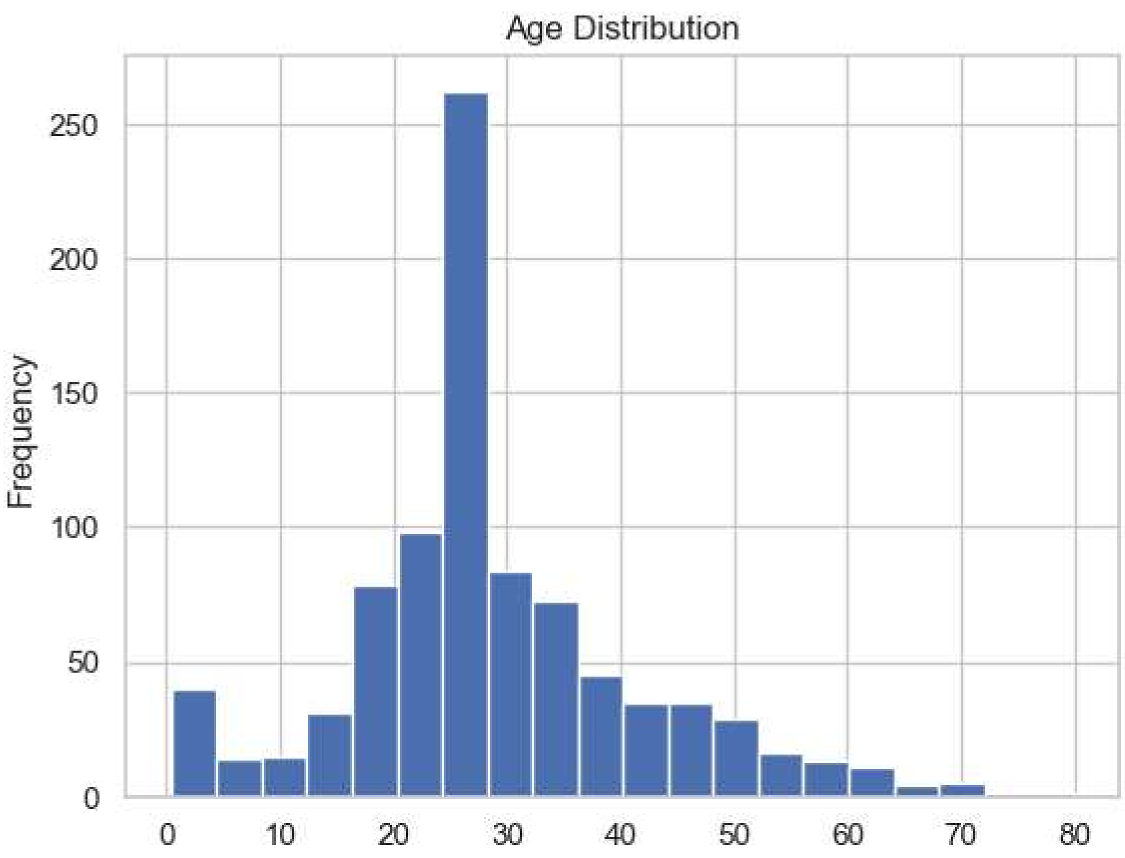


In [24]:
```
df['Age'].plot(kind='hist', bins=20, title='Age Distribution')

#Observation:

#The age distribution is right-skewed. Most passengers were between 20 and 40 years old. There were few infants and e
```

Out[24]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x211e1724888>
```

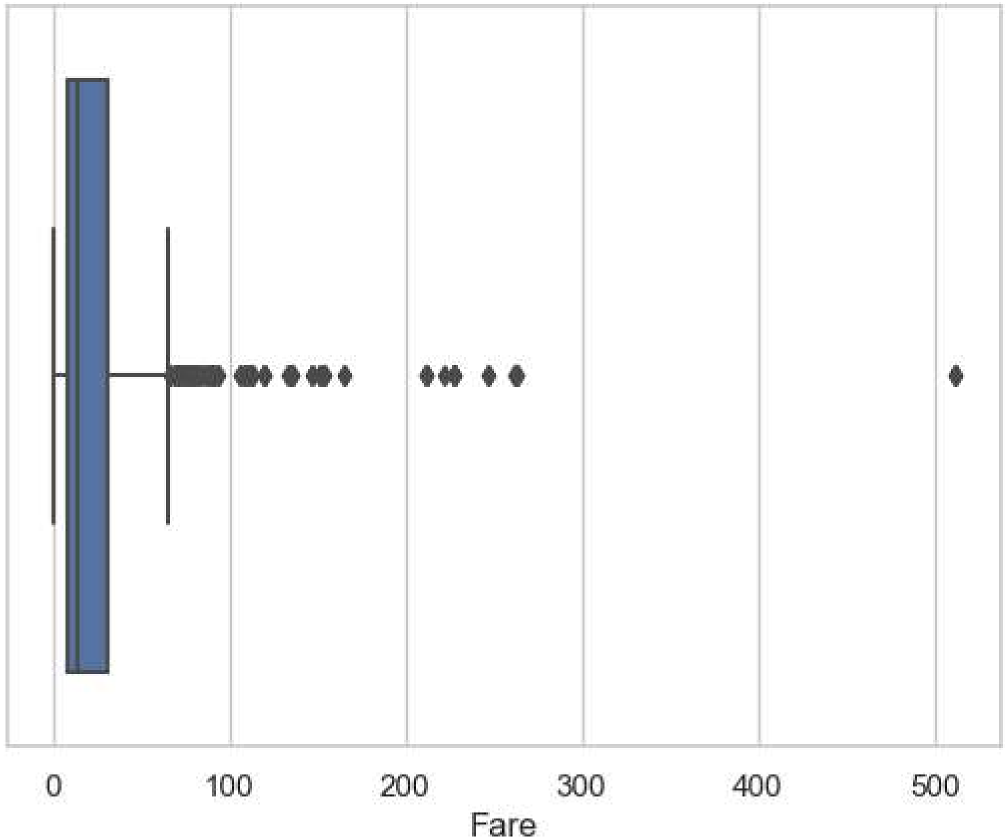


In [25]:
```
sns.boxplot(x='Fare', data=df)

#Observation:

#The fare distribution shows a lot of outliers. Most fares are below 100, but some go beyond 500, indicating premium-
```

Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x211e28ed1c8>

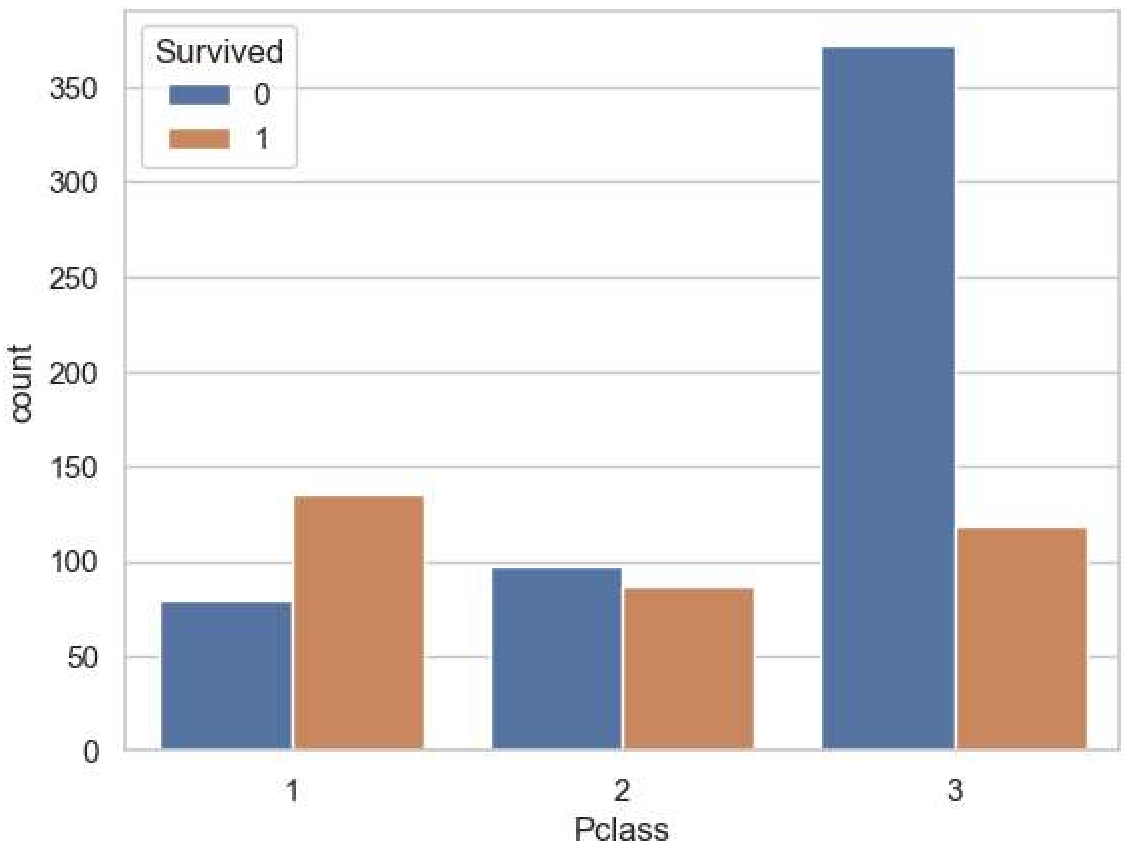


In [21]:
```
sns.countplot(data=df, x='Pclass', hue='Survived')

#Observation:

#Passengers in 1st class had the highest survival rate. Most passengers in 3rd class did not survive.
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x211e143b108>

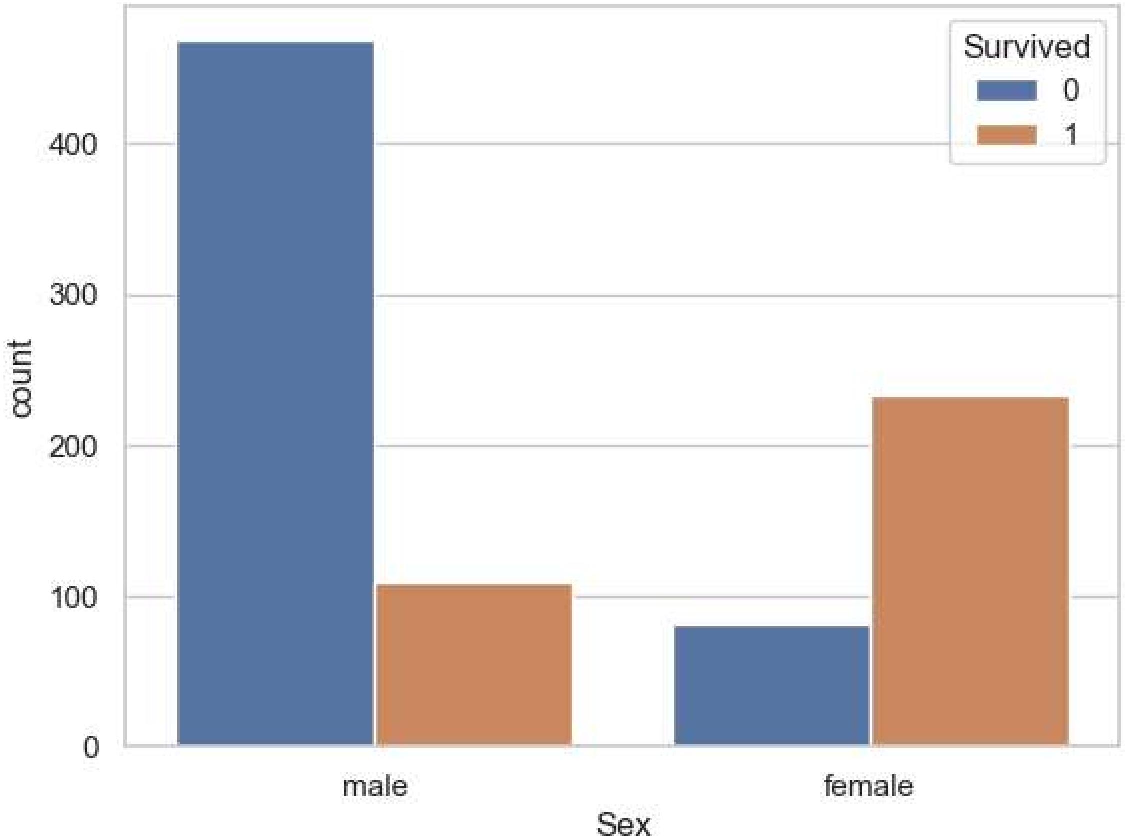


In [22]:
```
sns.countplot(data=df, x='Sex', hue='Survived')

#Observation:

#Female passengers had a significantly higher survival rate compared to males. "Women and children first" policy seem
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x211e166b0c8>

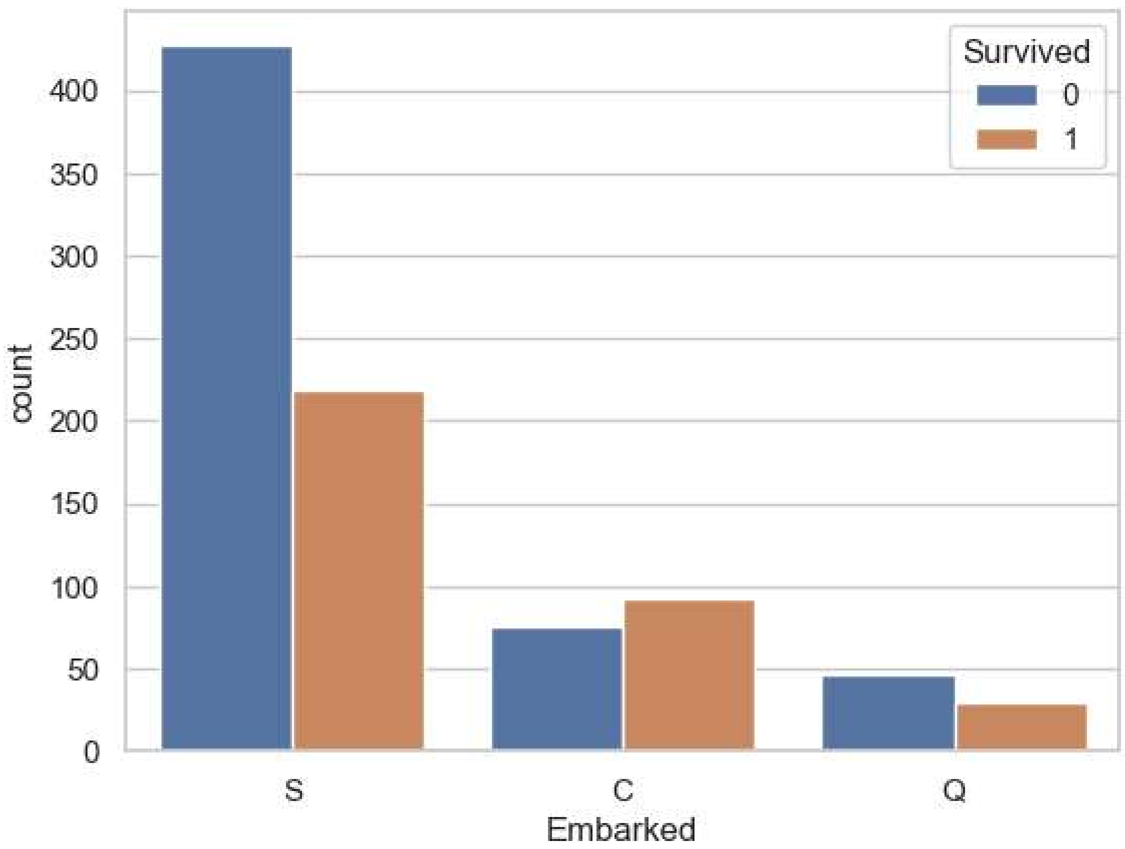


In [23]:
```
sns.countplot(data=df, x='Embarked', hue='Survived')

#Observation:

#Passengers who embarked from Cherbourg (C) had higher survival rates, possibly indicating more first-class travelers
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x211e16cec08>

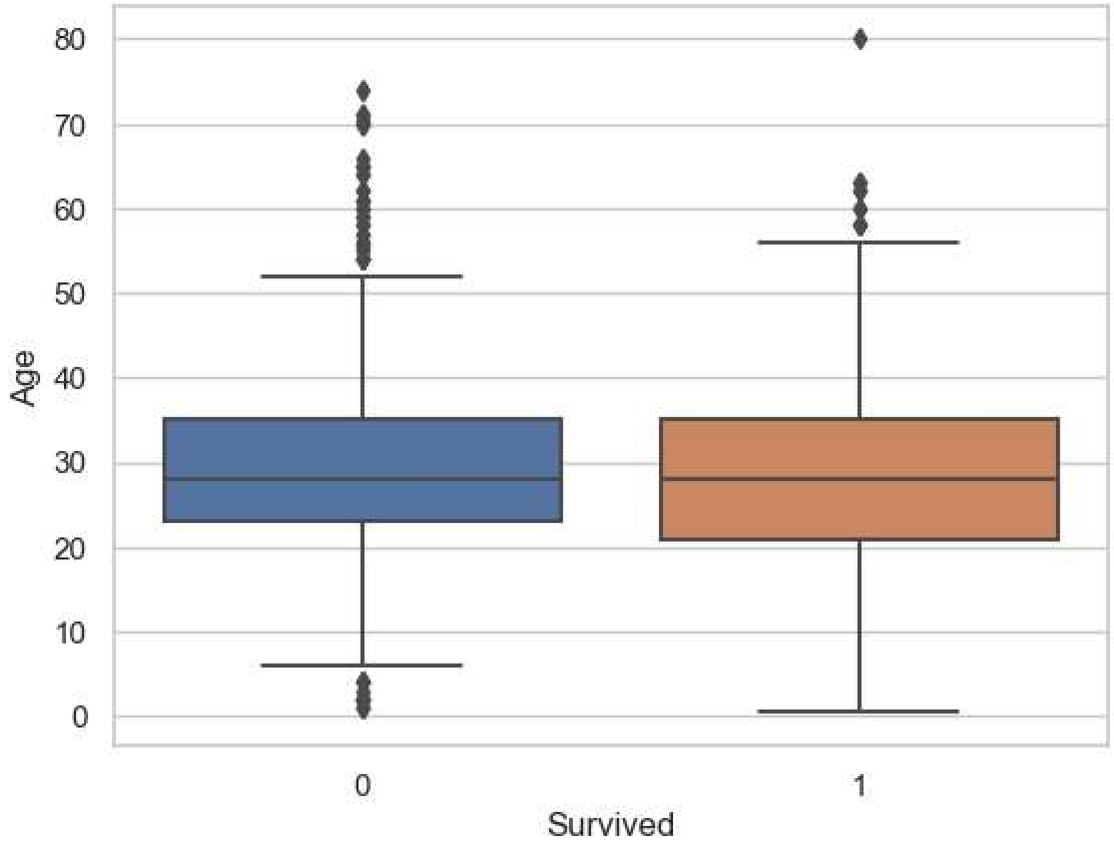


In [19]:
```python
sns.boxplot(x='Survived', y='Age', data=df)

#Observation:

#Survivors had a slightly lower average age. Many children and young adults survived compared to older passengers.
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x211e1347a08>

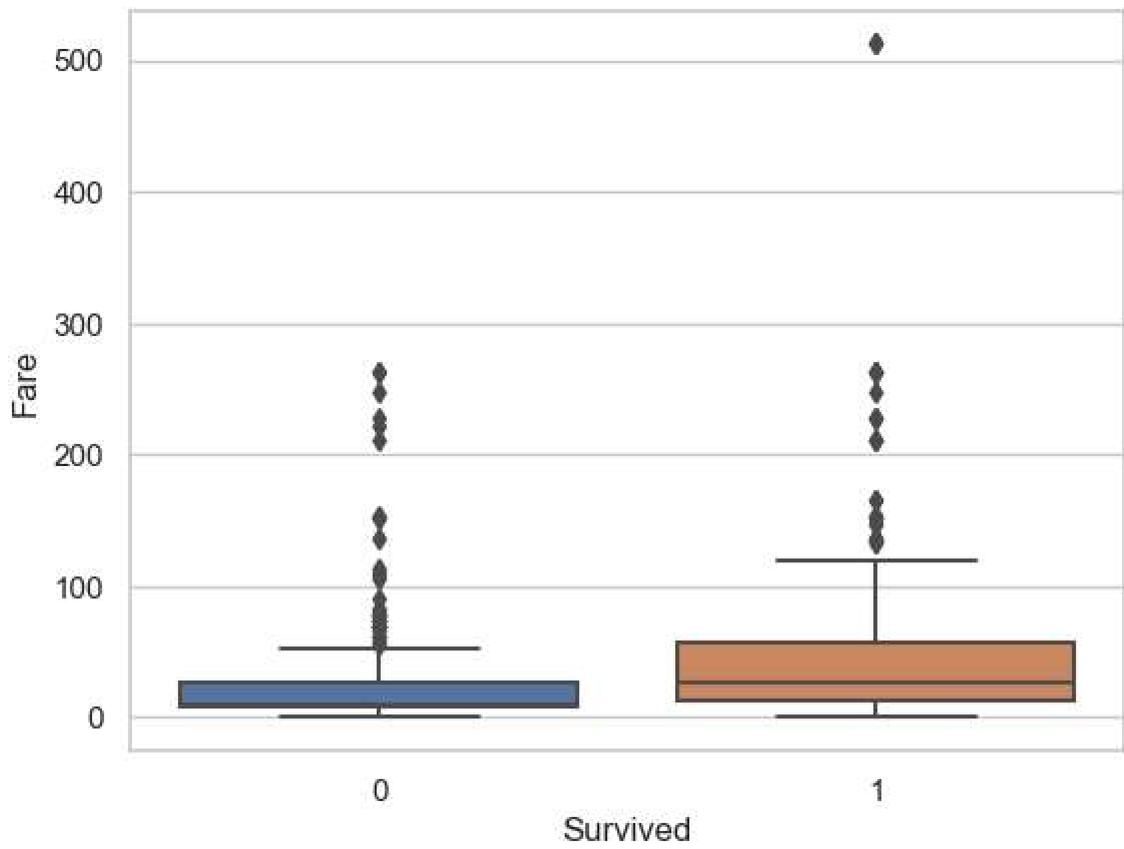


In [20]:
```
sns.boxplot(x='Survived', y='Fare', data=df)

#Observation:

#Survivors generally paid higher fares, again pointing to the advantage of first-class accommodations in survival lik
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x211e14926c8>

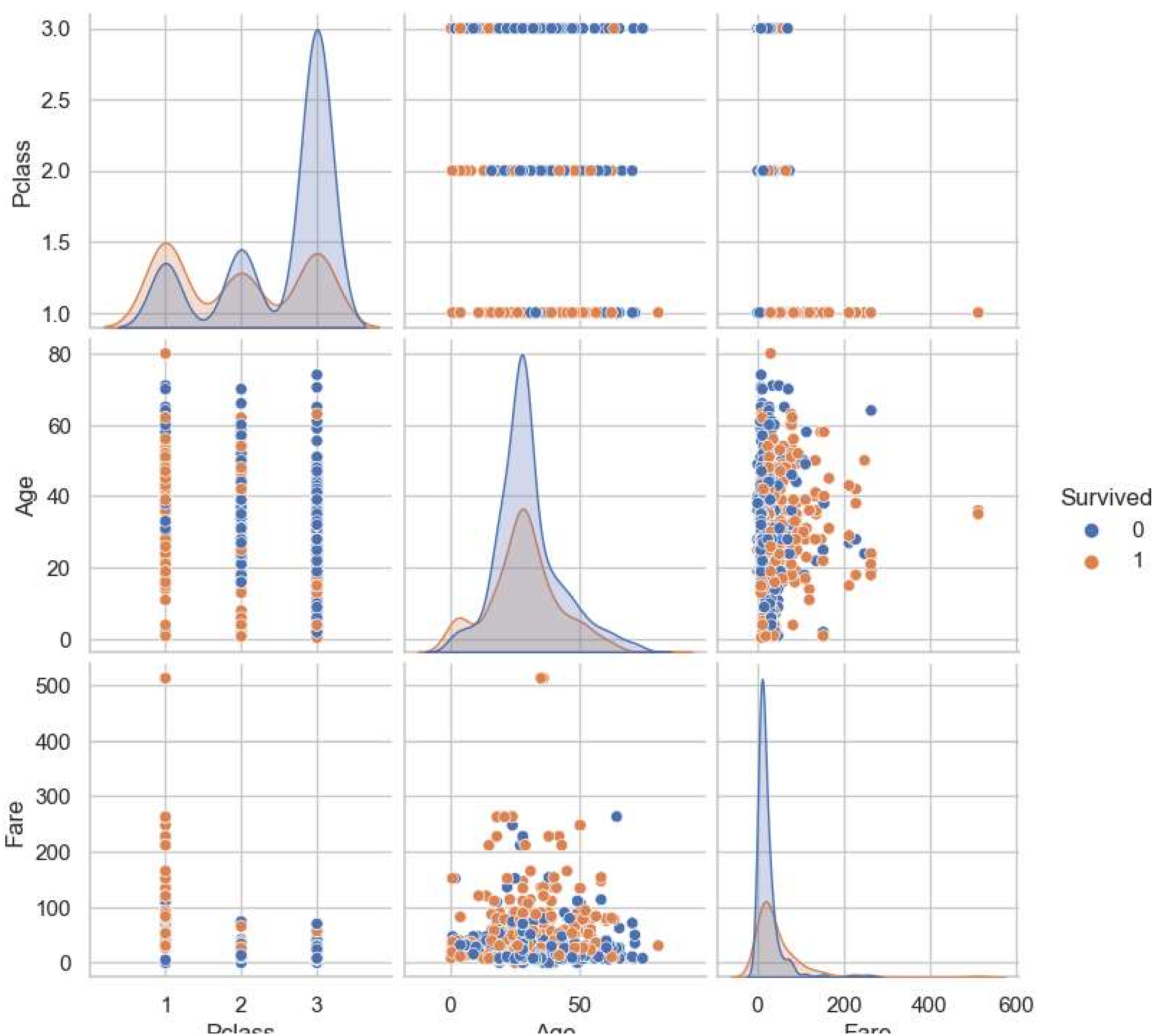


In [16]:
```
sns.pairplot(df[['Survived', 'Pclass', 'Age', 'Fare']], hue='Survived')

#Observation:

#Clear separation between higher fares and survival status. Pclass and Fare show strong patterns in survivor distribu
```

Out[16]: <seaborn.axisgrid.PairGrid at 0x211e04ccb48>



Pclass
Age
Fare
Survived
0
1
3.0
2.5
2.0
1.5
1.0
80
60
40
20
0
500
400
300
200
100
0
1
2
3
0
50
0
200
400
600
Pclass
Age
Fare

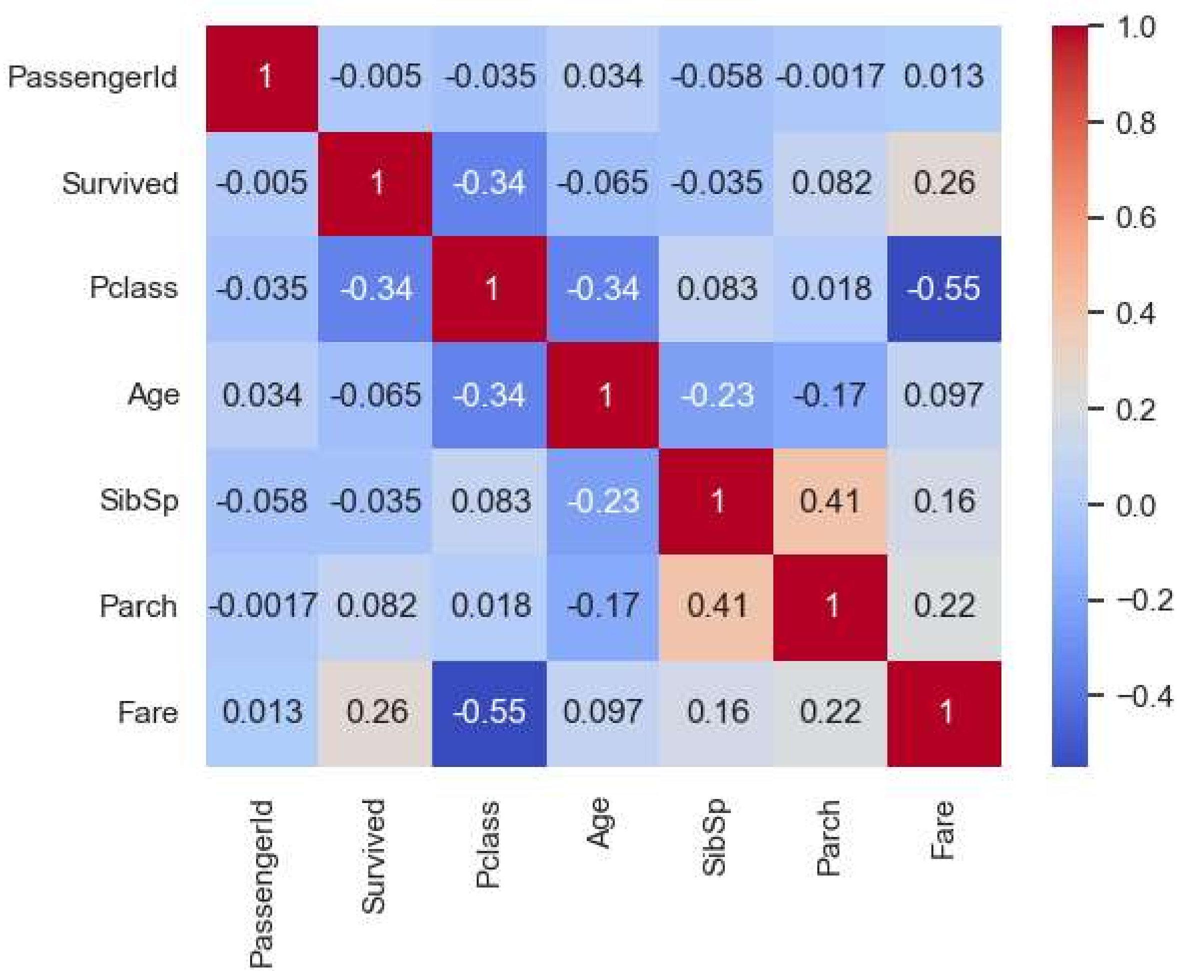
In [17]:

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

#Observation:

#The most positively correlated variable with survival is Fare (0.26), while Pclass has a moderate negative correlati
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x211e0d73408>



In [14]:
```
df['Age'].fillna(df['Age'].median(), inplace=True)
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)
```

In [ ]:
```
#Summary:
#Most survivors were women and passengers from Pclass 1.

#Higher fare was associated with better survival chances.

#Sex, Pclass, and Fare are key predictors of survival.

#Age has a slight influence; children had better chances.

#Missing values in Age, Cabin, and Embarked must be addressed.
```