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

## Observation:

We are importing three essential Python libraries for EDA:

- pandas: for data handling
- matplotlib.pyplot and seaborn: for creating visualizations

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

## Observation:

The Titanic dataset has been successfully loaded from the file "train.csv" into a pandas DataFrame called `df`.

In [3]:
```
print("Shape of dataset:", df.shape)
print("\nData types and non-null counts:")
print(df.info())
print("\nSummary statistics:")
print(df.describe(include='all'))
```

```
Shape of dataset: (891, 12)

Data types and non-null counts:
<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
None

Summary statistics:
        PassengerId    Survived      Pclass                 Name   Sex  \
count    891.000000  891.000000  891.000000                  891   891   
unique          NaN         NaN         NaN                  891     2   
top             NaN         NaN         NaN  Dooley, Mr. Patrick  male   
freq            NaN         NaN         NaN                    1   577   
mean     446.000000    0.383838    2.308642                  NaN   NaN   
std      257.353842    0.486592    0.836071                  NaN   NaN   
min        1.000000    0.000000    1.000000                  NaN   NaN   
25%      223.500000    0.000000    2.000000                  NaN   NaN   
50%      446.000000    0.000000    3.000000                  NaN   NaN   
75%      668.500000    1.000000    3.000000                  NaN   NaN   
max      891.000000    1.000000    3.000000                  NaN   NaN   

               Age       SibSp       Parch  Ticket        Fare Cabin Embarked  
count   714.000000  891.000000  891.000000     891  891.000000   204      889  
unique         NaN         NaN         NaN     681         NaN   147        3  
top            NaN         NaN         NaN  347082         NaN    G6        S  
freq           NaN         NaN         NaN       7         NaN     4      644  
mean     29.699118    0.523008    0.381594     NaN   32.204208   NaN      NaN  
std      14.526497    1.102743    0.806057     NaN   49.693429   NaN      NaN  
min       0.420000    0.000000    0.000000     NaN    0.000000   NaN      NaN  
25%      20.125000    0.000000    0.000000     NaN    7.910400   NaN      NaN  
50%      28.000000    0.000000    0.000000     NaN   14.454200   NaN      NaN  
75%      38.000000    1.000000    0.000000     NaN   31.000000   NaN      NaN  
max      80.000000    8.000000    6.000000     NaN  512.329200   NaN      NaN  
```

## Observation:

- The dataset contains 891 rows and 12 columns.
- Columns like `Age`, `Cabin`, and `Embarked` have missing values.
- Most passengers traveled in 3rd class ( `Pclass = 3` ).
- Several columns are categorical (e.g., Name, Sex, Embarked).

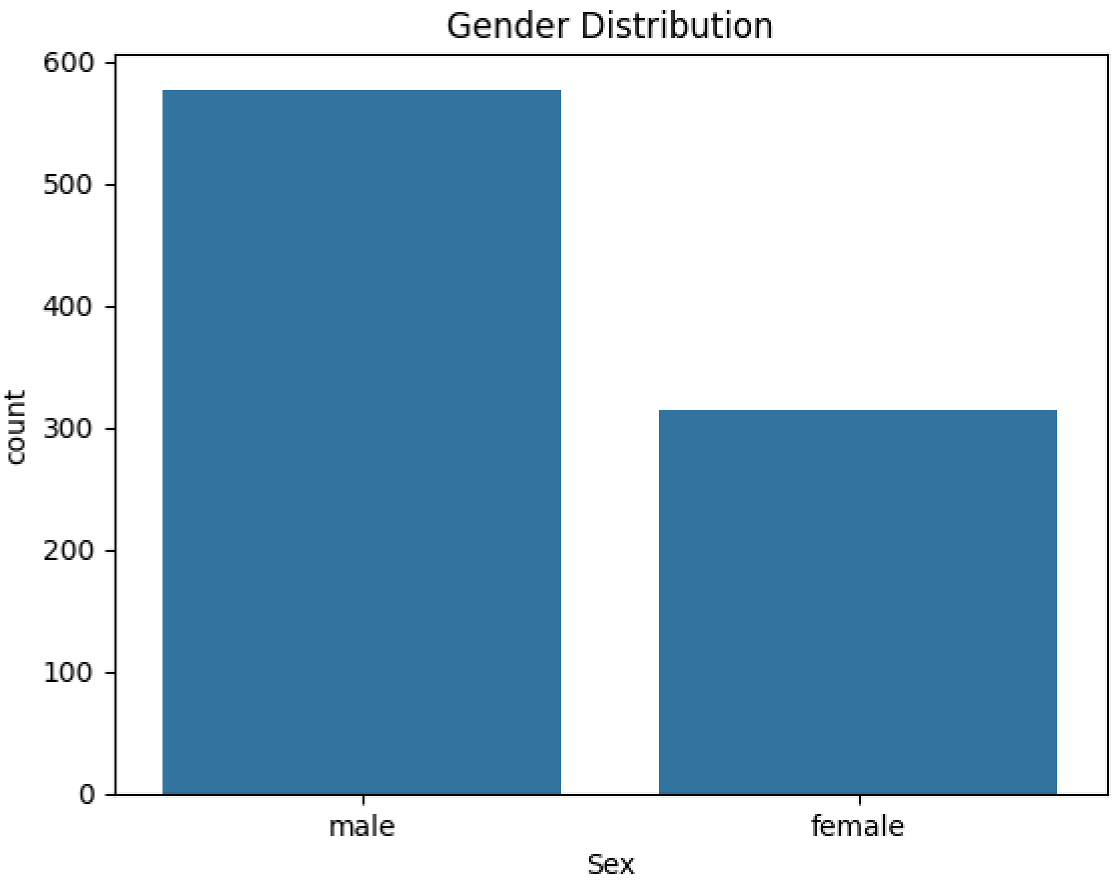
In [4]:
```
print("\nMissing values:\n", df.isnull().sum())
```

```
Missing values:
 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
```

## Observation:

- `Age` has 177 missing values.
- `Cabin` has a large number of missing values (687).
- `Embarked` has 2 missing values.
- These columns may need to be cleaned or handled before modeling.

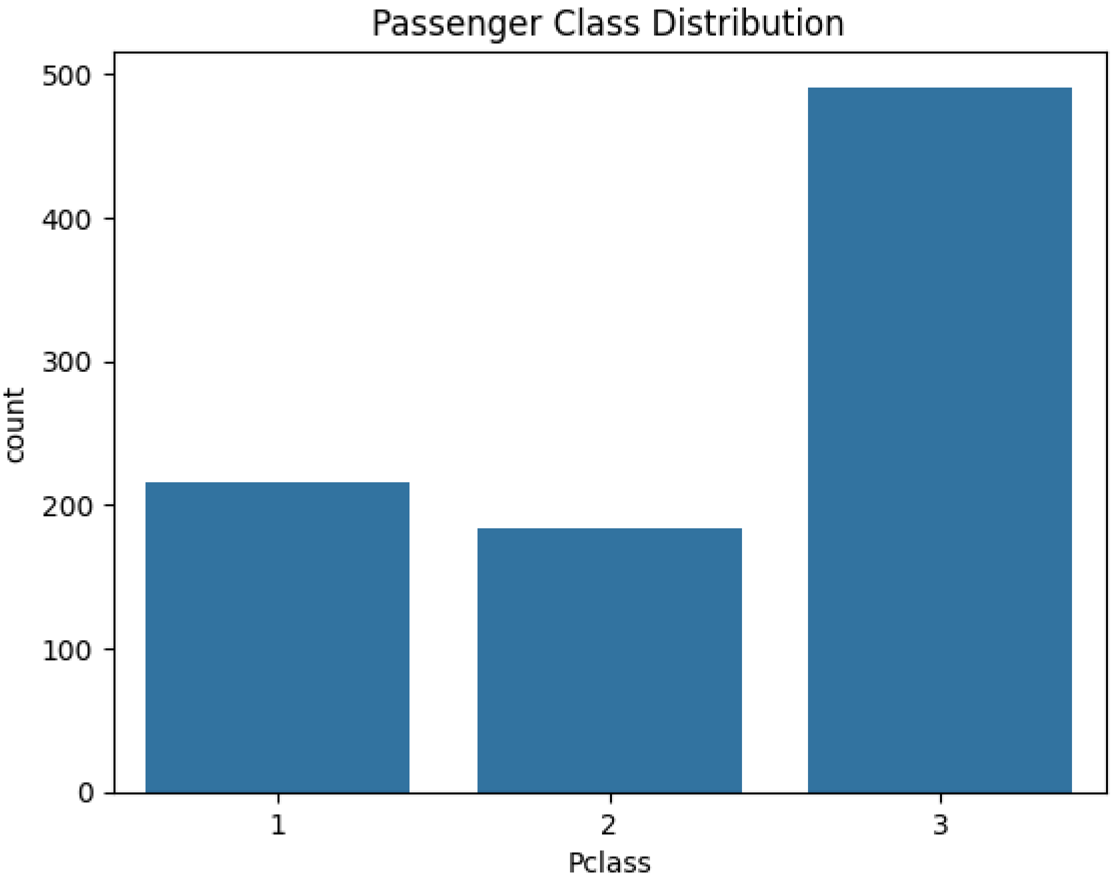
In [5]:
```
sns.countplot(x='Sex', data=df)
plt.title("Gender Distribution")
plt.show()
```




## Observation:

There were more male passengers than female on the Titanic. This gender imbalance may affect survival analysis.

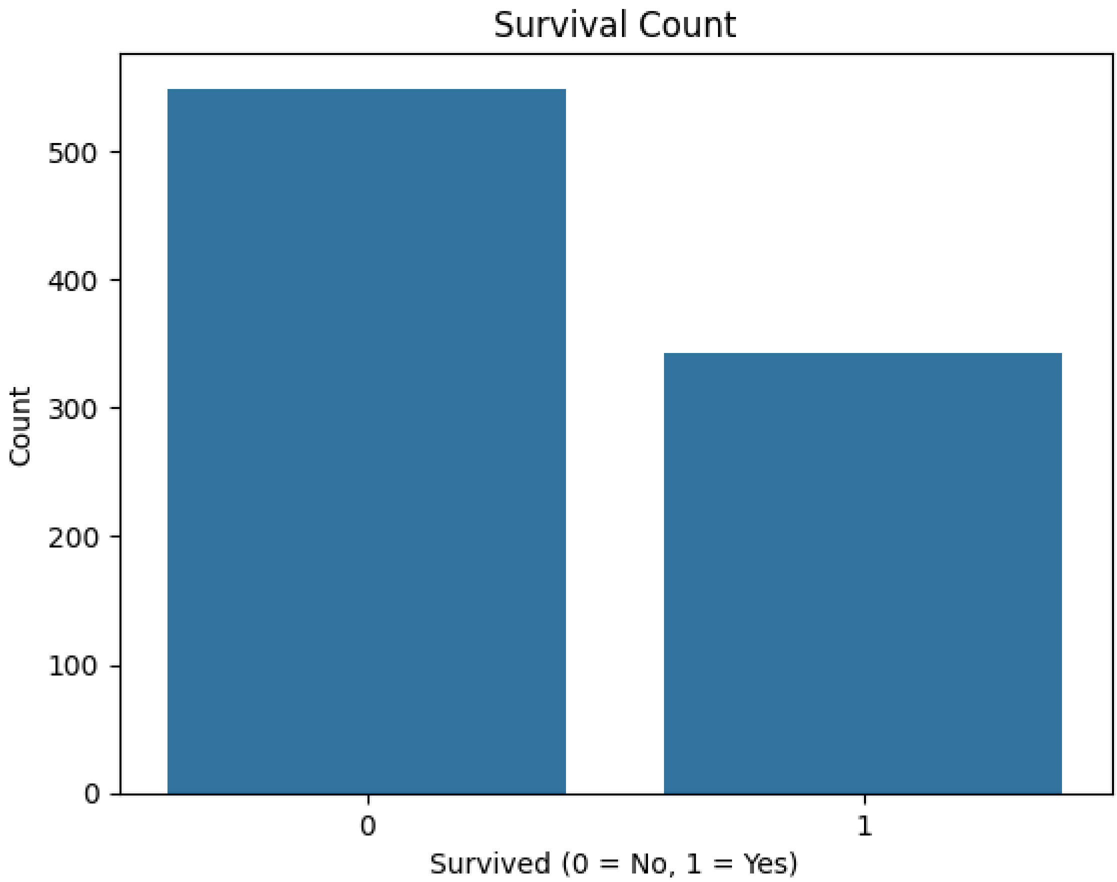
In [6]:
```
sns.countplot(x='Pclass', data=df)
plt.title("Passenger Class Distribution")
plt.show()
```




## Observation:

Most passengers were in 3rd class, followed by 1st and 2nd. This shows a majority of low-fare travelers.

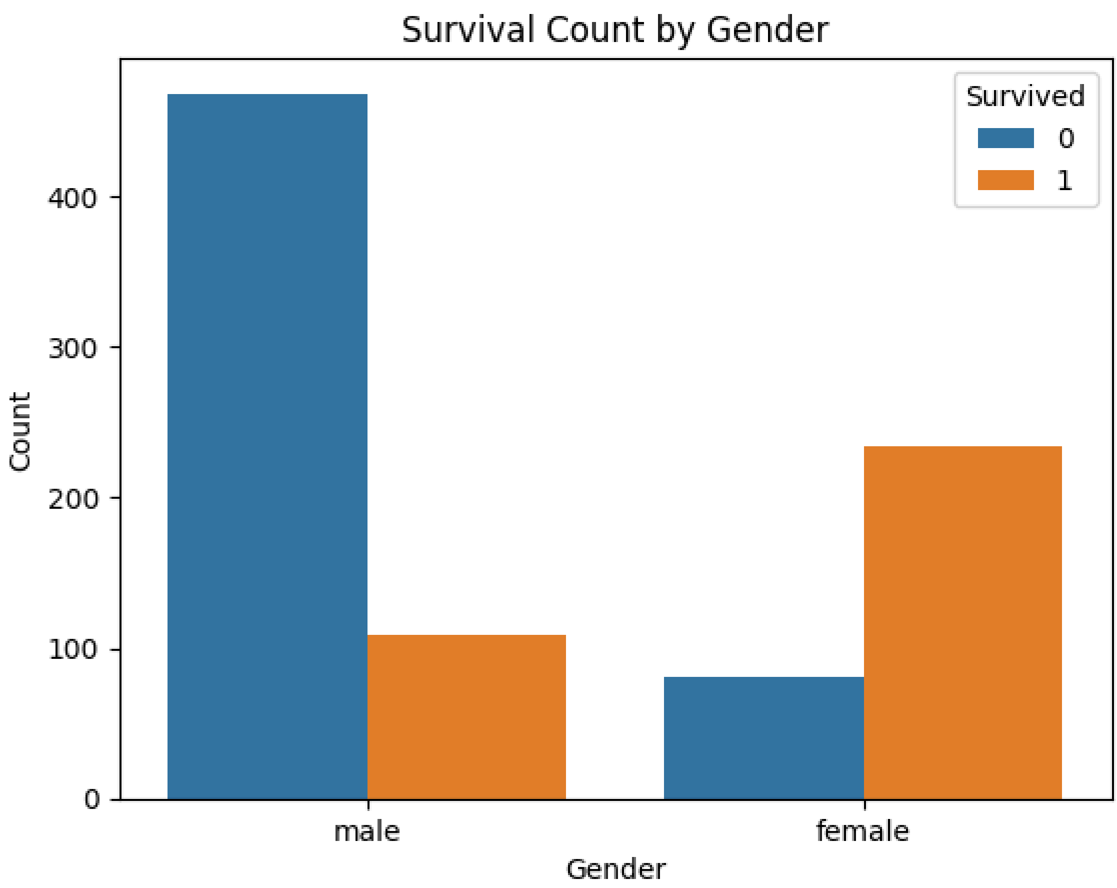
In [8]:
```
sns.countplot(x='Survived', data=df)
plt.title("Survival Count")
plt.xlabel("Survived (0 = No, 1 = Yes)")
plt.ylabel("Count")
plt.show()
```




## Observation:

The dataset shows that more passengers did not survive than those who did. The number of non-survivors (0) is higher than survivors (1).

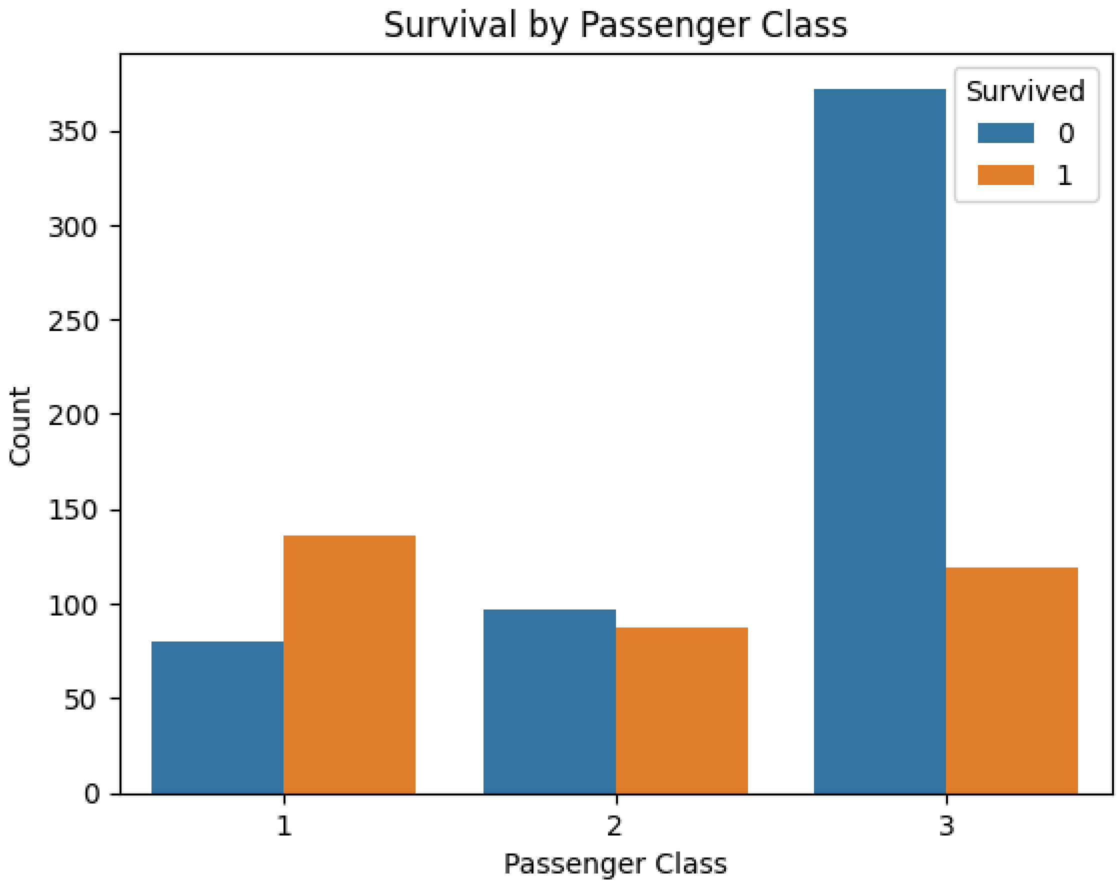
In [9]:
```
sns.countplot(x='Sex', hue='Survived', data=df)
plt.title("Survival Count by Gender")
plt.xlabel("Gender")
plt.ylabel("Count")
plt.legend(title='Survived')
plt.show()
```




## Observation:

Females had a much higher survival rate than males. Most male passengers did not survive, while most female passengers did.

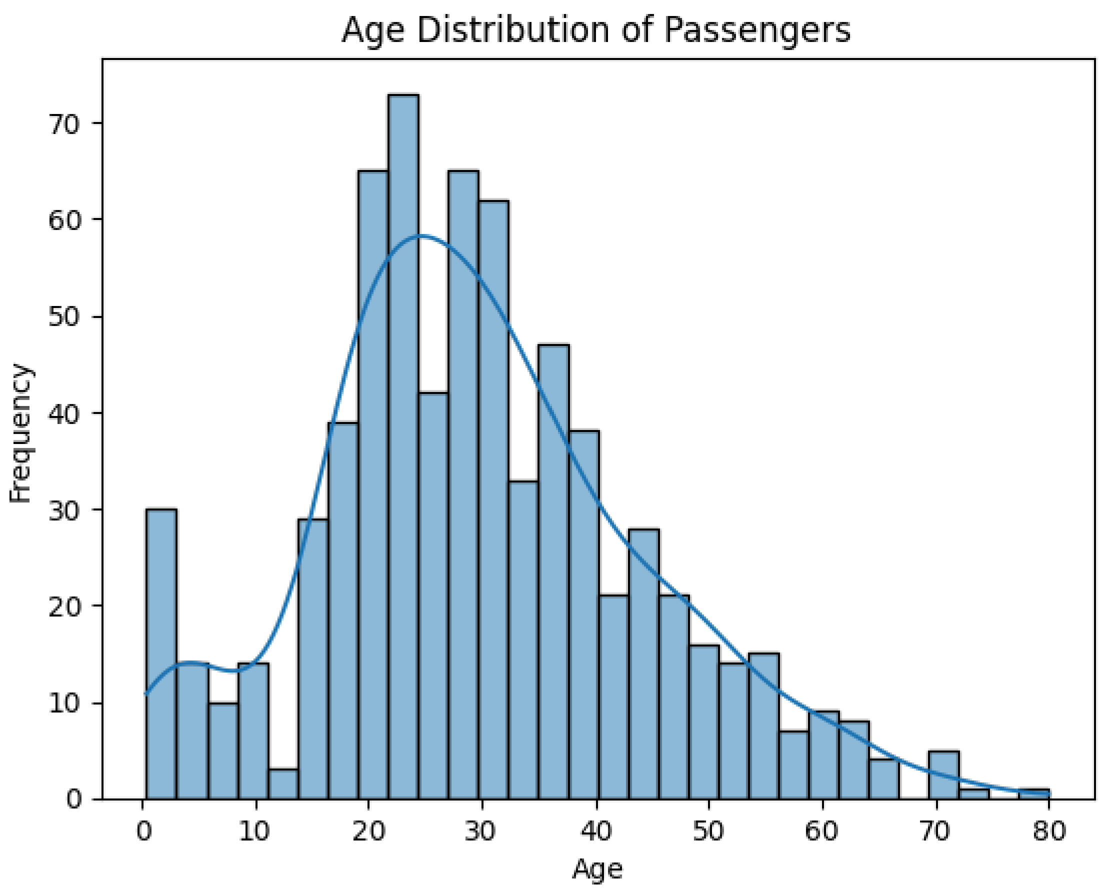
In [10]:
```
sns.countplot(x='Pclass', hue='Survived', data=df)
plt.title("Survival by Passenger Class")
plt.xlabel("Passenger Class")
plt.ylabel("Count")
plt.legend(title='Survived')
plt.show()
```




## Observation:

First-class passengers had a higher survival rate compared to second and third class. Passengers in third class had the lowest survival rate.

In [11]:
```
sns.histplot(data=df, x='Age', kde=True, bins=30)
plt.title("Age Distribution of Passengers")
plt.xlabel("Age")
plt.ylabel("Frequency")
plt.show()
```

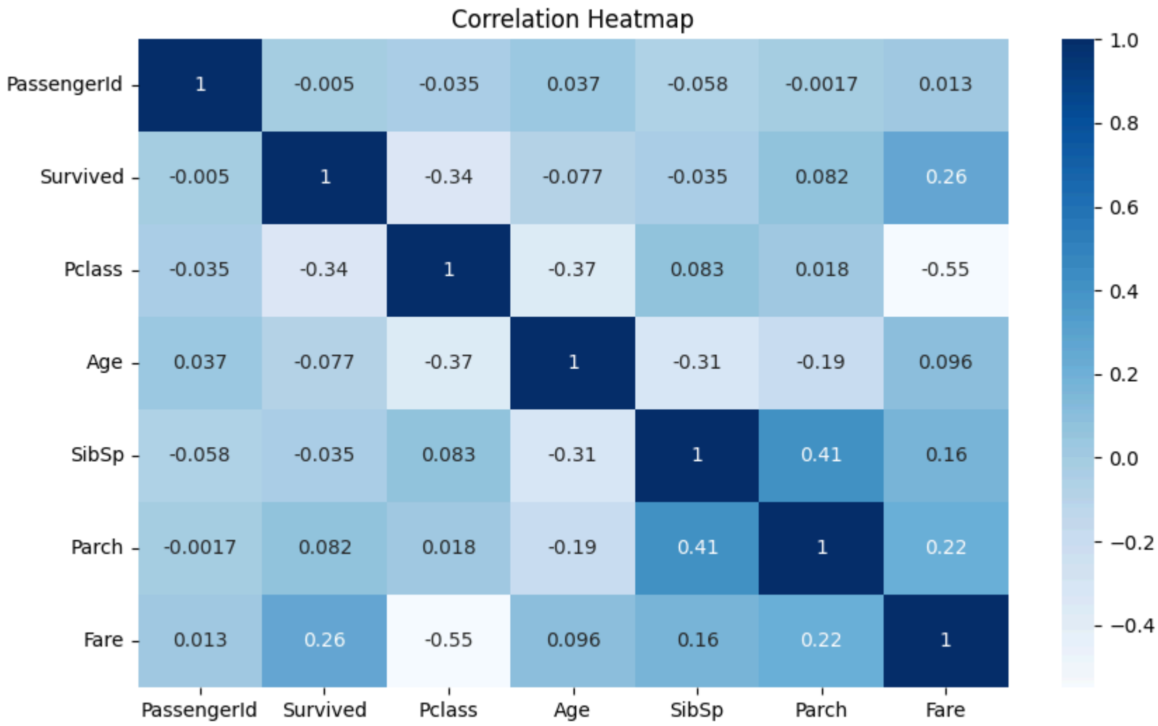



## Observation:

Most passengers were between 20 and 40 years old. There were also many children under 10 and some elderly passengers.

In [15]:
```
# Select only numeric columns for correlation
numeric_df = df.select_dtypes(include=['float64', 'int64'])

# Now draw the heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(numeric_df.corr(), annot=True, cmap='Blues')
plt.title("Correlation Heatmap")
plt.show()
```




## Observation:

The correlation heatmap shows that survival has a positive correlation with fare and a negative correlation with being in third class. Age and number of siblings/spouses show weak correlations.

## 📊 Summary of Findings:

- The majority of passengers were male and in 3rd class.
- Most passengers were aged between 20 to 40 years.
- There were more people who died than survived.
- Females had a higher survival rate than males.
- Passengers in 1st class had better chances of survival.
- Missing values are present in the `Age`, `Cabin`, and `Embarked` columns.
- `Pclass`, `Sex`, and `Fare` appear to be related to survival.