In [20]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# For better visuals
sns.set(style="whitegrid")
%matplotlib inline
```

Observation: You should see columns like: PassengerId, Survived, Pclass, Name, Sex, Age, SibSp, Parch, Ticket, Fare, Cabin, Embarked.

In [6]:
```
# Load Titanic dataset
df = pd.read_csv('train.csv')
df.head()
```

Out[6]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	I
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0

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

Out[7]:
```
<bound method DataFrame.info of      PassengerId  Survived  Pclass  \
0              1         0       3
1              2         1       1
2              3         1       3
3              4         1       1
4              5         0       3
..           ...       ...     ...
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3

                                                  Name     Sex   Age  SibSp  \
0                              Braund, Mr. Owen Harris    male  22.0      1
1    Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                               Heikkinen, Miss. Laina  female  26.0      0
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                             Allen, Mr. William Henry    male  35.0      0
..                                                 ...     ...   ...    ...
886                              Montvila, Rev. Juozas    male  27.0      0
887                       Graham, Miss. Margaret Edith  female  19.0      0
888           Johnston, Miss. Catherine Helen "Carrie"  female   NaN      1
889                              Behr, Mr. Karl Howell    male  26.0      0
890                                Dooley, Mr. Patrick    male  32.0      0

     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     ...               ...      ...   ...      ...
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]>
```

In [8]:
```
df.describe()
```

Out[8]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.00(
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329

Missing values in Age, Cabin, Embarked. Survived is binary (0 = did not survive, 1 = survived). Pclass is 1, 2, 3 – passenger class.

In [9]:

```
# Count unique values in categorical columns
df['Survived'].value_counts()
df['Pclass'].value_counts()
df['Sex'].value_counts()
df['Embarked'].value_counts()
```

Out[9]:

```
Embarked
S    644
C    168
Q     77
Name: count, dtype: int64
```

Age has missing data → could fill with median/mean later. Cabin has too many missing values → could drop or simplify. Embarked has few missing → fill with mode.

In [10]:

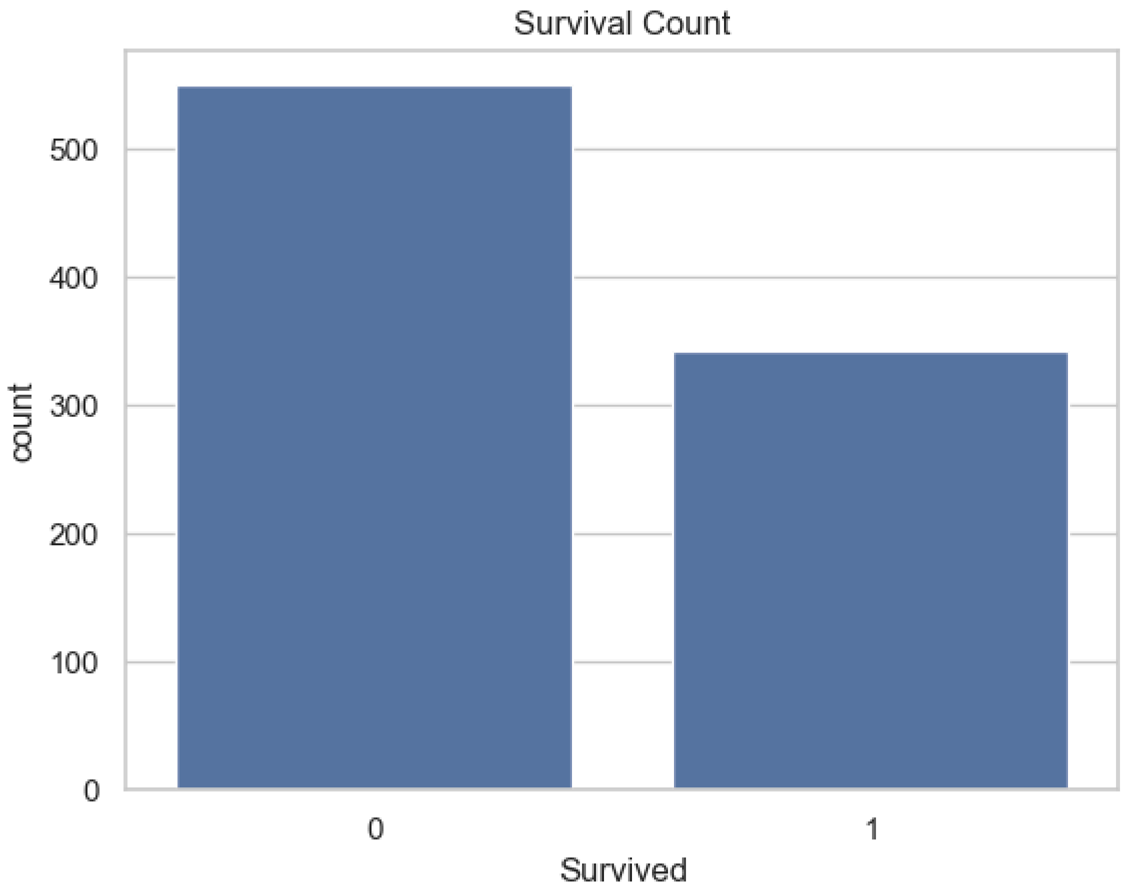
```
# Missing values
df.isnull().sum()
```

Out[10]:

```
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
```

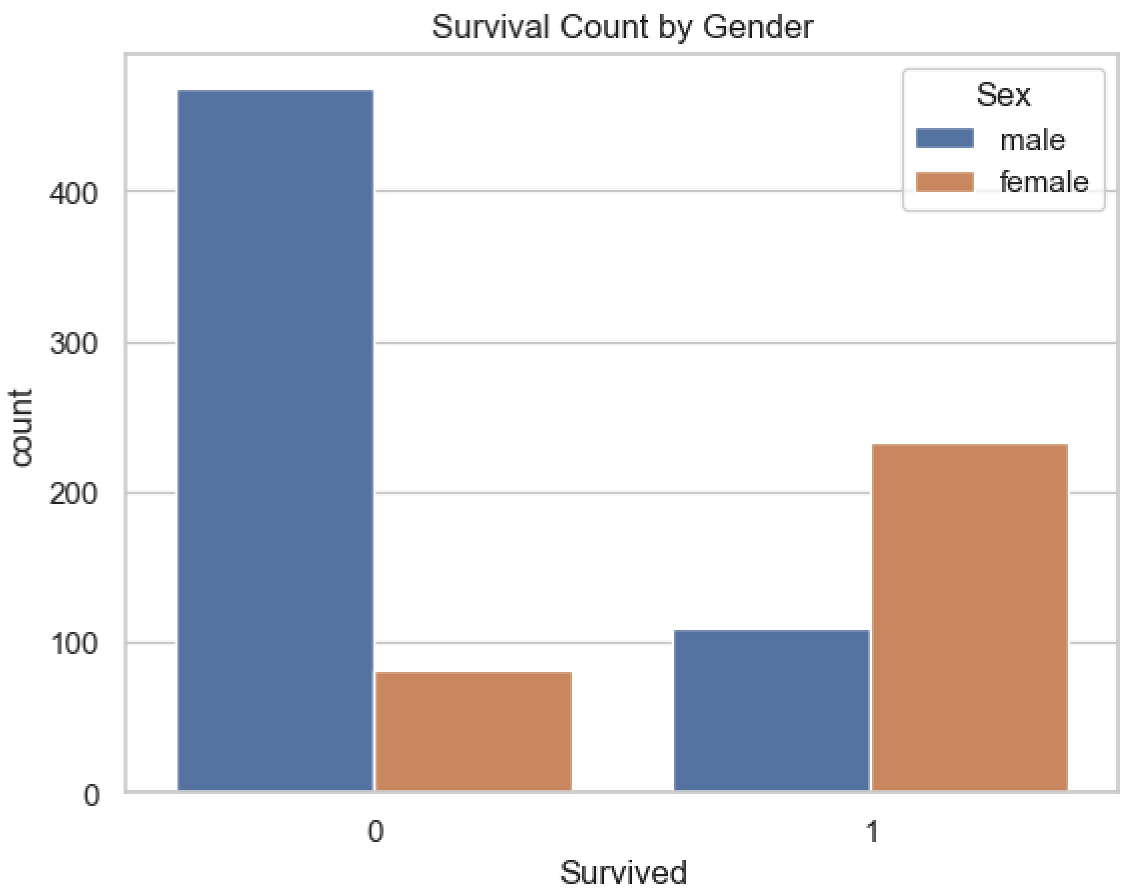
More passengers did not survive than survived.

In [11]:
```
sns.countplot(x='Survived', data=df)
plt.title('Survival Count')
plt.show()
```



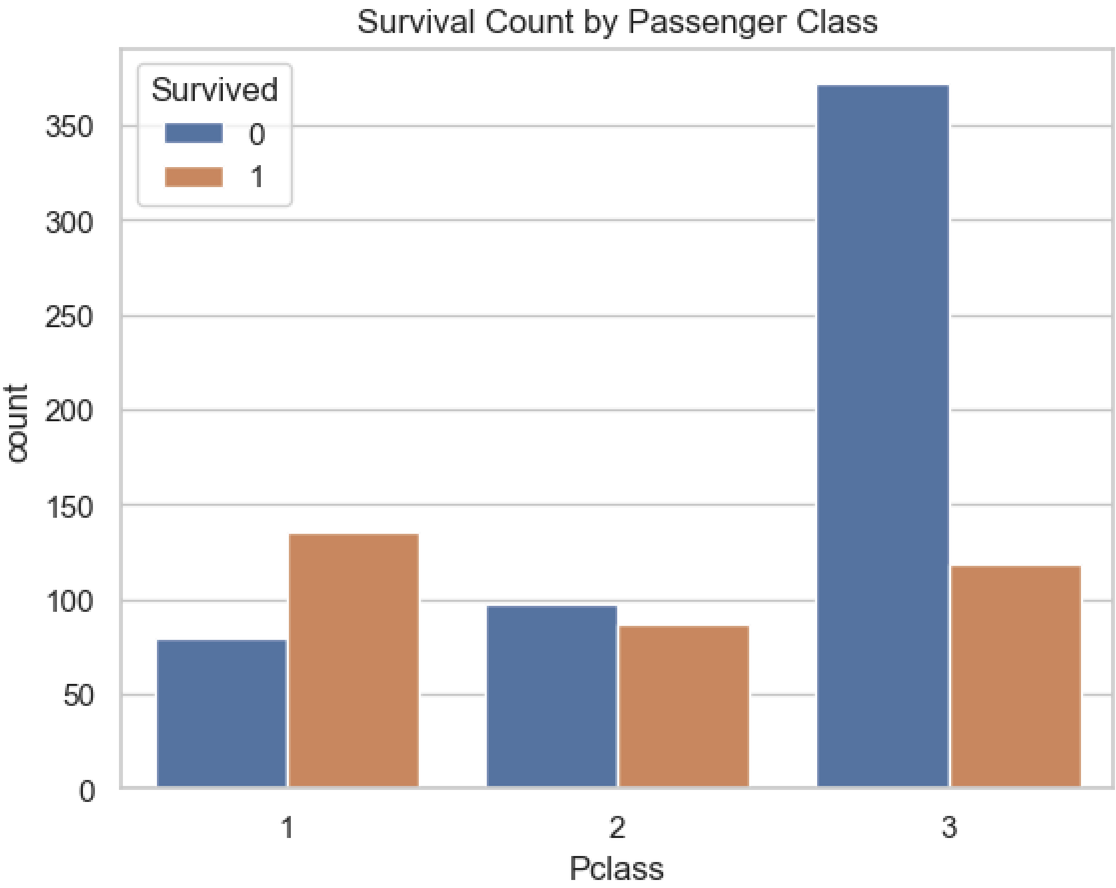
Females had a higher survival rate than males.

In [12]:
```
sns.countplot(x='Survived', hue='Sex', data=df)
plt.title('Survival Count by Gender')
plt.show()
```



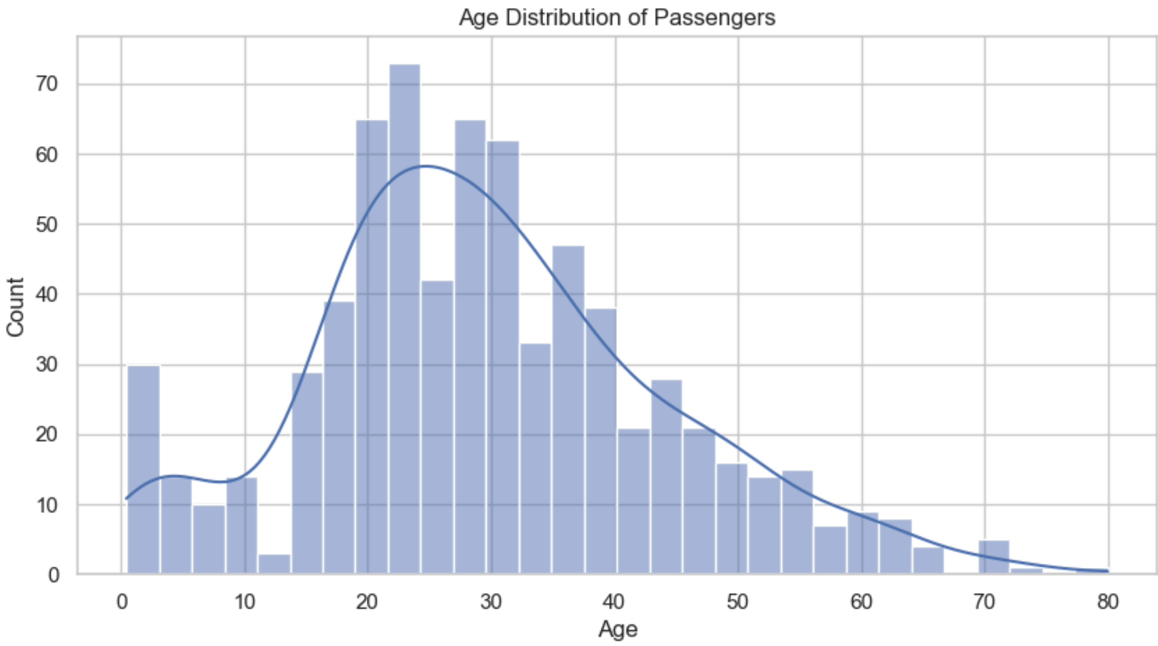
1st class had higher survival, 3rd class lower survival.

In [13]:
```
sns.countplot(x='Pclass', hue='Survived', data=df)
plt.title('Survival Count by Passenger Class')
plt.show()
```



Most passengers were young adults (20–40 years).

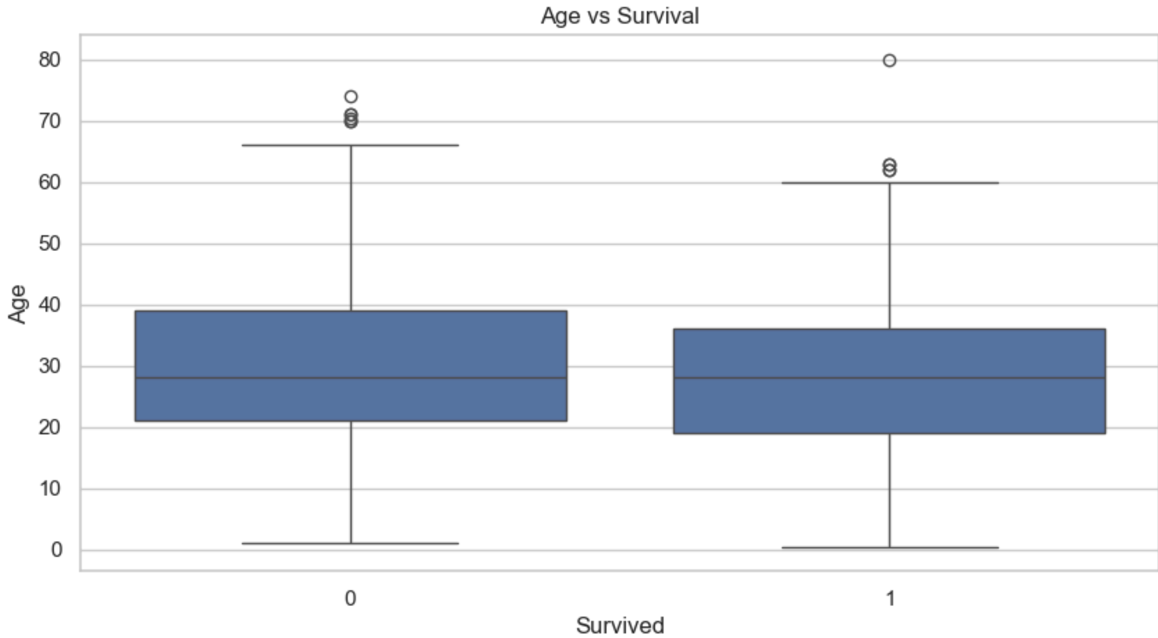
In [14]:
```
plt.figure(figsize=(10,5))
sns.histplot(df['Age'].dropna(), bins=30, kde=True)
plt.title('Age Distribution of Passengers')
plt.show()
```



Children (lower age) had slightly higher chance of survival.

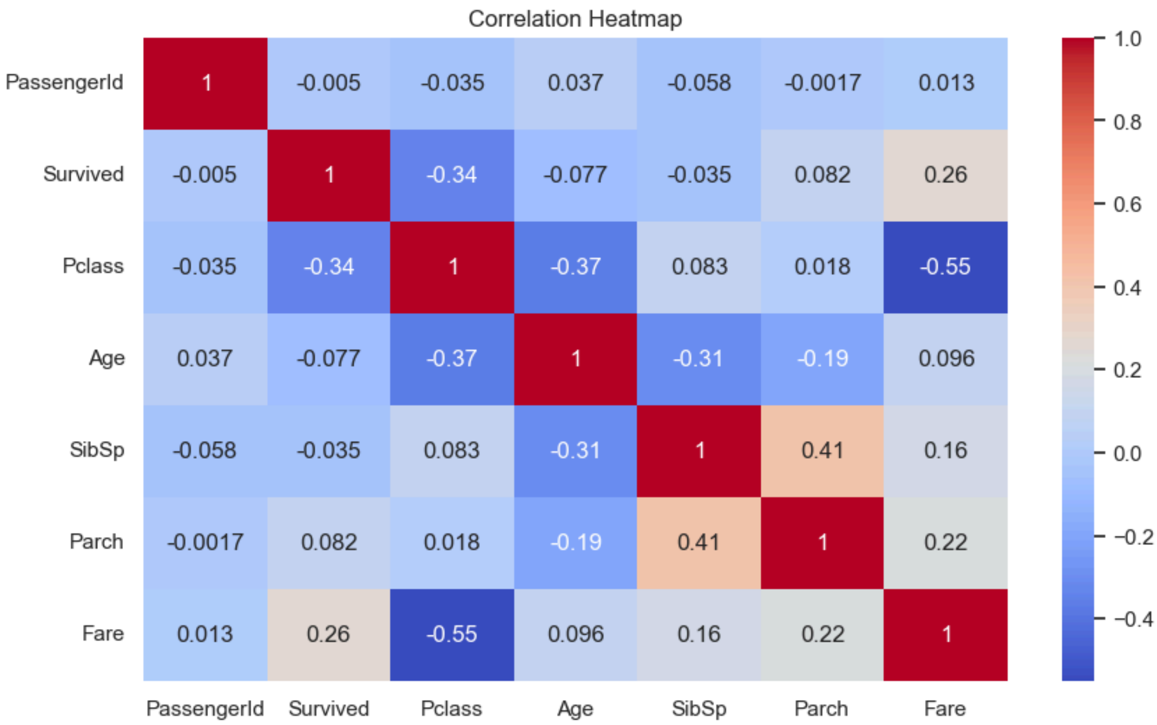
In [15]:
```
plt.figure(figsize=(10,5))
sns.boxplot(x='Survived', y='Age', data=df)
```

```
plt.title('Age vs Survival')
plt.show()
```



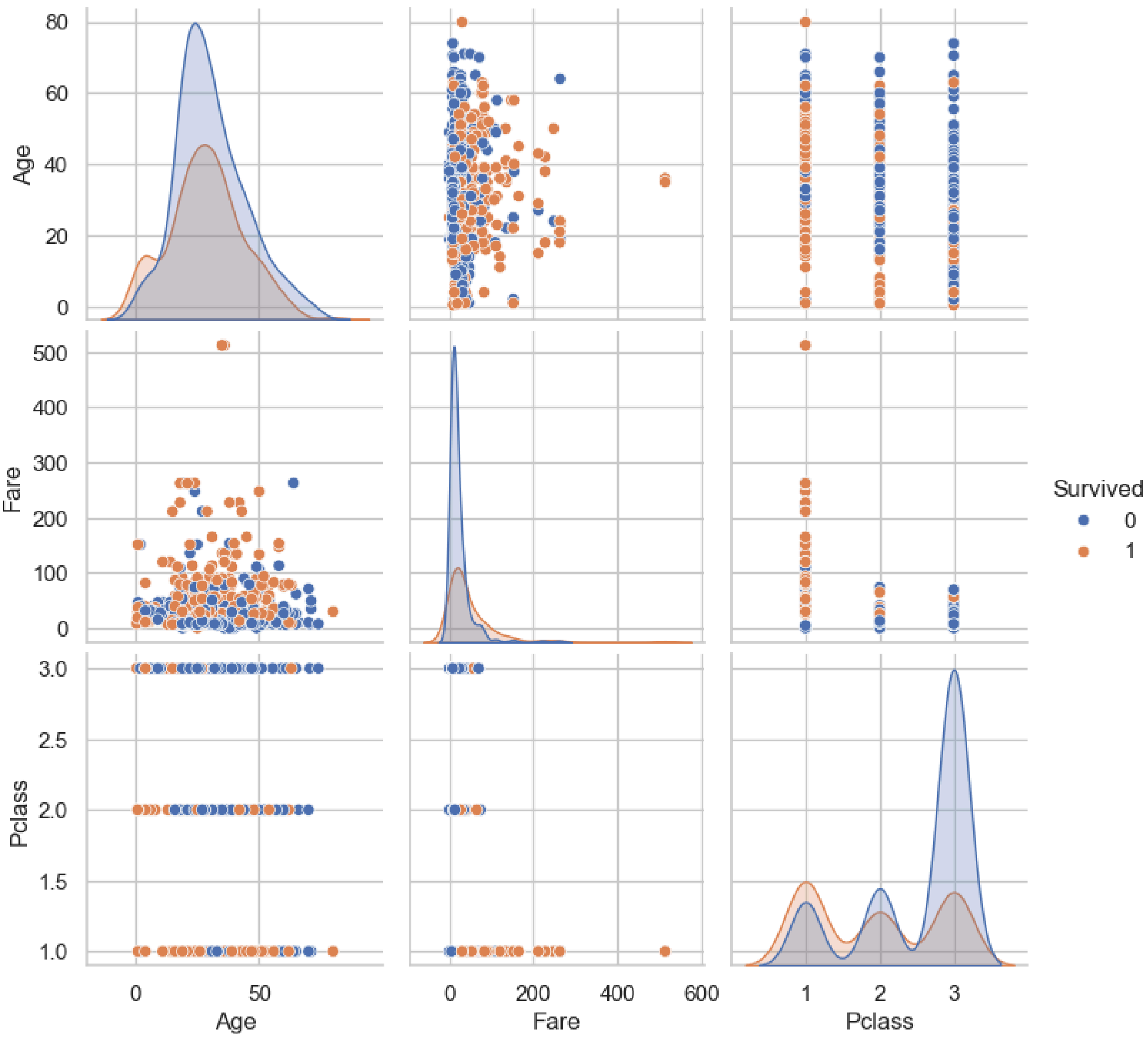
Pclass negatively correlated with Survived. Fare positively correlated with Pclass (1st class paid more).

In [19]:
```
plt.figure(figsize=(10,6))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show()
```



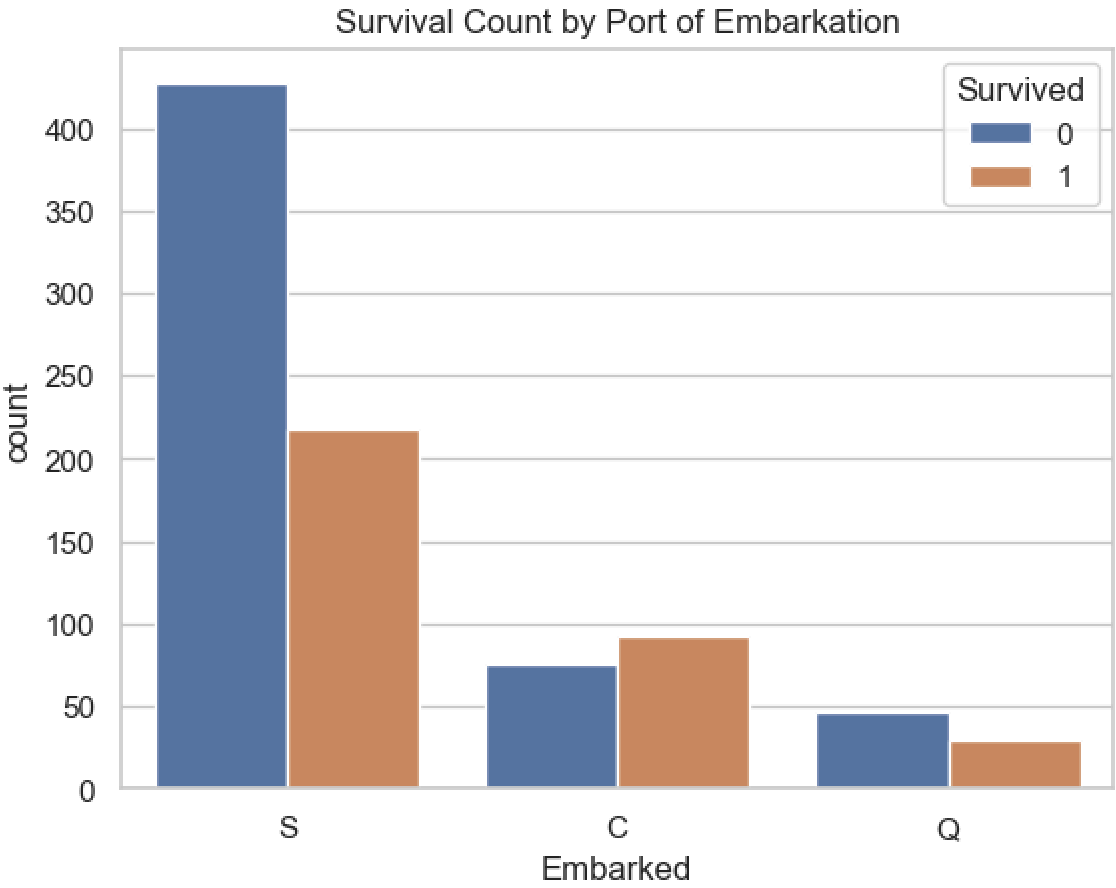
You can see clustering trends for fare and age with survival.

In [17]:
```
sns.pairplot(df[['Survived', 'Age', 'Fare', 'Pclass']], hue='Survived')
plt.show()
```



Passengers from C (Cherbourg) had better survival rate than S (Southampton).

In [18]:
```
sns.countplot(x='Embarked', hue='Survived', data=df)
plt.title('Survival Count by Port of Embarkation')
plt.show()
```



Summary of Findings

1. Overall survival rate: ~38% of passengers survived.
2. Gender effect: Females had higher survival rate than males.
3. Passenger class effect: 1st class passengers had higher survival than 3rd class.
4. Age effect: Children and young adults had slightly higher survival.
5. Fare correlation: Higher fare passengers had better survival (mostly 1st class).
6. Port of embarkation: Passengers from Cherbourg (C) had slightly better survival.
7. Missing values: Age and Cabin columns need treatment for modeling.

In [ ]:

In [ ]: