🚢 Titanic Survival Analysis – Exploratory Data Analysis (EDA)

In this notebook, we explore the Titanic dataset to uncover patterns that influenced passenger survival. We'll clean the data, visualize key features, and derive actionable insights.

1. Data Loading and Initial Exploration

In [10]:

```
import pandas as pd

df = pd.read_csv(r"C:\Users\LENOVO\Downloads\train (2).csv")
df.head()
```

Out[10]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.250C
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.925C
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.100C
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.050C

In [11]:

```
# Overview of dataset
df.info()

# Statistical summary of numeric columns
df.describe()

#  Value counts for categorical columns
```

```python
print("Survived:\n", df['Survived'].value_counts())
print("\nPclass:\n", df['Pclass'].value_counts())
print("\nSex:\n", df['Sex'].value_counts())
print("\nEmbarked:\n", df['Embarked'].value_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
Survived:
 Survived
0    549
1    342
Name: count, dtype: int64

Pclass:
 Pclass
3    491
1    216
2    184
Name: count, dtype: int64

Sex:
 Sex
male      577
female    314
Name: count, dtype: int64

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

2. Data Cleaning

In [12]:

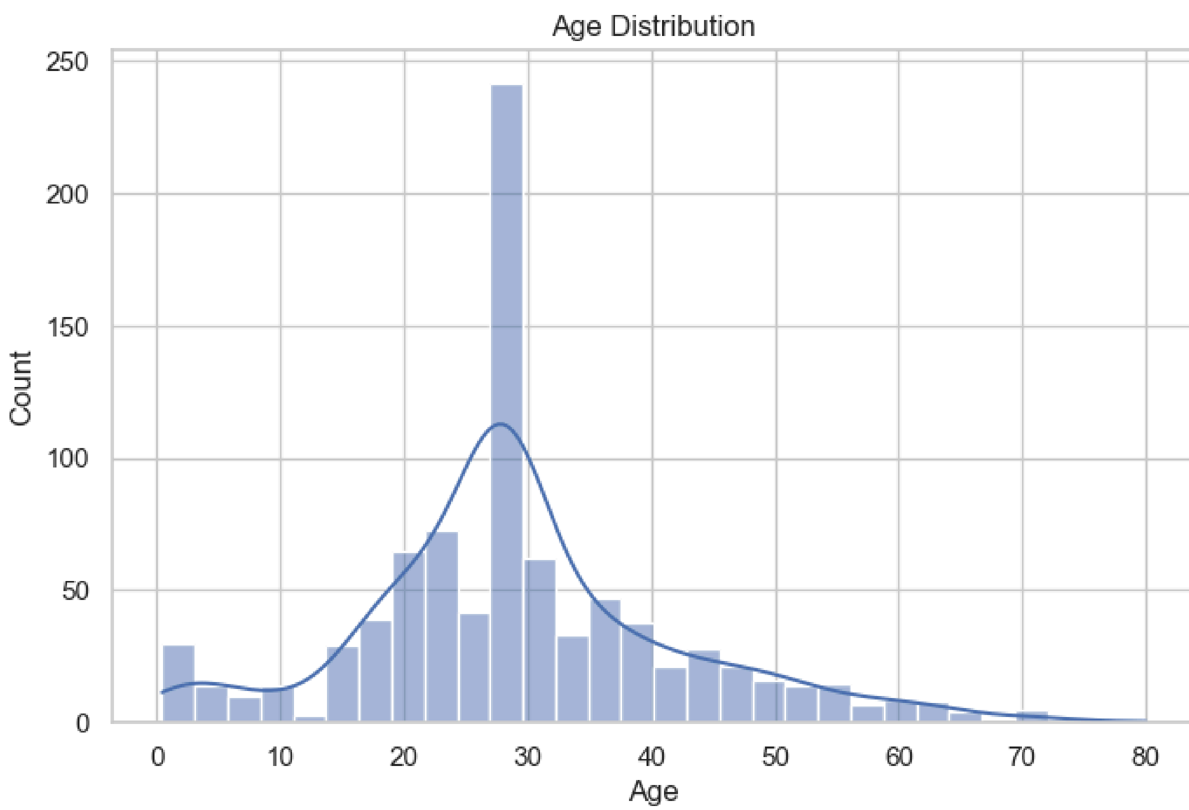
```python
# Fill missing Age with median
df.loc[:, 'Age'] = df['Age'].fillna(df['Age'].median())
```

```
# Fill missing Embarked with mode
df.loc[:, 'Embarked'] = df['Embarked'].fillna(df['Embarked'].mode()[0])

# Drop Cabin due to high missing values
df.drop(columns=['Cabin'], inplace=True)
```

3. Univariate Analysis

In [15]:

```
import seaborn as sns
import matplotlib.pyplot as plt
sns.set(style="whitegrid")

plt.figure(figsize=(8, 5))
sns.histplot(df['Age'], kde=True)
plt.title("Age Distribution")
plt.xlabel("Age")
plt.ylabel("Count")
plt.show()
```



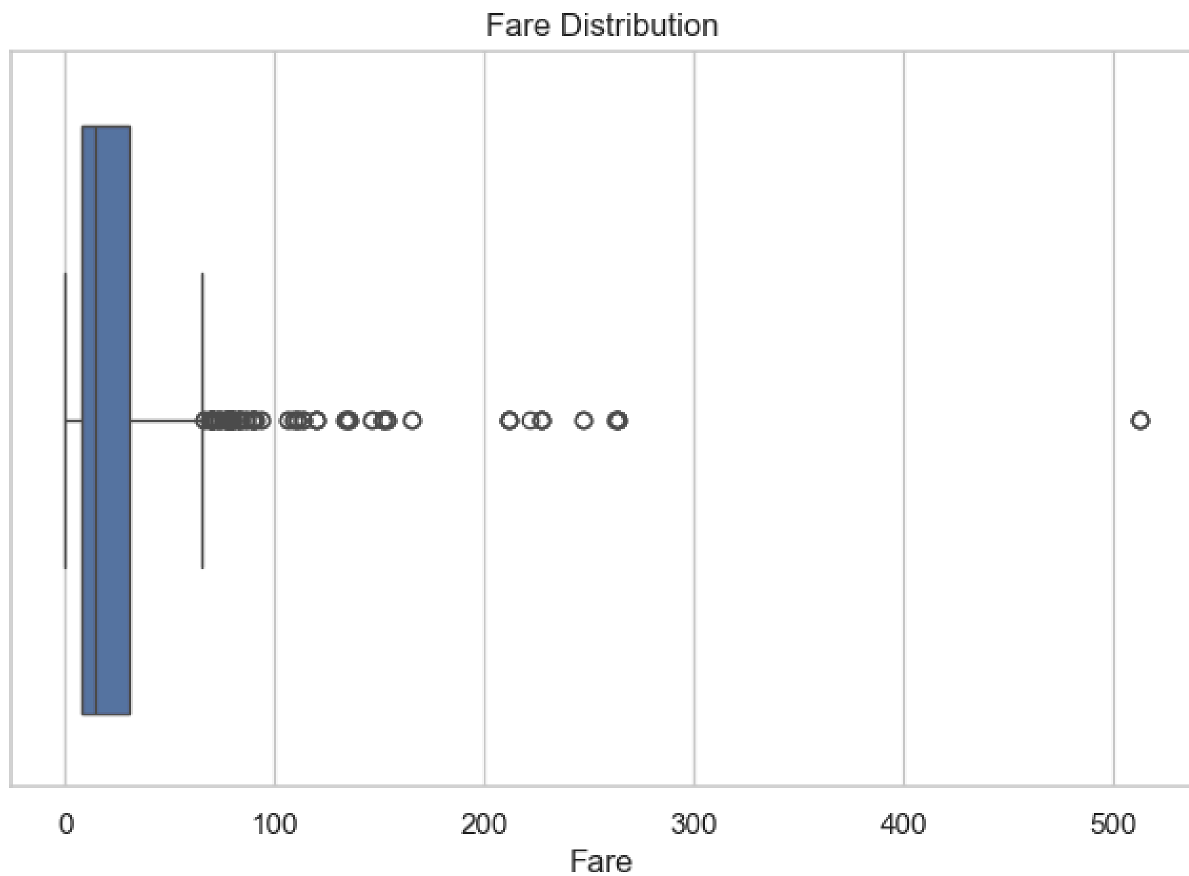
Age Distribution

- Most passengers are between 20–40 years old.
- Distribution is right-skewed, showing more younger passengers on board.
- A few children and elderly passengers were also present.

In [16]:

```
plt.figure(figsize=(8, 5))
sns.boxplot(x=df['Fare'])
```

```
plt.title("Fare Distribution")
plt.show()
```

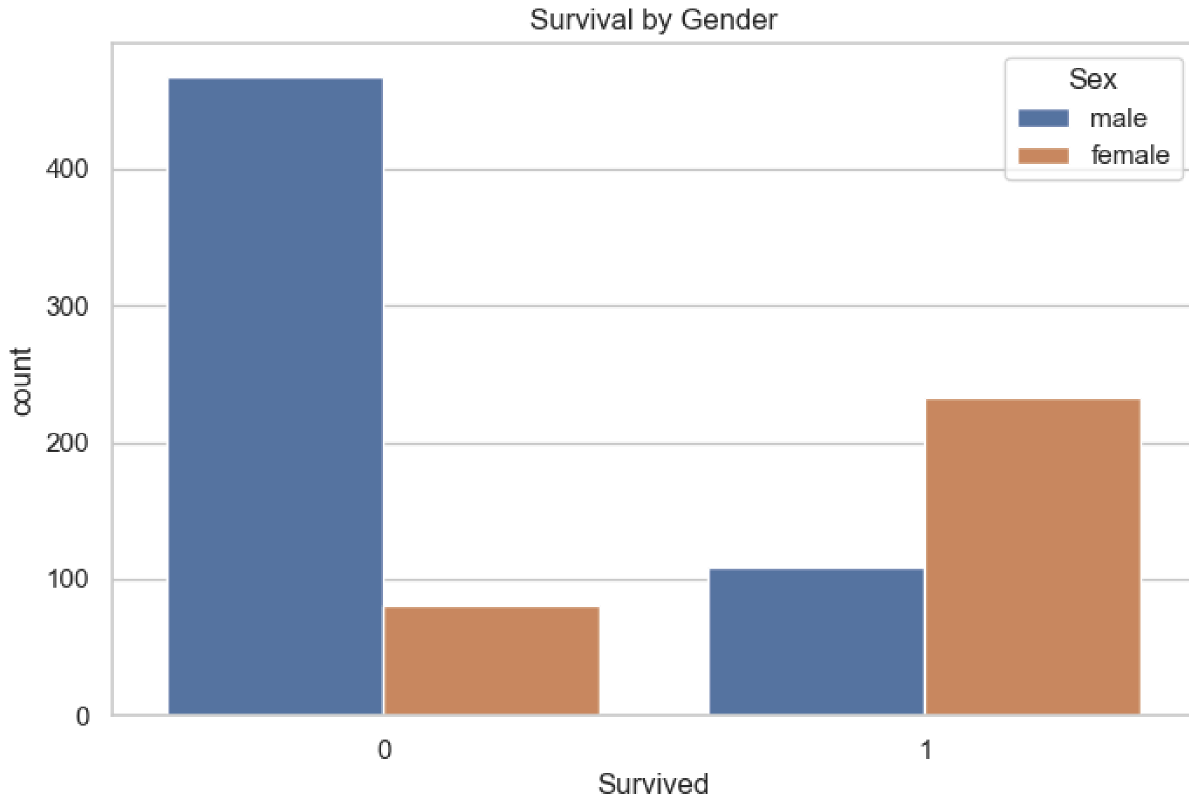


Fare Distribution

- Fare distribution is heavily skewed with many outliers.
- Most fares are below $100, butsomeexceed500$.
- The spread shows a wide range of socioeconomic backgrounds among passengers.

4. Bivariate and Multivariate Analysis

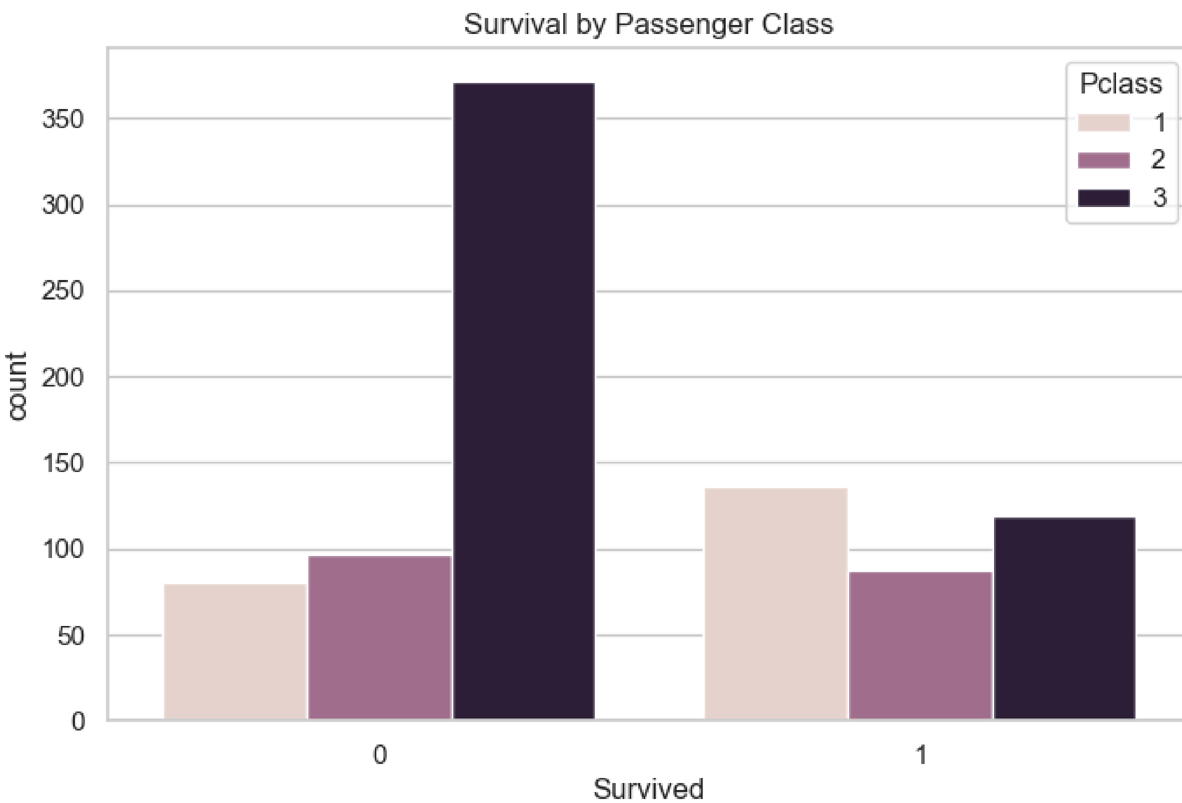
In [17]:
```
plt.figure(figsize=(8, 5))
sns.countplot(x='Survived', hue='Sex', data=df)
plt.title("Survival by Gender")
plt.show()
```



Survival by Gender

- Female passengers had a much higher survival rate than males.
- This aligns with the "women and children first" policy followed during the evacuation.
- Male survival was significantly lower, regardless of class.

In [18]:
```
plt.figure(figsize=(8, 5))
sns.countplot(x='Survived', hue='Pclass', data=df)
plt.title("Survival by Passenger Class")
plt.show()
```

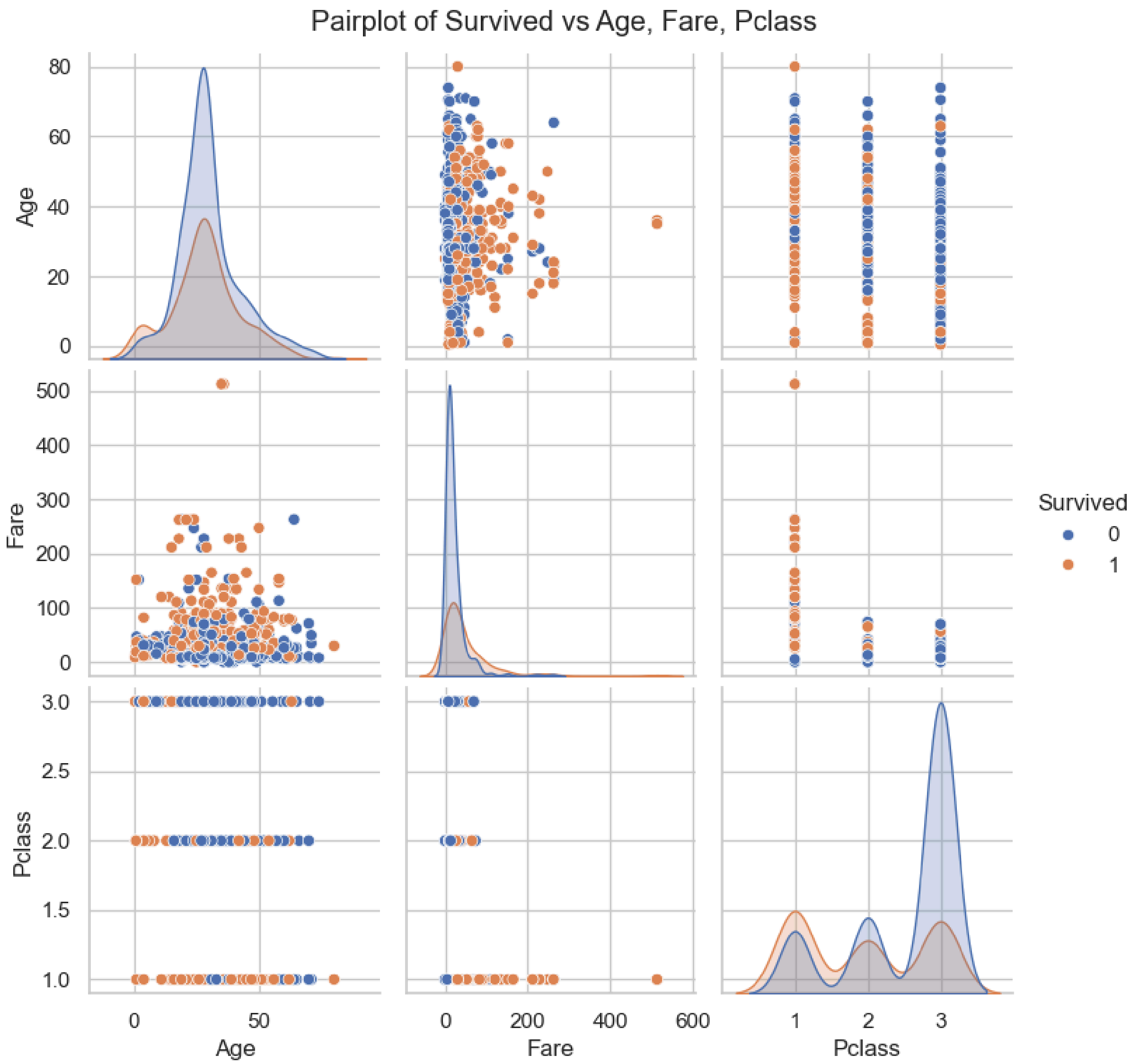


Survival by passenger Class

- 1st class passengers had the highest survival rate.
- 3rd class passengers had the lowest survival rate.
- Strong indication that socioeconomic status influenced survival priority.

In [19]:
```
plt.figure(figsize=(8, 5))
sns.pairplot(df[['Survived', 'Age', 'Fare', 'Pclass']].dropna(), hue='Survived')
plt.suptitle("Pairplot of Survived vs Age, Fare, Pclass", y=1.02)
plt.show()
```

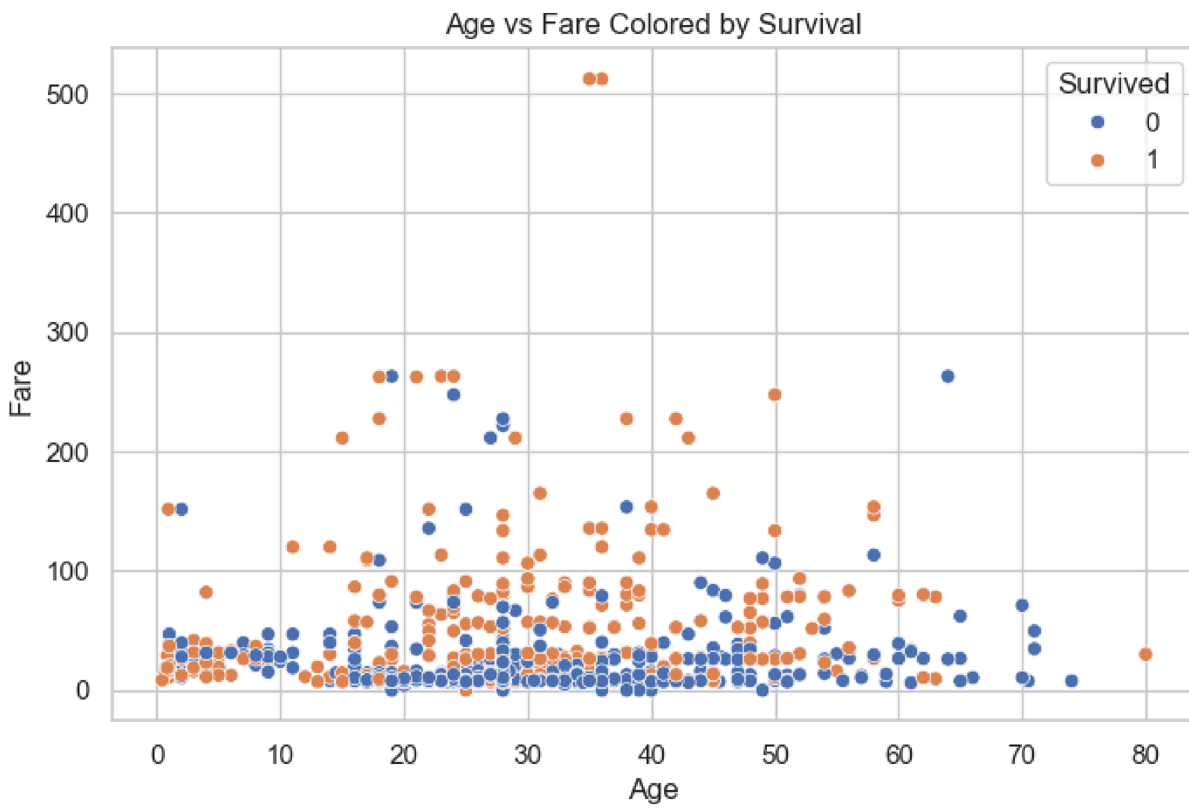
```
<Figure size 800x500 with 0 Axes>
```



Observation – Pairplot of Survived vs Age, Fare, Pclass

- Fare vs Pclass: As expected, 1st class passengers paid higher fares, and many of them survived (orange dots in top fare range).
- Age Distribution: Most passengers were between 20–40 years old, with a slightly right-skewed distribution.
- Survival Trends:
  - Many survivors had mid-to-high fares and belonged to 1st class.
  - In the Age vs Fare plot, survivors cluster around moderate age and higher fare areas.
  - 3rd class passengers (Pclass=3) show high density of non-survivors (blue dots).
- General Pattern: Higher fare and lower class (Pclass=1) seem associated with survival.

In [20]:
```
plt.figure(figsize=(8, 5))
sns.scatterplot(x='Age', y='Fare', hue='Survived', data=df)
plt.title("Age vs Fare Colored by Survival")
plt.show()
```

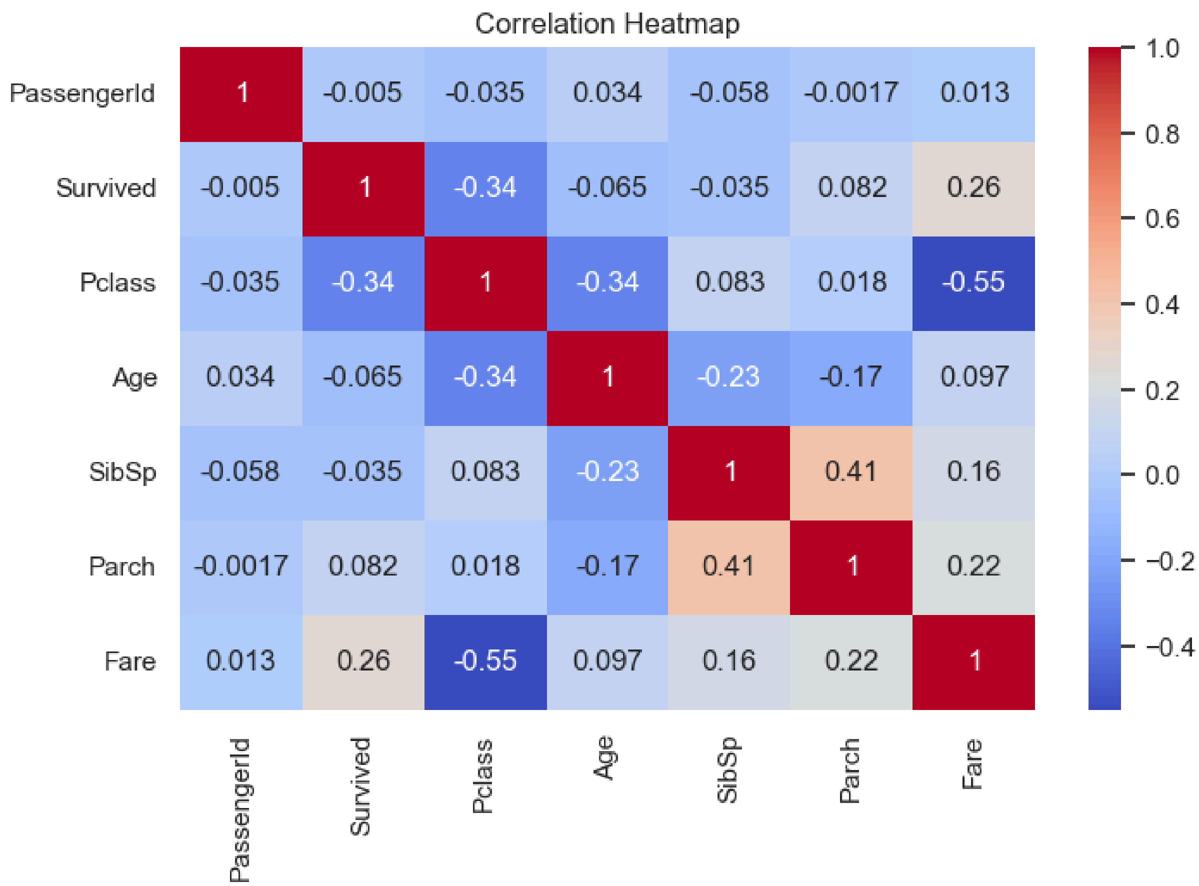


Age vs Fare Colored by Survival

- Survivors (orange) are more common in higher fare regions.
- Non-survivors (blue) mostly paid lower fares and fall across all age groups.
- Age alone doesn't guarantee survival, but higher fare (i.e., class) seems positively related to survival.

5. Correlation Analysis

In [22]:
```
plt.figure(figsize=(8, 5))
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='coolwarm')
plt.title("Correlation Heatmap")
plt.show()
```



Correlation Heatmap

- `Fare` has the strongest positive correlation with survival (0.26).
- `Pclass` has the strongest negative correlation with survival (-0.34).
- Family-related columns (`SibSp` , `Parch`) are moderately correlated with each other.
- `Age` , `Sex` , and `Embarked` are not directly shown here (non-numeric), but Age shows weak correlation.

6. Key Observations & Takeaways

- Female and 1st class passengers had higher survival rates.
- Fare shows a positive correlation with survival.
- Most passengers were aged between 20–40.
- Many 3rd class passengers did not survive.