In [55]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [56]:
```
df=pd.read_csv("C:\\Users\\farhi\\OneDrive\\Desktop\\Titanic Dataset.csv")
```

In [57]:
```
df.head()
```

Out[57]:

	pclass	survived	name	sex	age	sibsp	parch	ticket	fare	cabin	emba
0	1	1	Allen, Miss. Elisabeth Walton	female	29.00	0	0	24160	211.3375	B5	
1	1	1	Allison, Master. Hudson Trevor	male	0.92	1	2	113781	151.5500	C22 C26	
2	1	0	Allison, Miss. Helen Loraine	female	2.00	1	2	113781	151.5500	C22 C26	
3	1	0	Allison, Mr. Hudson Joshua Creighton	male	30.00	1	2	113781	151.5500	C22 C26	
4	1	0	Allison, Mrs. Hudson J C (Bessie Waldo Daniels)	female	25.00	1	2	113781	151.5500	C22 C26	

In [58]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1309 entries, 0 to 1308
Data columns (total 14 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   pclass     1309 non-null   int64  
 1   survived   1309 non-null   int64  
 2   name       1309 non-null   object 
 3   sex        1309 non-null   object 
 4   age        1046 non-null   float64
 5   sibsp      1309 non-null   int64  
 6   parch      1309 non-null   int64  
 7   ticket     1309 non-null   object 
 8   fare       1308 non-null   float64
 9   cabin      295 non-null    object 
 10  embarked   1307 non-null   object 
 11  boat       486 non-null    object 
 12  body       121 non-null    float64
 13  home.dest  745 non-null    object 
dtypes: float64(3), int64(4), object(7)
memory usage: 143.3+ KB
```

In [59]:
```
df.describe()
```

Out[59]:

	pclass	survived	age	sibsp	parch	fare	
count	1309.000000	1309.000000	1046.000000	1309.000000	1309.000000	1308.000000	121.0
mean	2.294882	0.381971	29.881138	0.498854	0.385027	33.295479	160.8
std	0.837836	0.486055	14.413493	1.041658	0.865560	51.758668	97.6
min	1.000000	0.000000	0.170000	0.000000	0.000000	0.000000	1.0
25%	2.000000	0.000000	21.000000	0.000000	0.000000	7.895800	72.0
50%	3.000000	0.000000	28.000000	0.000000	0.000000	14.454200	155.0
75%	3.000000	1.000000	39.000000	1.000000	0.000000	31.275000	256.0
max	3.000000	1.000000	80.000000	8.000000	9.000000	512.329200	328.0

In [60]:
```
df.isnull().sum()
```

Out[60]:
```
pclass          0
survived        0
name            0
sex             0
age           263
sibsp           0
parch           0
ticket          0
fare            1
cabin        1014
embarked        2
boat          823
body         1188
home.dest     564
dtype: int64
```

In [61]:
```
#first force 'age' column to numeric ignore the weird non-numeric junk
df['age']=pd.to_numeric(df['age'], errors='coerce')

#filling missing age with median
df['age']=df["age"].fillna(df["age"].median())
```

In [62]:
```
#fill missing fare with median
df['fare']=df['fare'].fillna(df['fare'].median())
```

In [63]:
```
#fill missing embarked with mode
df['embarked']=df['embarked'].fillna(df['embarked'].mode()[0])
```

In [64]:
```
#drop usless columns
df.drop(columns=['cabin','boat','body',"home.dest"], inplace=True)
```

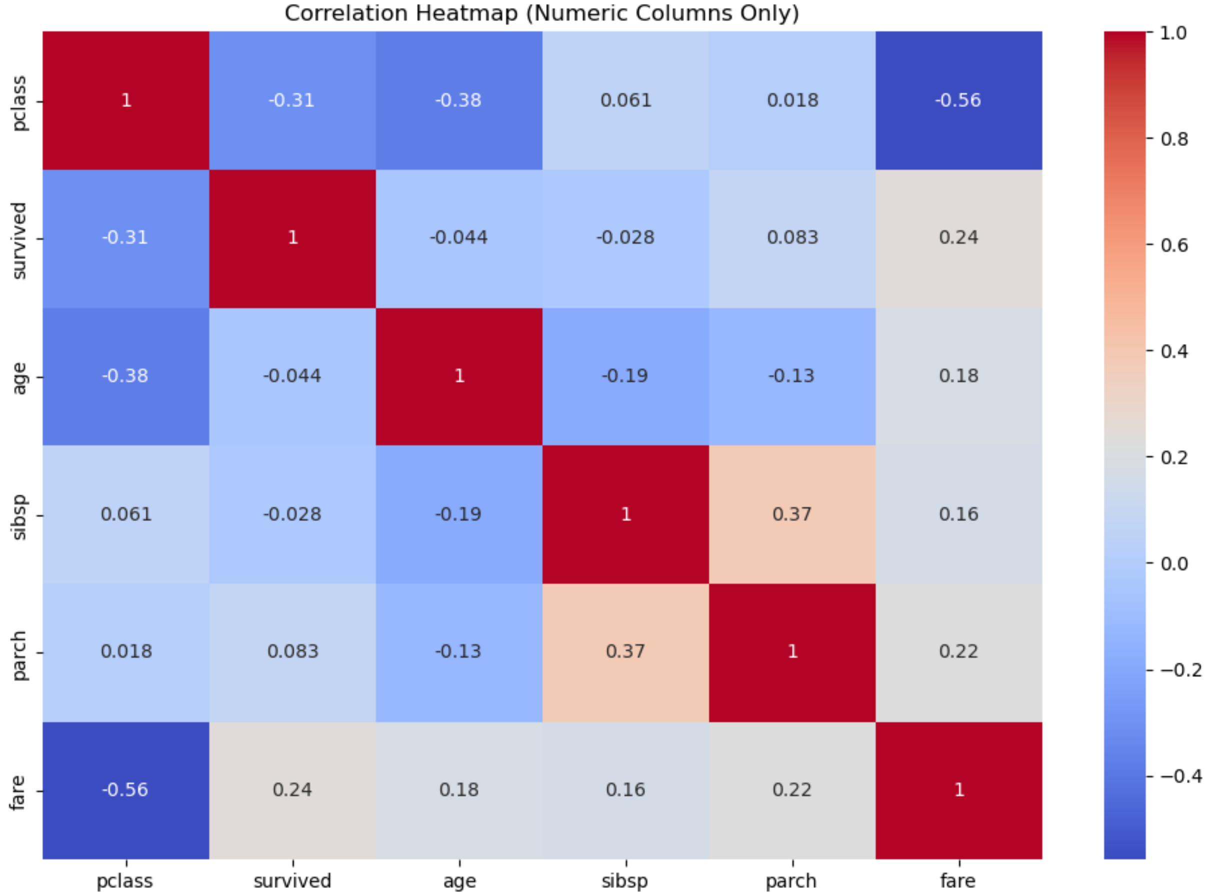
In [65]:
```
print(df.isnull().sum())
```

```
pclass      0
survived    0
name        0
sex         0
age         0
sibsp       0
parch       0
ticket      0
fare        0
embarked    0
dtype: int64
```

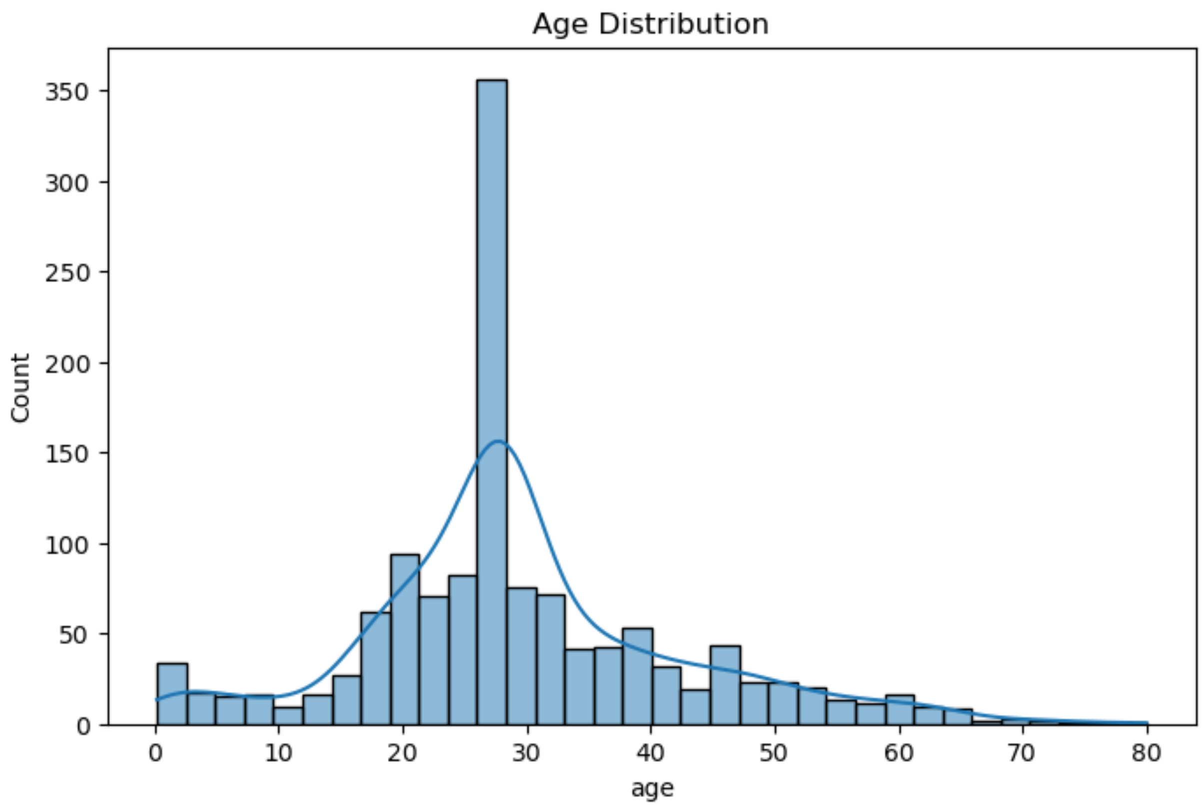
In [67]:
```
#correlation heatmat(find feature relationship)
plt.figure(figsize=(12,8))
plt.figure(figsize=(12,8))
sns.heatmap(df.select_dtypes(include=['number']).corr(), annot=True, cmap='coolwarm

plt.title('Correlation Heatmap (Numeric Columns Only)')
plt.show()

#  Observations:
# - Positive correlation between 'sibsp' and 'parch' (family size related).
```

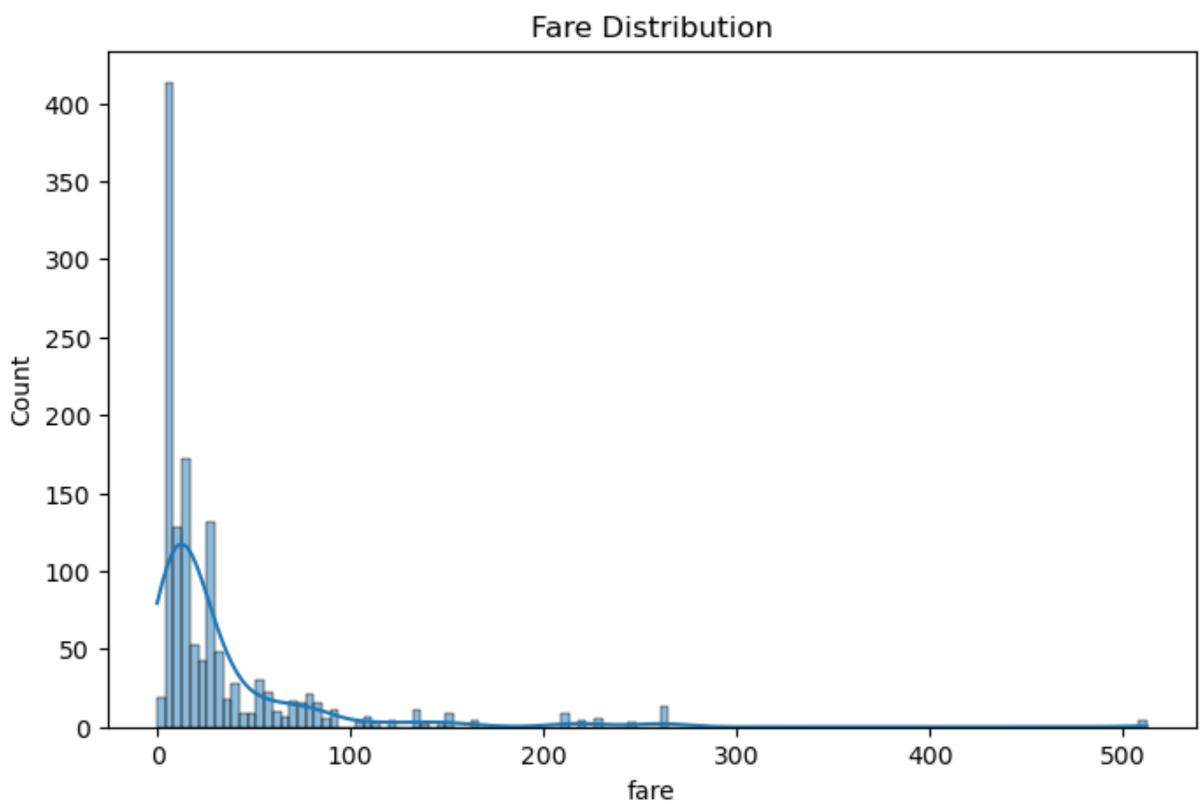
```
# - Fare and pclass are negatively correlated (higher class -> more fare).
# - Survival has weak but visible positive correlation with 'fare' (rich survived m
```

<Figure size 1200x800 with 0 Axes>



In [68]:
```
#plotting distributin (histrogram for age and fare
# Age distribution
plt.figure(figsize=(8,5))
sns.histplot(df['age'], kde=True)
plt.title('Age Distribution')
plt.show()
#Shows the frequency of different age groups

# Fare distribution
plt.figure(figsize=(8,5))
sns.histplot(df['fare'], kde=True)
plt.title('Fare Distribution')
plt.show()
# - Displays the frequency of different fare values
```

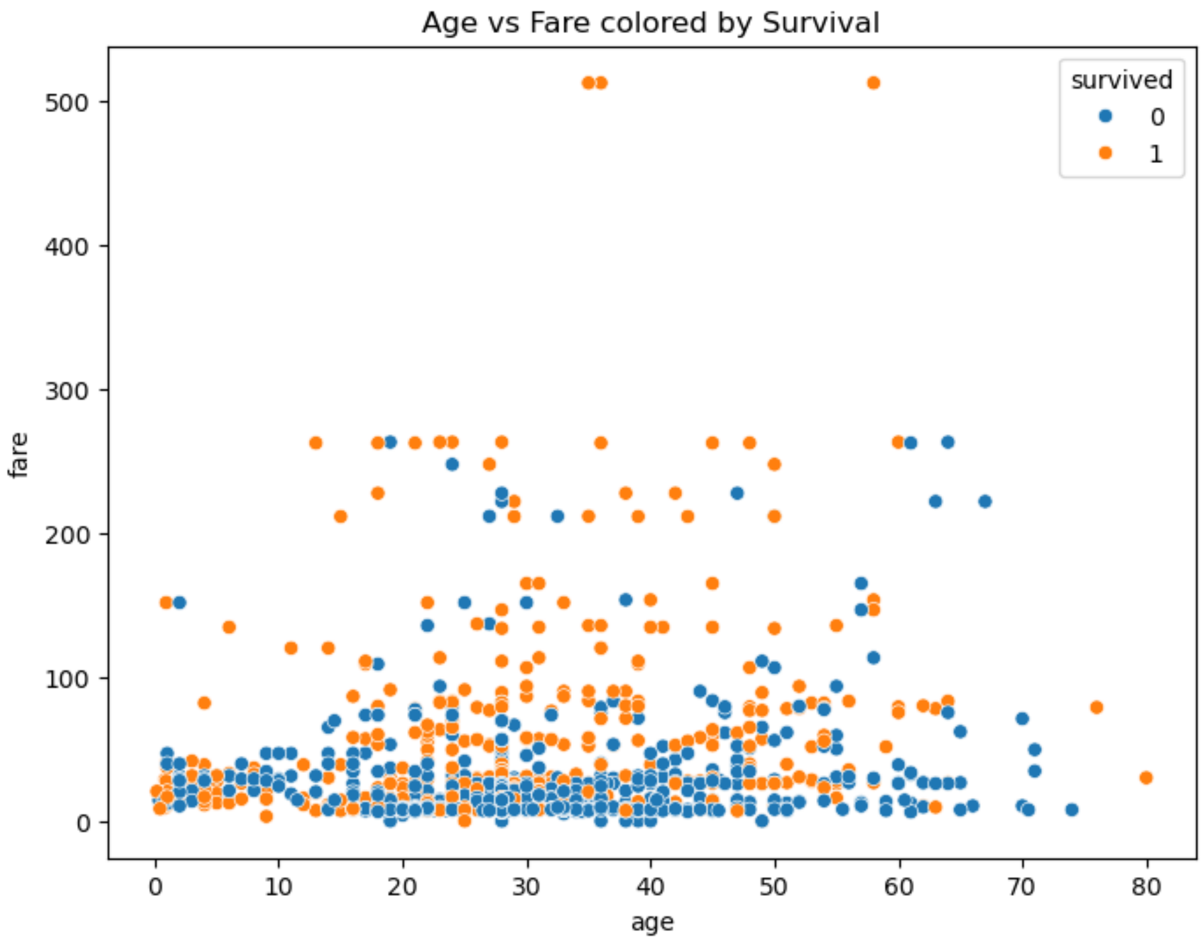




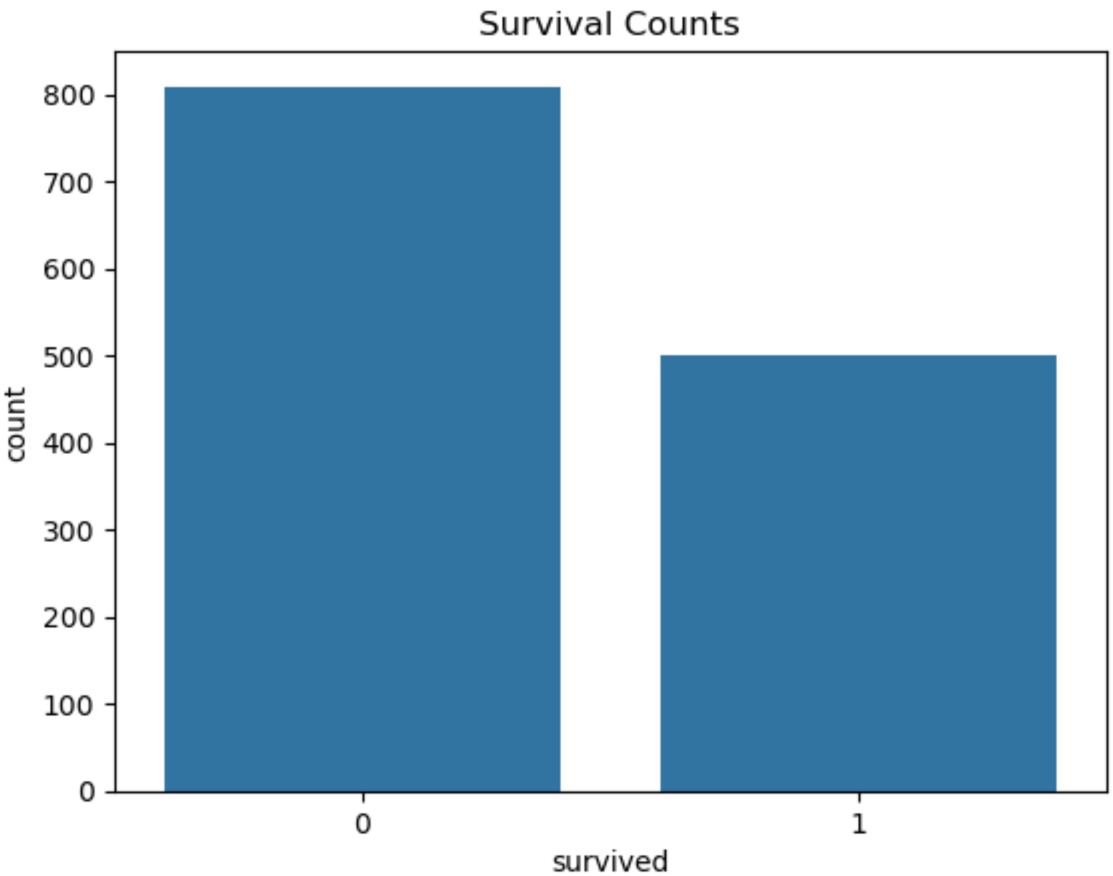
In [69]:

```
#relationship between variable(scatter plot age vs fare)
plt.figure(figsize=(8,6))
sns.scatterplot(x='age', y='fare', hue='survived', data=df)
plt.title('Age vs Fare colored by Survival')
plt.show()
 #-This plot shows how age and fare are related.
```

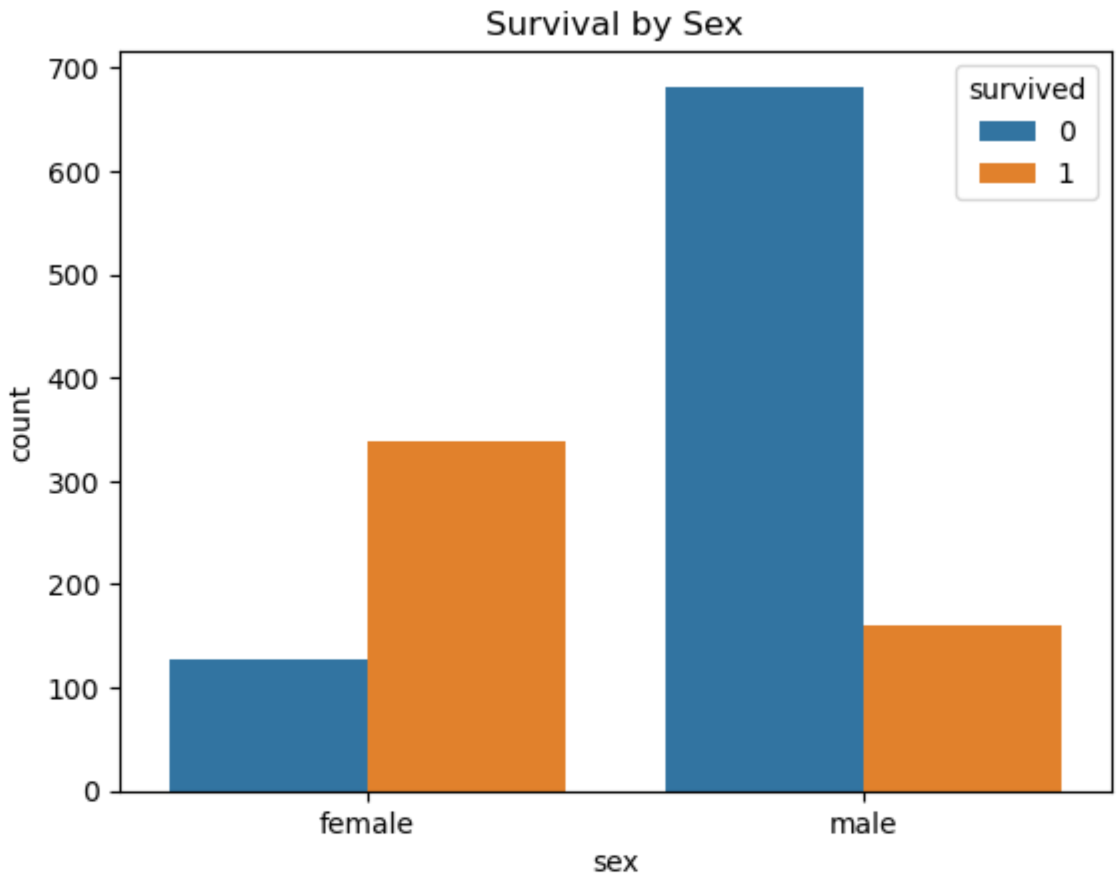
```
# - Each point represents a person, with age on the X-axis and fare on the Y-axis.
# - The color of the points shows whether the person survived or not (hue='survived
```



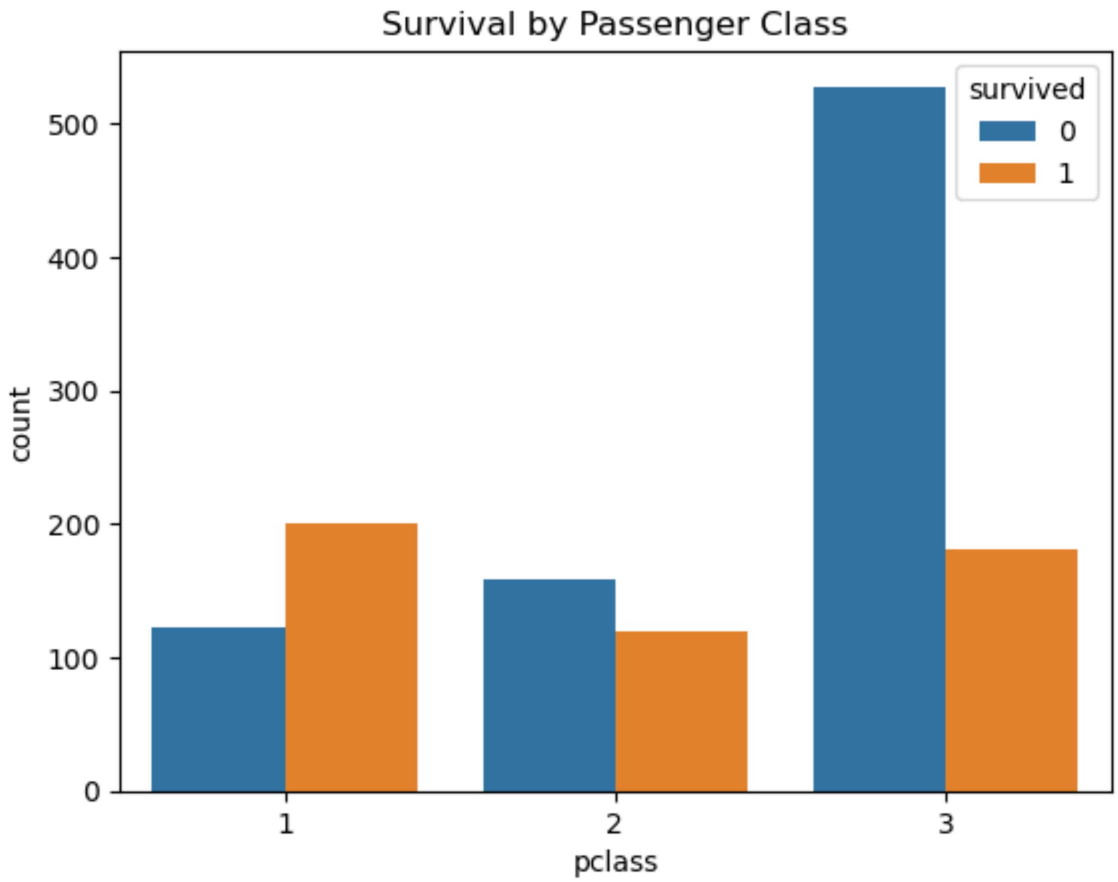
In [70]:
```
#categorical analysis(countplot)
# Survived vs Not
sns.countplot(x='survived', data=df)
plt.title('Survival Counts')
plt.show()
# - This plot shows how many people survived vs. how many didn't.
# - The X-axis represents whether a person survived (0 = No, 1 = Yes).
# - The Y-axis shows the count of people in each category (survived or not).
```

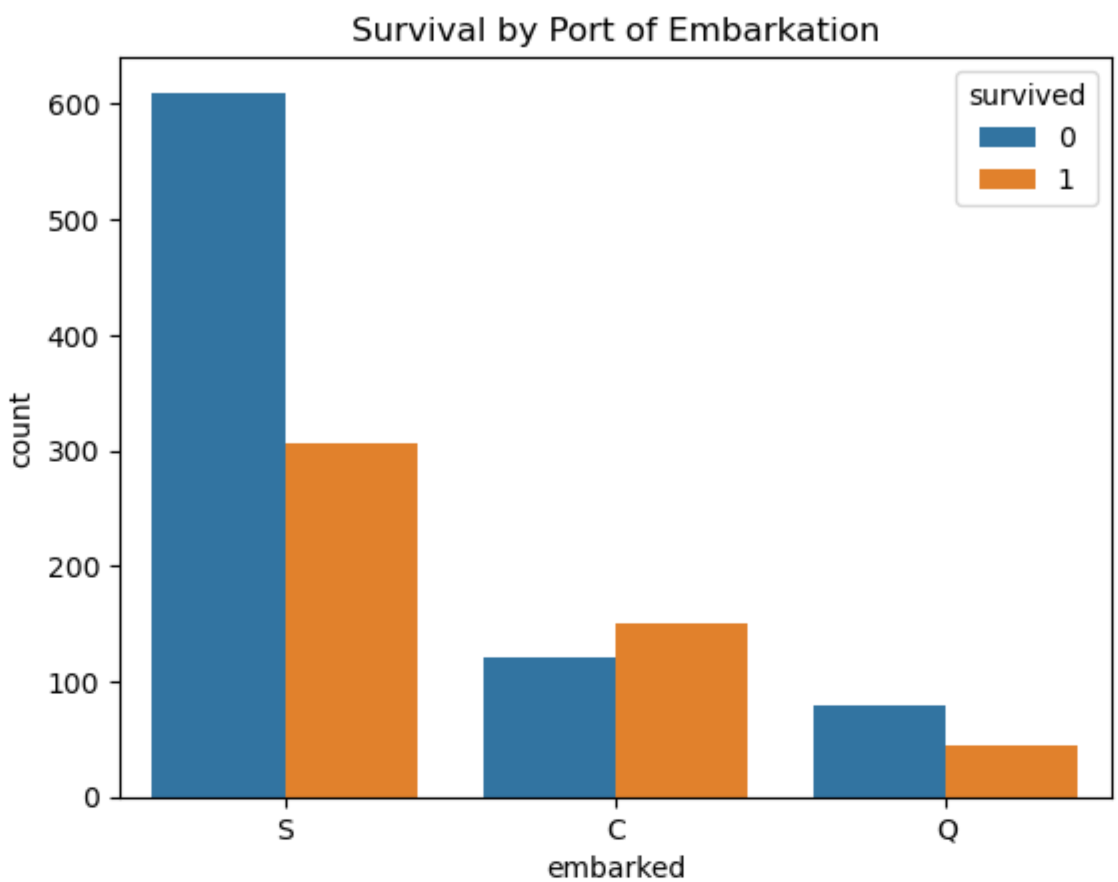


In [71]:
```
# Survival by Gender
sns.countplot(x='sex', hue='survived', data=df)
plt.title('Survival by Sex')
plt.show()
# - This plot shows the survival counts grouped by gender.
# - The X-axis represents gender (male or female).
# - The hue (color) distinguishes whether a person survived (1) or didn’t survive (
# - The Y-axis shows the count of survivors and non-survivors within each gender gr
```



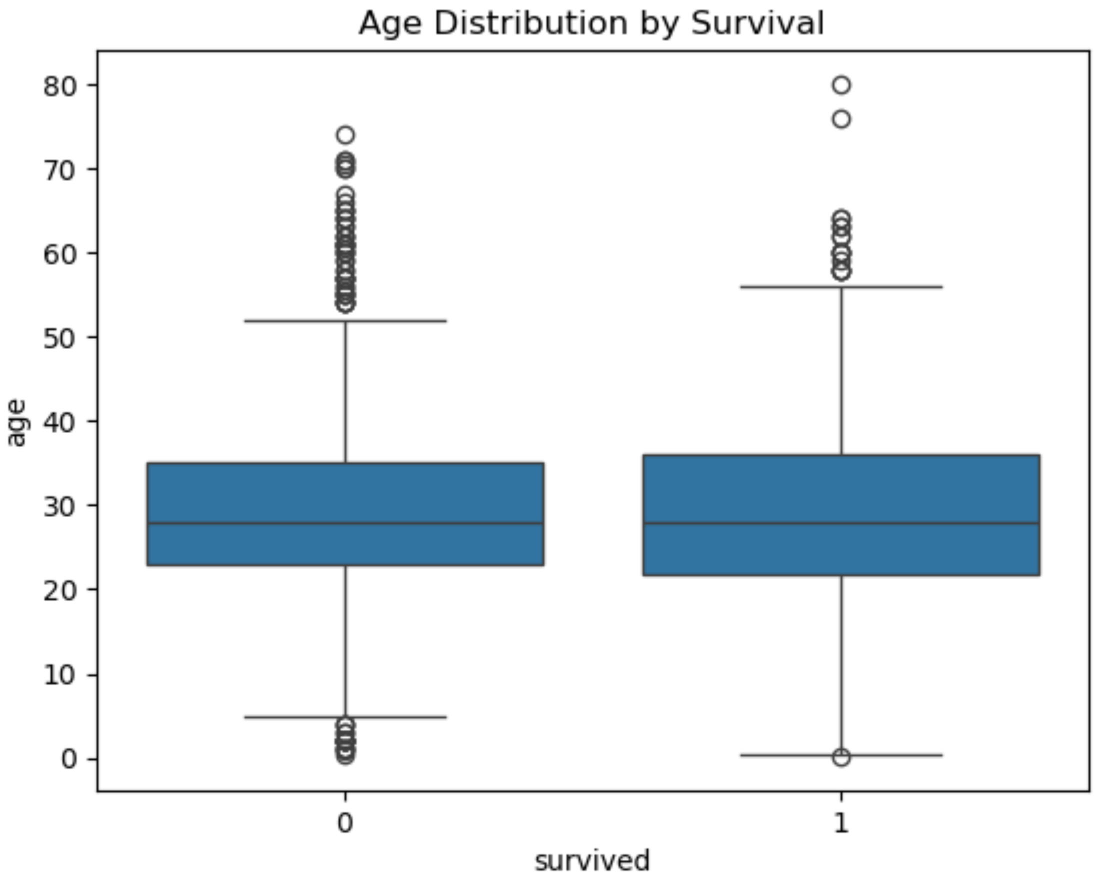
In [72]:
```
# Survival by Pclass
sns.countplot(x='pclass', hue='survived', data=df)
plt.title('Survival by Passenger Class')
plt.show()
#  Shows how survival rates vary by passenger class (1st, 2nd, 3rd)
# Typically, passengers in higher classes had better chances of survival

# Survival by Embarked
sns.countplot(x='embarked', hue='survived', data=df)
plt.title('Survival by Port of Embarkation')
plt.show()
#  Displays survival counts for passengers from different embarkation ports (C, Q, .
#  Can reveal whether boarding location influenced survival outcomes
```





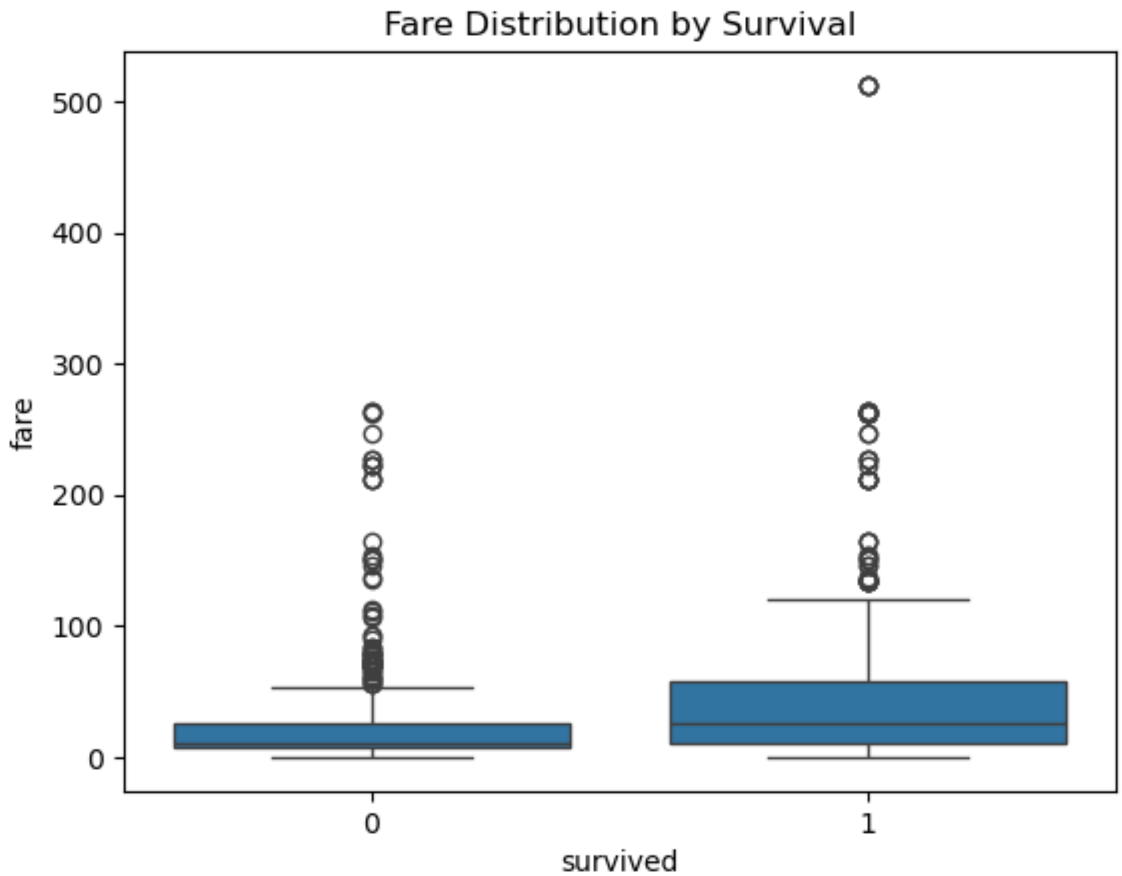
In [73]:
```
# Age vs Survived
```

```
sns.boxplot(x='survived', y='age', data=df)
plt.title('Age Distribution by Survival')
plt.show()
#  Compares the age ranges of survivors and non-survivors
# Helps identify if younger or older people were more likely to survive
```

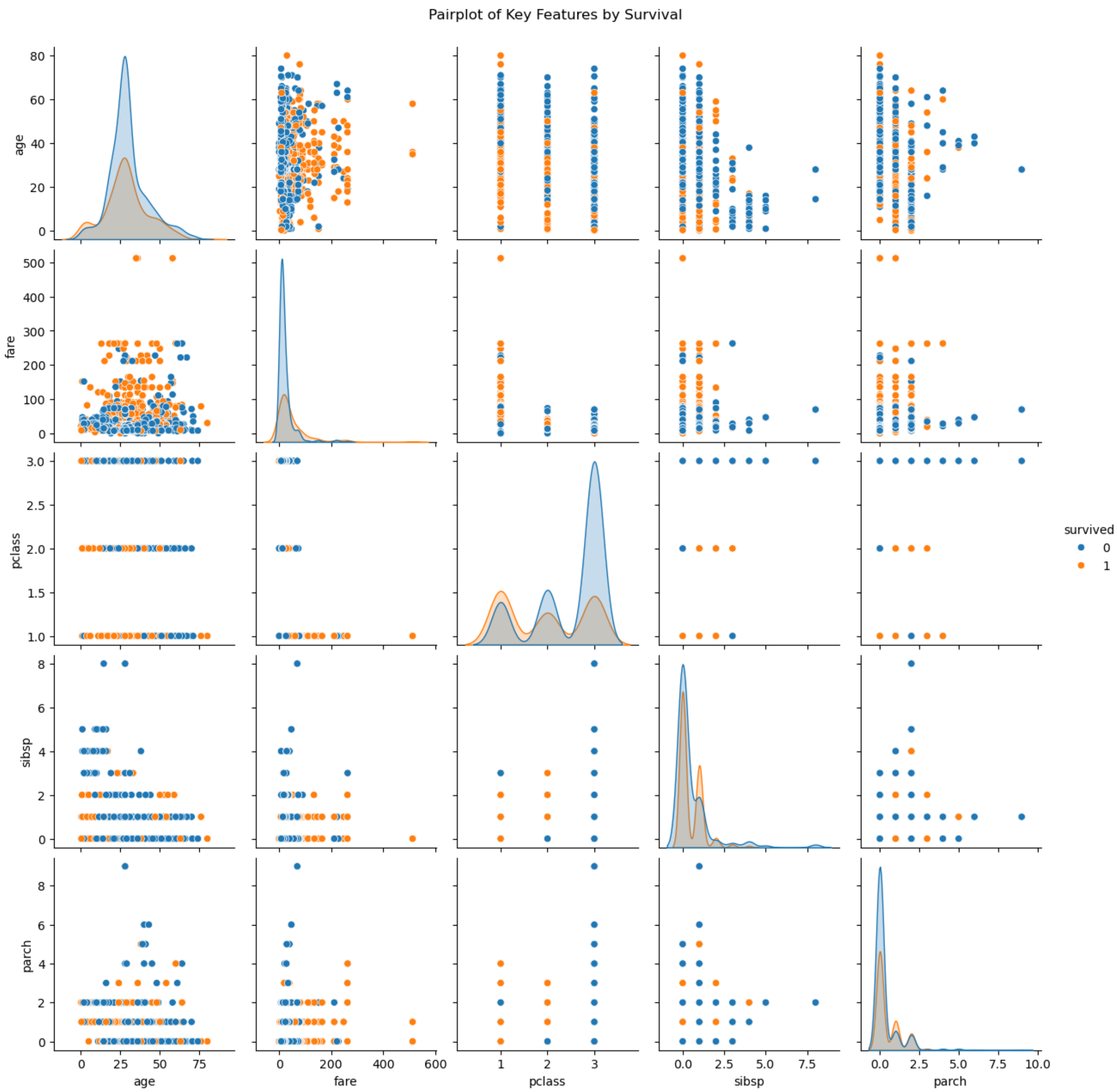


In [74]:

```
# Fare vs Survived
sns.boxplot(x='survived', y='fare', data=df)
plt.title('Fare Distribution by Survival')
plt.show()
# Compares the fare amounts between survivors and non-survivors
# Indicates whether passengers who paid higher fares were more likely to survive
```



In [75]:
```
selected_cols = ['survived', 'age', 'fare', 'pclass', 'sibsp', 'parch']
sns.pairplot(df[selected_cols], hue='survived')
plt.suptitle('Pairplot of Key Features by Survival', y=1.02)
plt.show()
# Shows pairwise relationships between multiple features colored by survival
# Helps identify patterns or groupings based on survival status
# Useful for spotting correlations and how features interact visually
```



In [76]:
```python
print(df['sex'].value_counts())
#  Shows the number of male and female passengers
#  Helps identify gender distribution in the dataset

print(df['embarked'].value_counts())
#  Shows how many passengers boarded from each port (C = Cherbourg, Q = Queenstown,
#  Useful to understand the most common embarkation points

print(df['pclass'].value_counts())
# Displays the number of passengers in each passenger class (1st, 2nd, 3rd)
# Helps identify class distribution and possible data imbalance
```

```
sex
male      843
female    466
Name: count, dtype: int64
embarked
S    916
C    270
Q    123
Name: count, dtype: int64
pclass
3    709
1    323
2    277
Name: count, dtype: int64
```

In [ ]:

```
# Summary

# Most passengers were between 20-40 years old.
# Higher **fare** was positively related to **survival**.
# **Females** had a much higher survival rate than **males**.
# **1st class** passengers had better survival chances.
# Passengers who embarked from **Cherbourg (C)** had better survival odds.
# **SibSp** and **Parch** are positively correlated (family size).
```