Task 5: Exploratory Data Analysis (EDA) - Titanic Dataset

Libraries Import

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

%matplotlib inline
```

Dataset

In [3]:
```
df = pd.read_csv(r"C:\Users\AAFALKAZI\OneDrive\Documents\Titanic-Dataset.csv")
df.head()
```

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	F
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 [4]:
```
df.columns
```

Out[4]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

In [5]:
```
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 [6]:
```
df.describe()
```

Out[6]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000
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

Count of Survivors

In [7]:
```
df['Survived'].value_counts()
```

Out[7]:
```
Survived
0    549
1    342
Name: count, dtype: int64
```

Observation:

0 represents passengers who did not survive, and 1 represents passengers who survived. Most passengers did not survive the Titanic disaster.

Count of Passengers by Gender

In [8]:
```python
df['Sex'].value_counts()
```

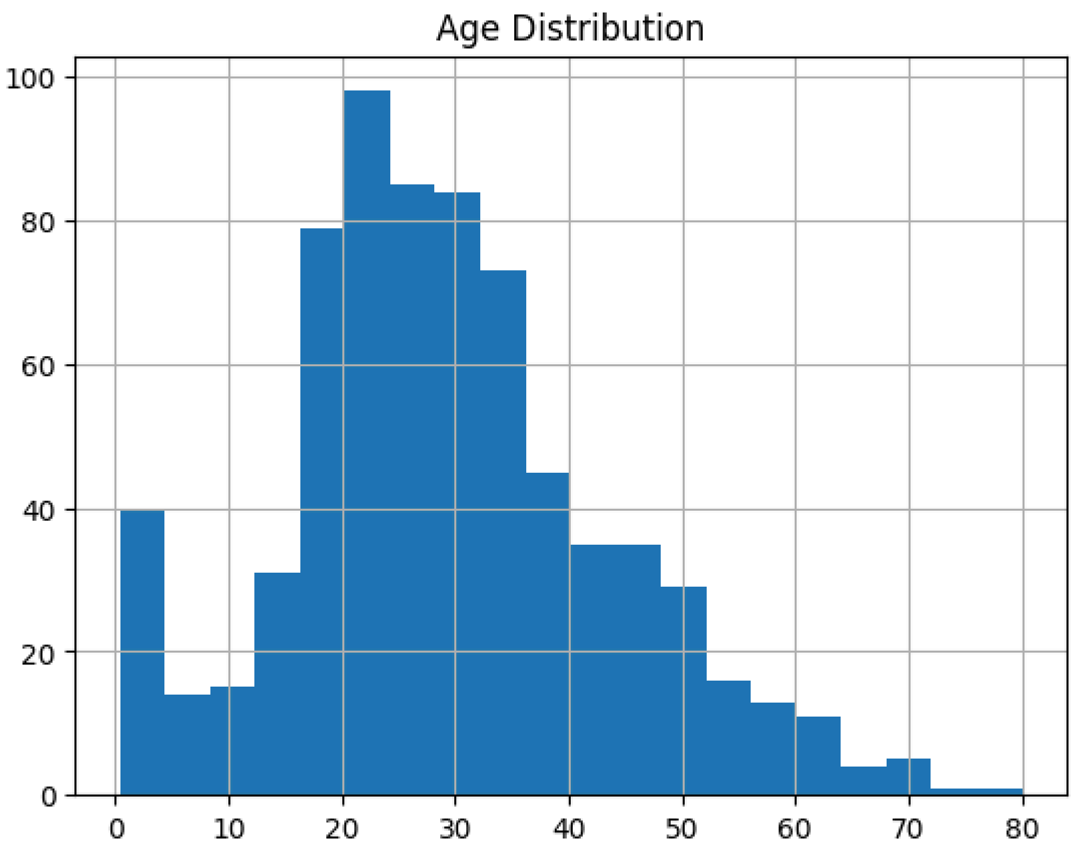
Out[8]:
```
Sex
male      577
female    314
Name: count, dtype: int64
```

Observation:

There are more male passengers than female passengers on the Titanic. Gender distribution may affect survival analysis.

Age Distribution of Passengers

In [9]:
```python
df['Age'].hist(bins=20)
plt.title("Age Distribution")
plt.show()
```

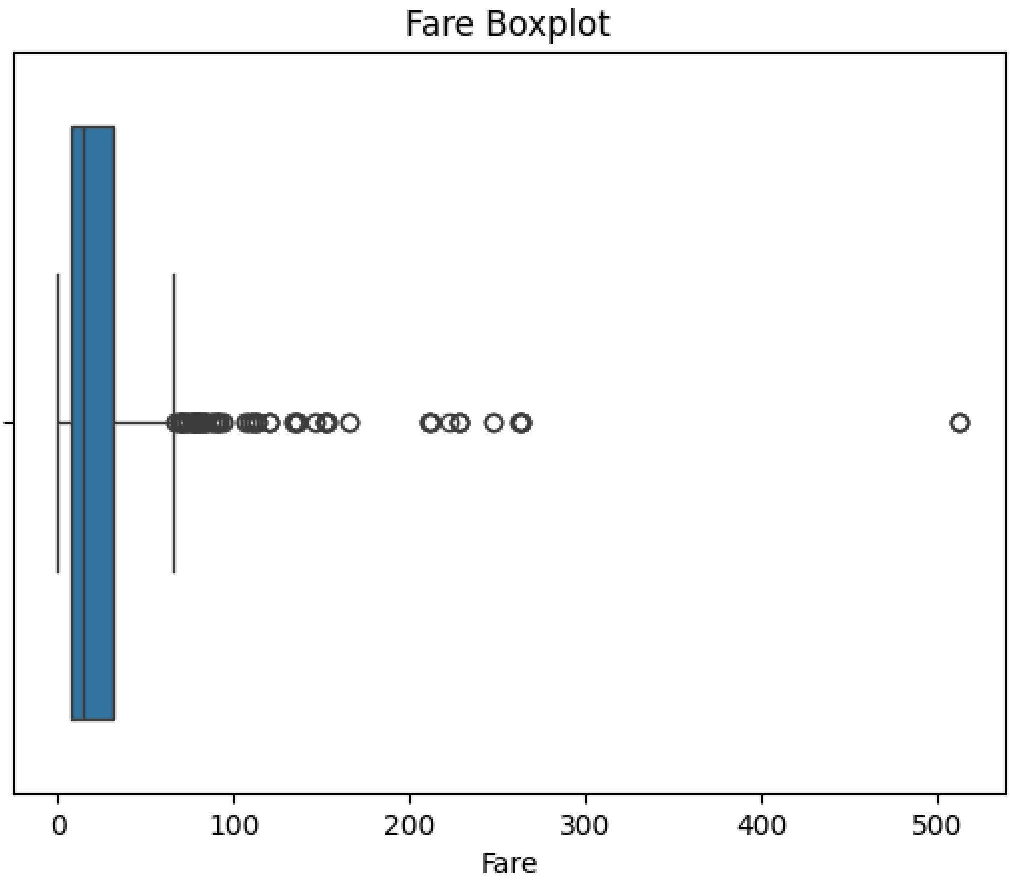


Observation:

The histogram shows that most passengers were between 20 and 40 years old. Very few passengers were below 10 or above 70 years. The age distribution is slightly right-skewed.

Fare Distribution Boxplot

In [21]:
```
sns.boxplot(x=df['Fare'])
plt.title("Fare Boxplot")
plt.show()
```

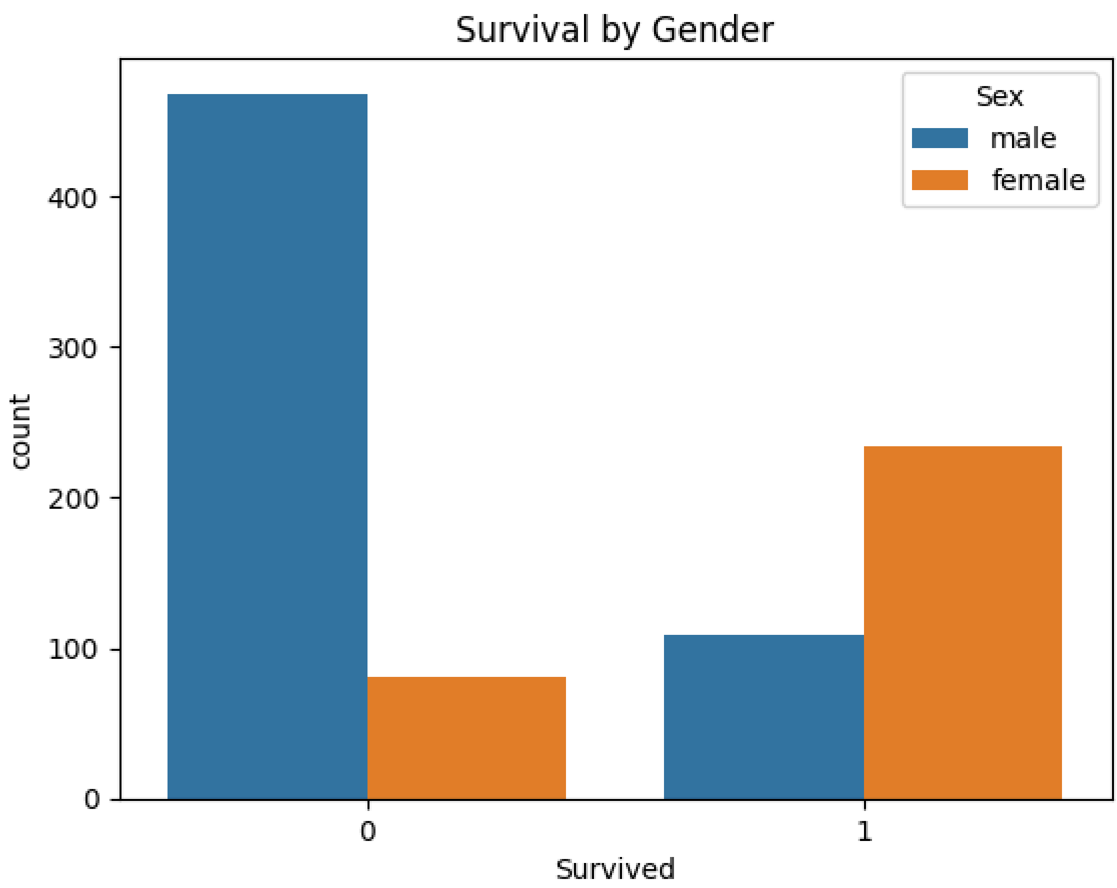


Observation:

The boxplot shows that fare values are highly skewed. There are several outliers, indicating some passengers paid very high fares. Most passengers paid lower fares.

Survival Count by Gender

In [11]:
```
sns.countplot(x='Survived', hue='Sex', data=df)
plt.title("Survival by Gender")
plt.show()
```

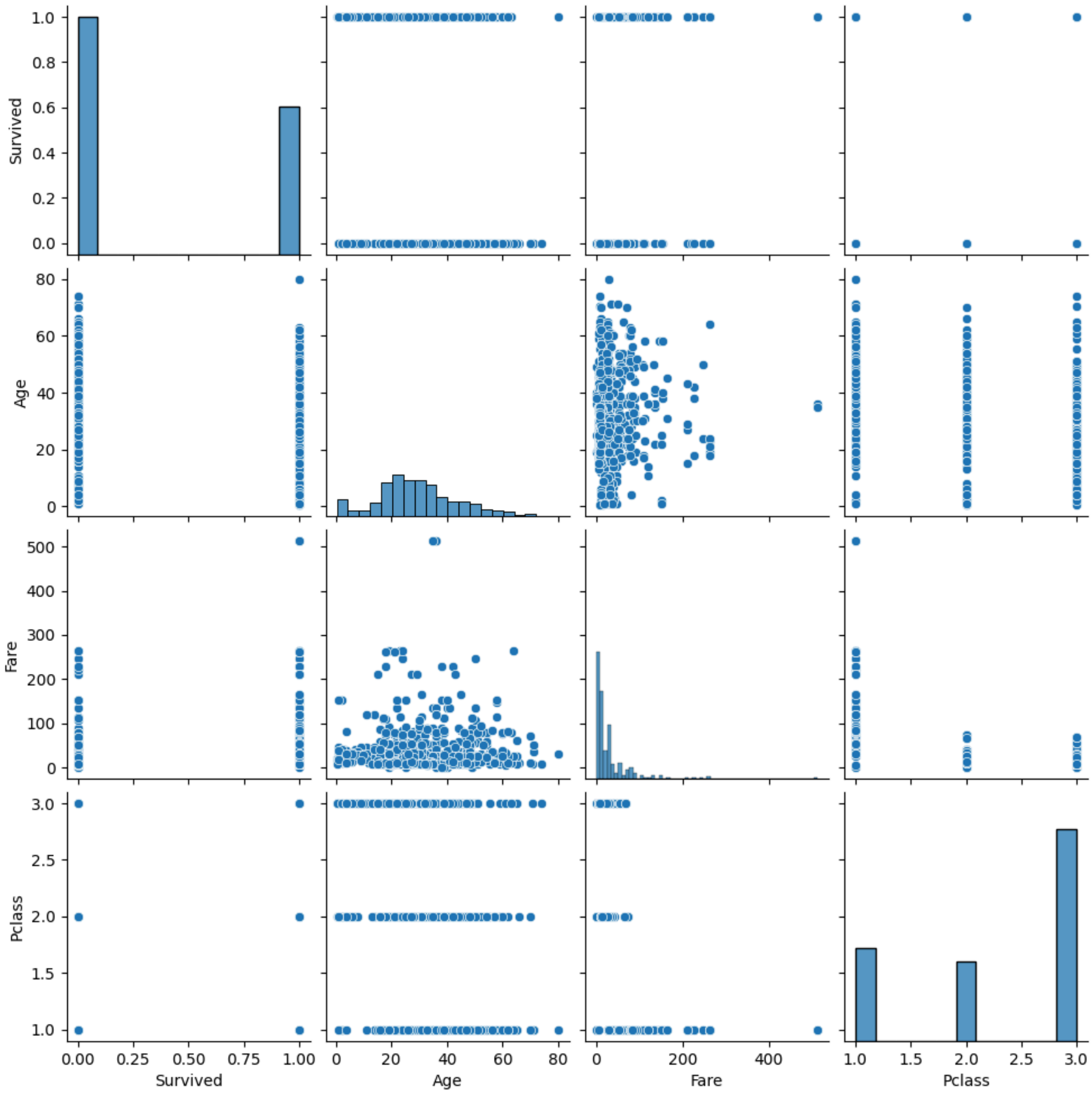


Observation:

Female passengers had a higher survival rate compared to male passengers. Most male passengers did not survive. Gender played an important role in survival.

Pairplot of Key Numerical Features

In [12]:
```
sns.pairplot(df[['Survived','Age','Fare','Pclass']])
plt.show()
```



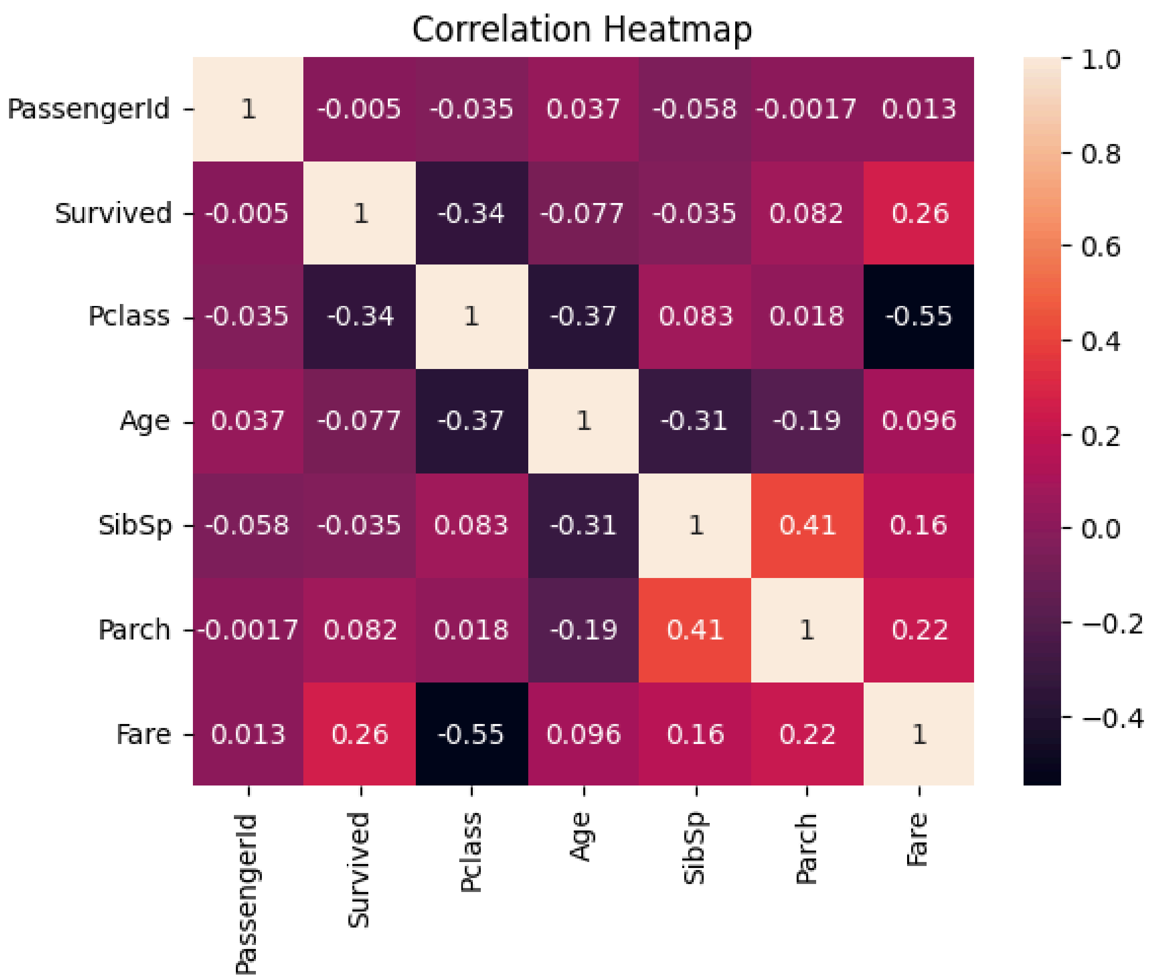
Observation:

The pairplot shows relationships between numerical variables. Survival is positively related to Fare. Passengers with higher fares had better chances of survival.

Correlation Heatmap of Numerical Features

In [14]:
```
numeric_df = df.select_dtypes(include='number')

sns.heatmap(numeric_df.corr(), annot=True)
plt.title("Correlation Heatmap")
plt.show()
```

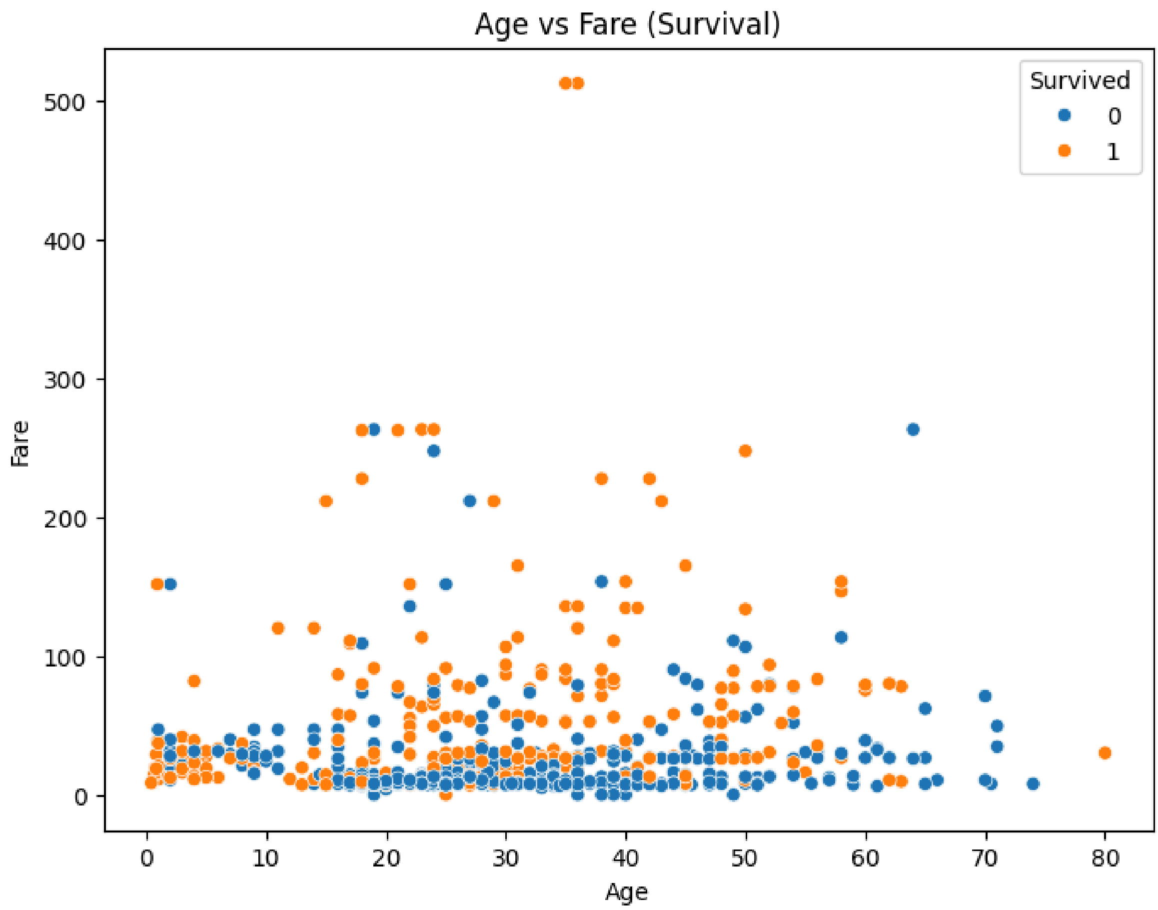


Observation:

The heatmap shows correlation between numerical features. Fare has a positive correlation with survival. Pclass has a negative correlation with survival.

Scatterplot of Age vs Fare by Survival

In [15]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(
    x='Age',
    y='Fare',
    hue='Survived',
    data=df
)
plt.title("Age vs Fare (Survival)")
plt.show()
```



Observation:

The scatterplot shows a weak relationship between Age and Fare. Most passengers paid lower fares across all age groups. A few high-fare outliers are visible.

Summary

- Female passengers had a significantly higher survival rate than male passengers.
- Passengers traveling in higher classes (Pclass 1) had better chances of survival.
- Higher fare was positively associated with survival, indicating that wealthier passengers survived more.
- Age showed a moderate impact on survival, with children having slightly better survival chances.
- Overall, gender and passenger class were the most influential factors affecting survival.

```
In [ ]:
```