Titanic — Exploratory Data Analysis (EDA)

Task: Perform EDA on the Titanic dataset (train.csv).
Tools: pandas, numpy, matplotlib, seaborn.

Deliverables:

- Jupyter Notebook with code, plots, and observations.
- PDF report with the same content for submission.

Dataset source: `train.csv` (use the uploaded file).

In [7]:
```
# Imports and settings
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os

sns.set(style="whitegrid", palette="muted")
%matplotlib inline
plt.rcParams['figure.figsize'] = (10,6)
```

In [8]:
```
# Load data
df = pd.read_csv("train.csv")
df.shape
```

Out[8]: (891, 12)

In [11]:
```
# Quick peek
display(df.head())
display(df.info())
display(df.describe(include='all').T)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fa
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.25(
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.28
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.92!
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.10(
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.05(

```
<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
```

	count	unique	top	freq	mean	std	min	25%	50%
PassengerId	891.0	NaN	NaN	NaN	446.0	257.353842	1.0	223.5	446.0
Survived	891.0	NaN	NaN	NaN	0.383838	0.486592	0.0	0.0	0.0
Pclass	891.0	NaN	NaN	NaN	2.308642	0.836071	1.0	2.0	3.0
Name	891	891	Braund, Mr. Owen Harris	1	NaN	NaN	NaN	NaN	NaN
Sex	891	2	male	577	NaN	NaN	NaN	NaN	NaN
Age	714.0	NaN	NaN	NaN	29.699118	14.526497	0.42	20.125	28.0
SibSp	891.0	NaN	NaN	NaN	0.523008	1.102743	0.0	0.0	0.0
Parch	891.0	NaN	NaN	NaN	0.381594	0.806057	0.0	0.0	0.0
Ticket	891	681	347082	7	NaN	NaN	NaN	NaN	NaN
Fare	891.0	NaN	NaN	NaN	32.204208	49.693429	0.0	7.9104	14.4542
Cabin	204	147	G6	4	NaN	NaN	NaN	NaN	NaN
Embarked	889	3	S	644	NaN	NaN	NaN	NaN	NaN

Initial Observations

- Columns: PassengerId, Survived, Pclass, Name, Sex, Age, SibSp, Parch, Ticket, Fare, Cabin, Embarked.
- Target column: **Survived** (0 = did not survive, 1 = survived).
- Missing values likely in **Age**, **Cabin**, and maybe **Embarked**.
- Will handle missing values, engineer a few features, then visualize.

In [12]:

```
# Missing values summary
missing = df.isnull().sum().sort_values(ascending=False)
missing[missing > 0]
```

Out[12]:

```
Cabin       687
Age         177
Embarked      2
dtype: int64
```

Plan

1. Handle missing values (Age, Embarked, Cabin).
2. Feature engineering: Title from Name, FamilySize, IsAlone, AgeGroup.
3. Univariate analysis (distributions).
4. Bivariate analysis (Survived vs features).
5. Correlation and multivariate checks.
6. Summary of insights and interview Q&A.

In [14]:
```
# Create a copy to work on
data = df.copy()

# 1) Extract Title from Name
data['Title'] = data['Name'].str.extract(r',\s*([^\.]+)\.', expand=False).str.st

# Simplify titles
title_map = {
    'Mlle': 'Miss', 'Ms': 'Miss', 'Mme': 'Mrs',
    'Lady': 'Royal', 'Countess': 'Royal', 'Dona': 'Royal', 'Sir': 'Royal', 'Don'
    'Jonkheer': 'Royal', 'Col': 'Officer', 'Major': 'Officer', 'Capt': 'Officer'
    'Rev': 'Officer'
}
data['Title'] = data['Title'].replace(title_map)

# Replace rare titles
rare_titles = data['Title'].value_counts()[data['Title'].value_counts() < 10].in
data['Title'] = data['Title'].replace(rare_titles, 'Other')

# 2) Family Size
data['FamilySize'] = data['SibSp'] + data['Parch'] + 1

# 3) IsAlone
data['IsAlone'] = (data['FamilySize'] == 1).astype(int)

# 4) Fill Embarked with mode (no chained assignment to avoid warnings)
data['Embarked'] = data['Embarked'].fillna(data['Embarked'].mode()[0])

# 5) Fill Age: use median by Title (better than global)
data['Age'] = data['Age'].fillna(
    data.groupby('Title')['Age'].transform('median')
)

# 6) Cabin: create HasCabin flag (many missing values so drop original Cabin)
data['HasCabin'] = (~data['Cabin'].isnull()).astype(int)
data = data.drop('Cabin', axis=1)

# 7) Fare: check and fill if needed
data['Fare'] = data['Fare'].fillna(data['Fare'].median())

# 8) Convert categorical columns to category dtype for nicer displays
for col in ['Pclass', 'Sex', 'Embarked', 'Title', 'IsAlone', 'HasCabin']:
    data[col] = data[col].astype('category')

# Show resulting columns and missing
display(data.info())
display(data.isnull().sum()[data.isnull().sum() > 0])
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    category
 3   Name         891 non-null    object
 4   Sex          891 non-null    category
 5   Age          891 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  Embarked     891 non-null    category
 11  Title        891 non-null    category
 12  FamilySize   891 non-null    int64
 13  IsAlone      891 non-null    category
 14  HasCabin     891 non-null    category
dtypes: category(6), float64(2), int64(5), object(2)
memory usage: 68.8+ KB
None
Series([], dtype: int64)
```

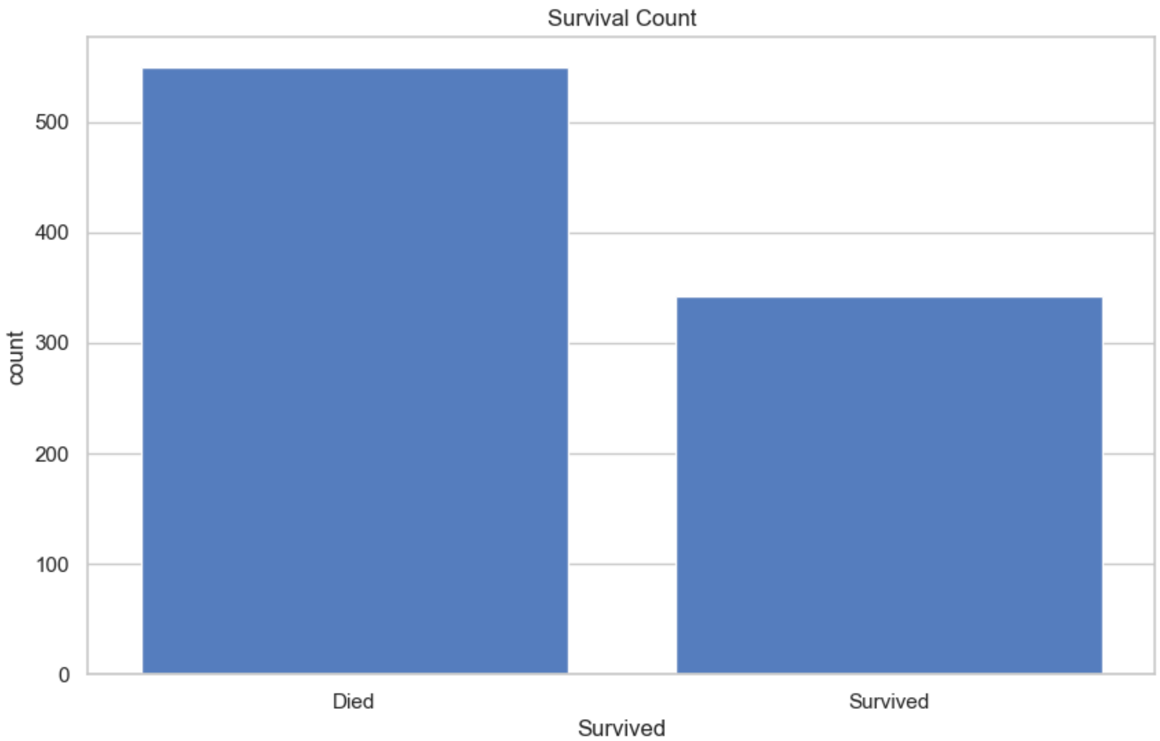
Feature engineering notes:

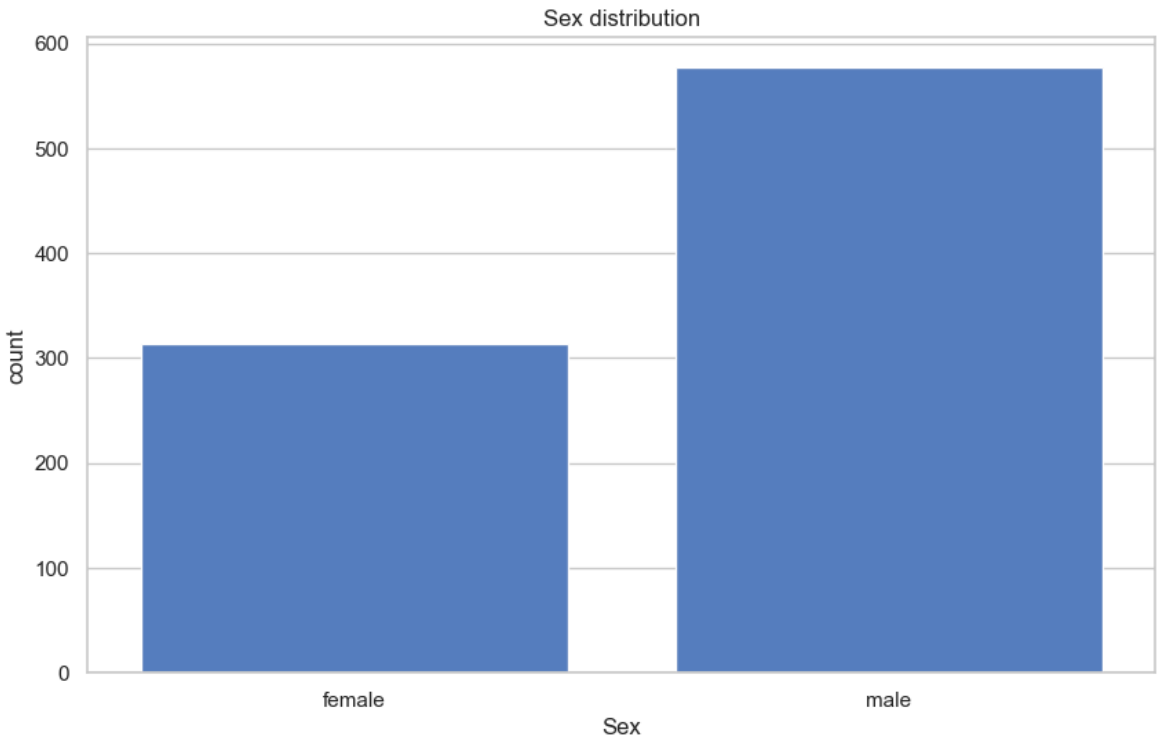
- `Title` captures social status (Mrs, Miss, Mr, Officer, Other).
- `FamilySize` and `IsAlone` can show the impact of family on survival.
- `HasCabin` as a proxy for deck/class (Cabin presence often correlates with higher class).
- Age filled per Title to better approximate missing ages.

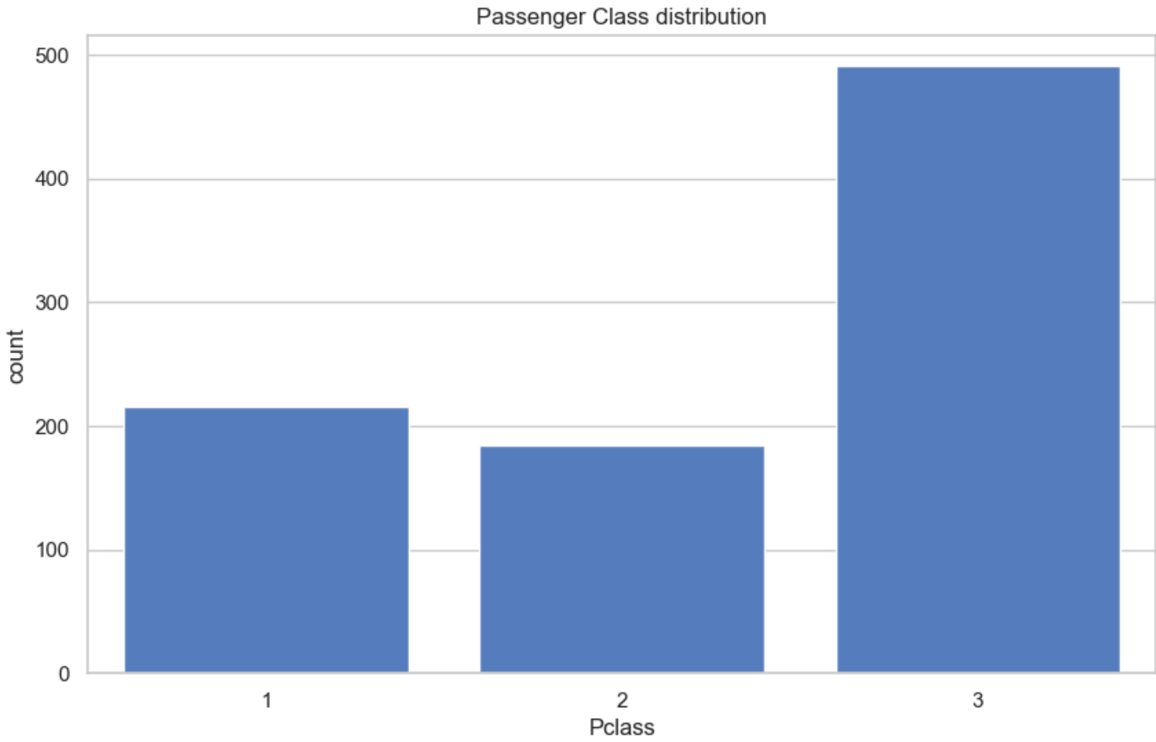
In [15]:

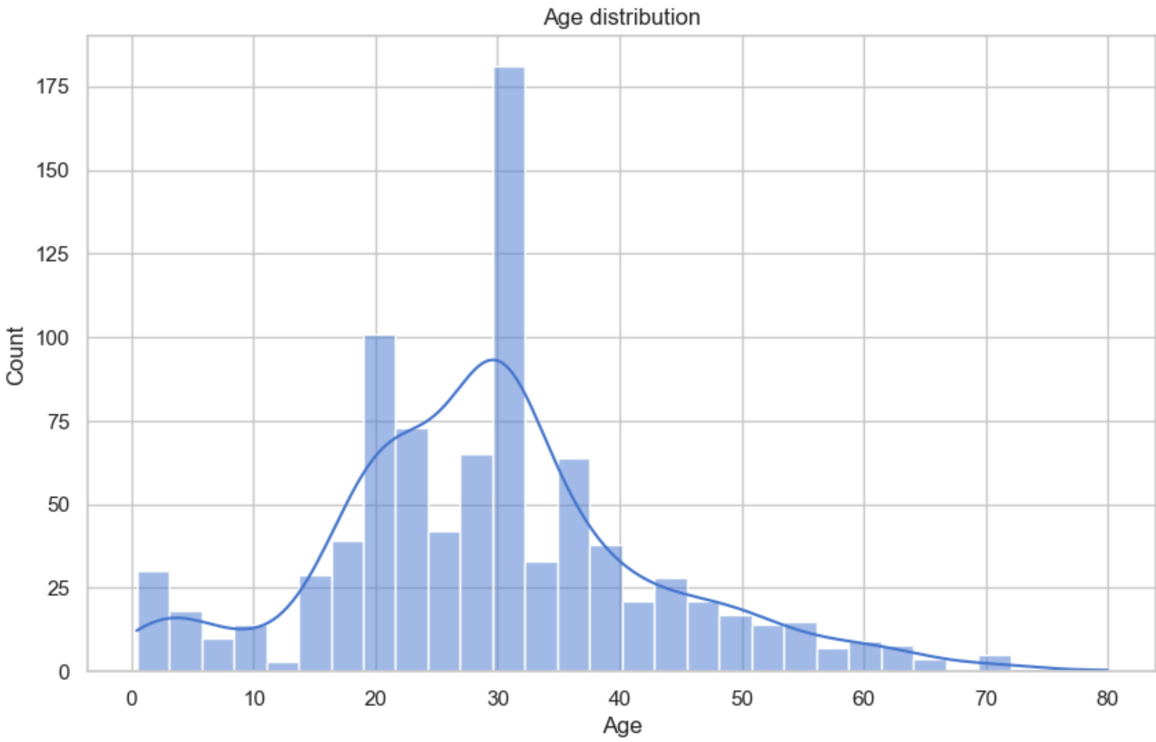
```
# 1. Survival counts
plt.figure()
sns.countplot(x='Survived', data=data)
plt.title('Survival Count')
plt.xticks([0,1], ['Died','Survived'])
plt.show()

# 2. Sex distribution
plt.figure()
sns.countplot(x='Sex', data=data)
plt.title('Sex distribution')
plt.show()

# 3. Pclass distribution
plt.figure()
sns.countplot(x='Pclass', data=data)
plt.title('Passenger Class distribution')
plt.show()

# 4. Age histogram
plt.figure()
sns.histplot(data['Age'], kde=True, bins=30)
plt.title('Age distribution')
plt.show()
```

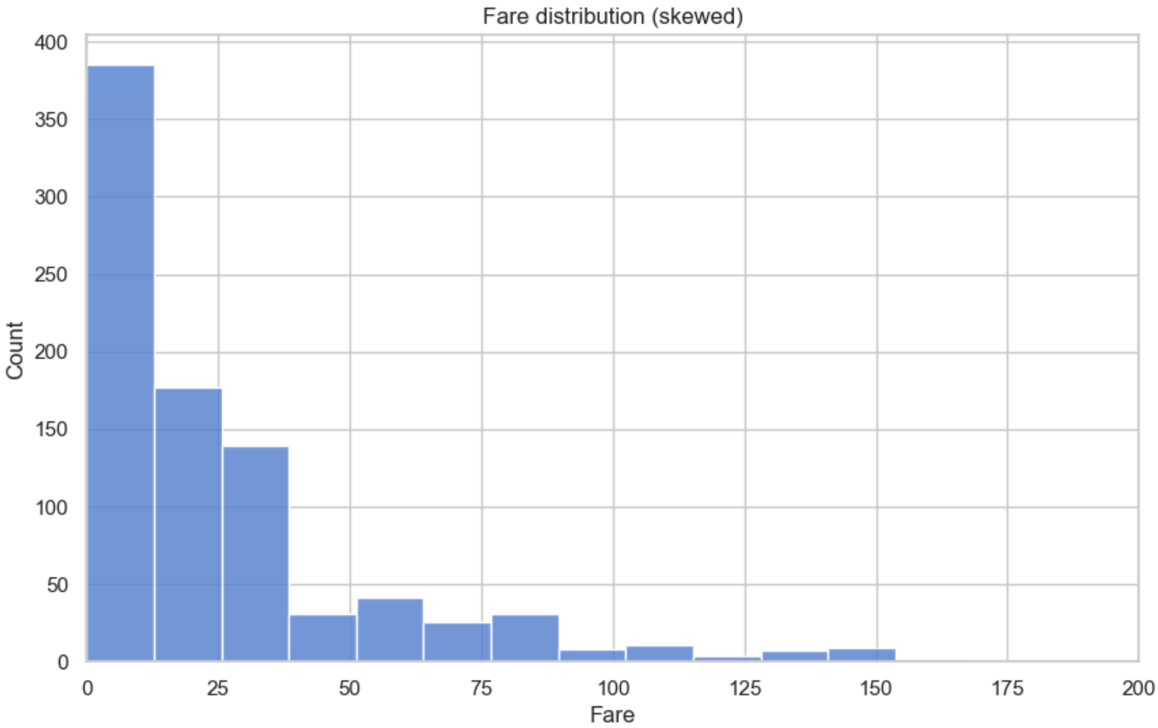
```
# 5. Fare distribution (skewed)
plt.figure()
sns.histplot(data['Fare'], bins=40)
plt.title('Fare distribution (skewed)')
plt.xlim(0, 200)
plt.show()
```






Passenger Class distribution
count
500
400
300
200
100
0
1
2
3
Pclass


Age distribution
Count
175
150
125
100
75
50
25
0
0
10
20
30
40
50
60
70
80
Age



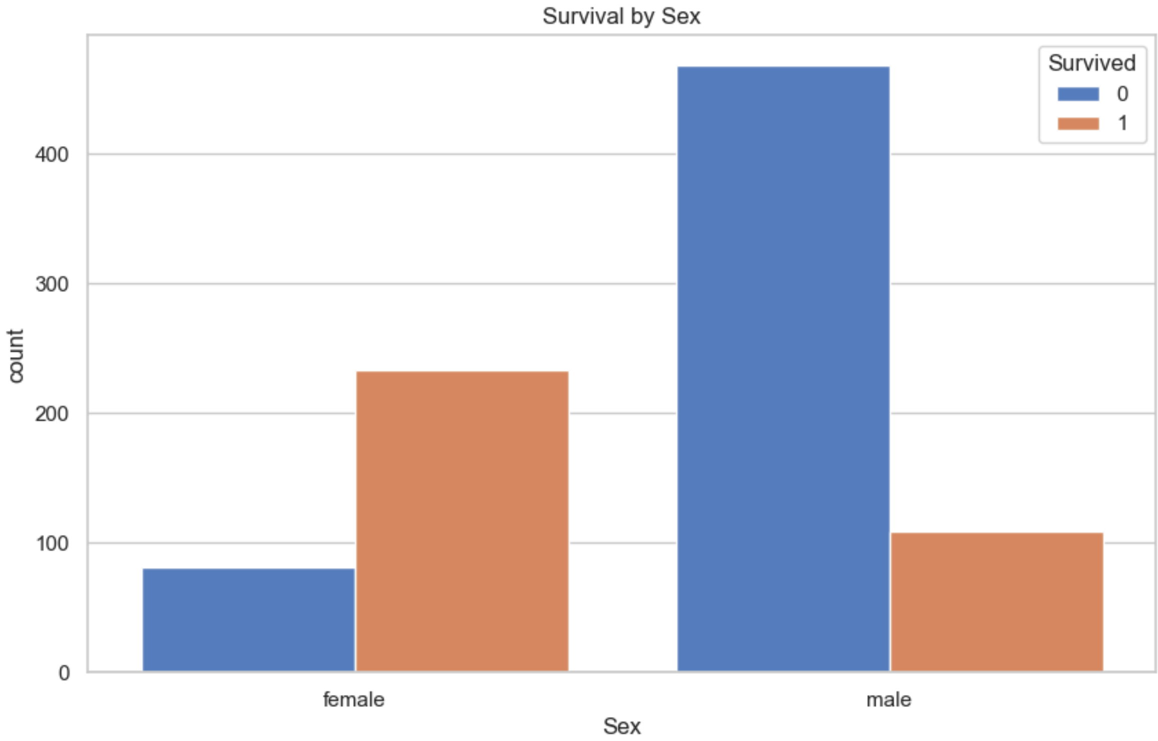
Univariate Observations

- More passengers did not survive than survived.
- Fewer passengers are in 1st class; majority in 3rd class.
- Age distribution is roughly right-skewed; many young passengers.
- Fare is heavily right-skewed (some very high fares).

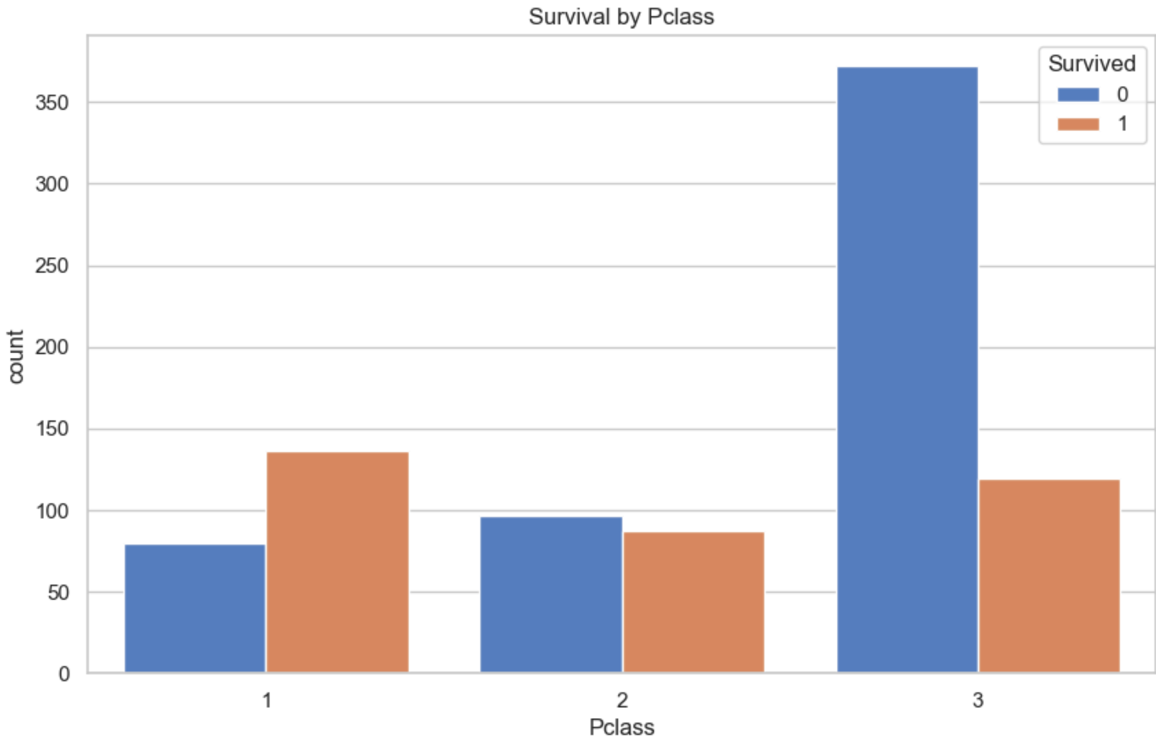
In [16]:

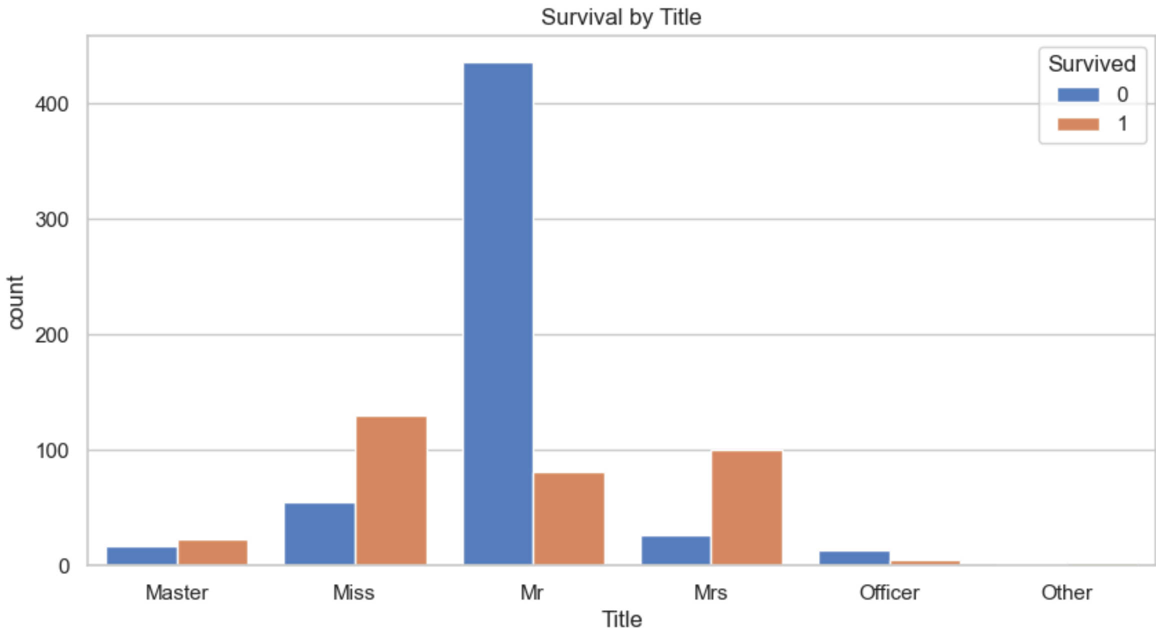
```
# Survival rate by Sex
display(pd.crosstab(data['Sex'], data['Survived'], normalize='index') * 100)

# Plot
plt.figure()
sns.countplot(x='Sex', hue='Survived', data=data)
plt.title('Survival by Sex')
plt.show()

# Survival by Pclass
display(pd.crosstab(data['Pclass'], data['Survived'], normalize='index') * 100)
plt.figure()
sns.countplot(x='Pclass', hue='Survived', data=data)
plt.title('Survival by Pclass')
plt.show()

# Survival by Title
plt.figure(figsize=(10,5))
sns.countplot(x='Title', hue='Survived', data=data)
plt.title('Survival by Title')
plt.show()
```

Survived	0	1
Sex		
female	25.796178	74.203822
male	81.109185	18.890815



Survived	0	1
Pclass		
1	37.037037	62.962963
2	52.717391	47.282609
3	75.763747	24.236253



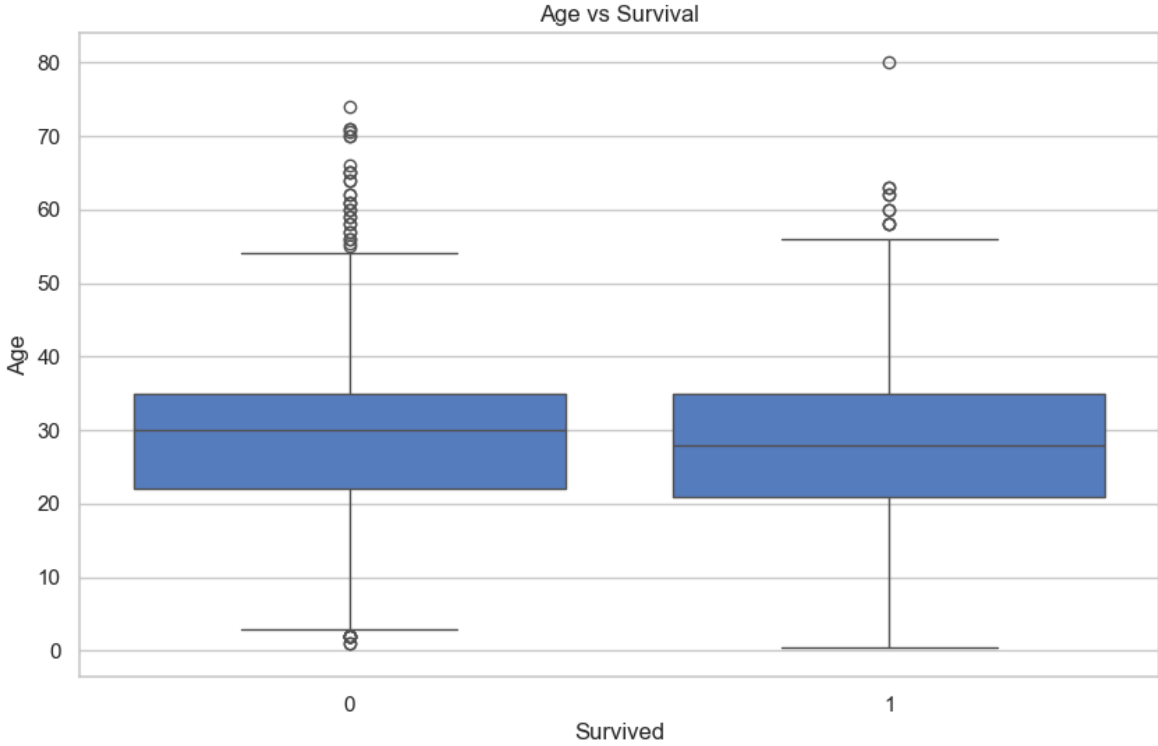


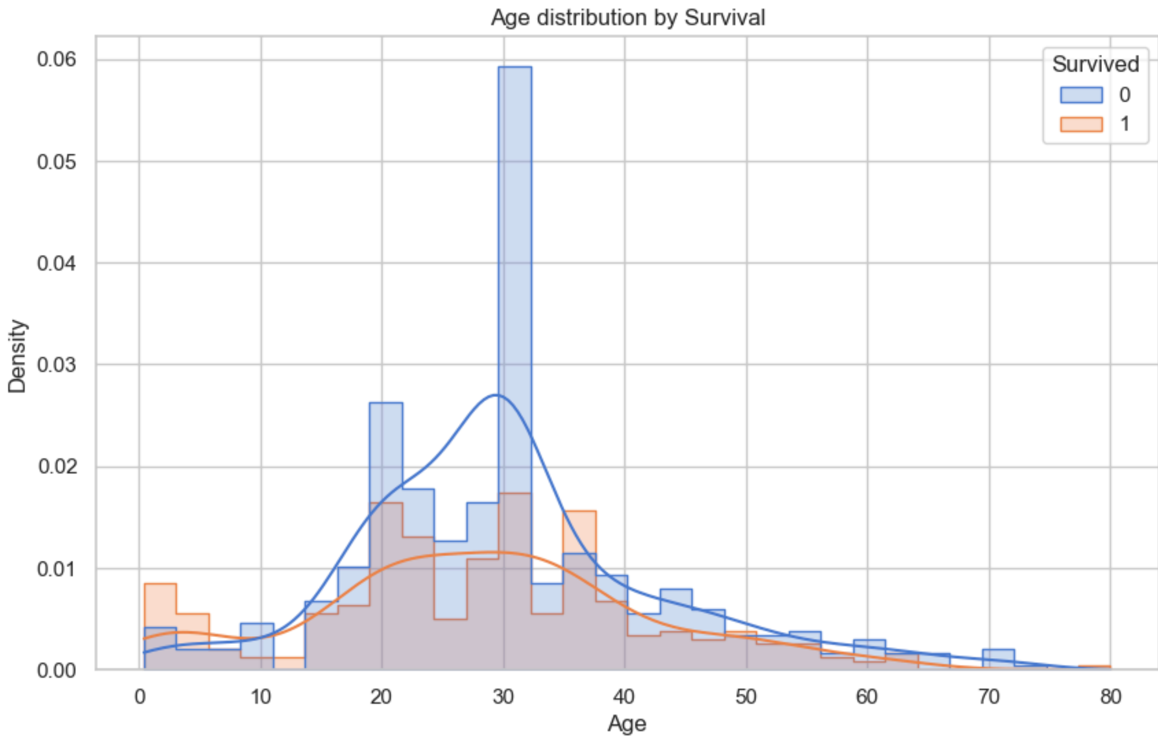
Bivariate Observations (categorical)

- **Sex:** Females have a much higher survival rate than males.
- **Pclass:** 1st class passengers survived at a higher rate than 3rd class.
- **Title:** Higher-status titles (Mrs, Miss) show different survival patterns — useful for modeling.

In [17]:
```
# Boxplot Age vs Survived
plt.figure()
sns.boxplot(x='Survived', y='Age', data=data)
plt.title('Age vs Survival')
plt.show()

# Age distribution by Survived
plt.figure()
sns.histplot(data=data, x='Age', hue='Survived', bins=30, kde=True, element="ste
```

```
plt.title('Age distribution by Survival')
plt.show()
```





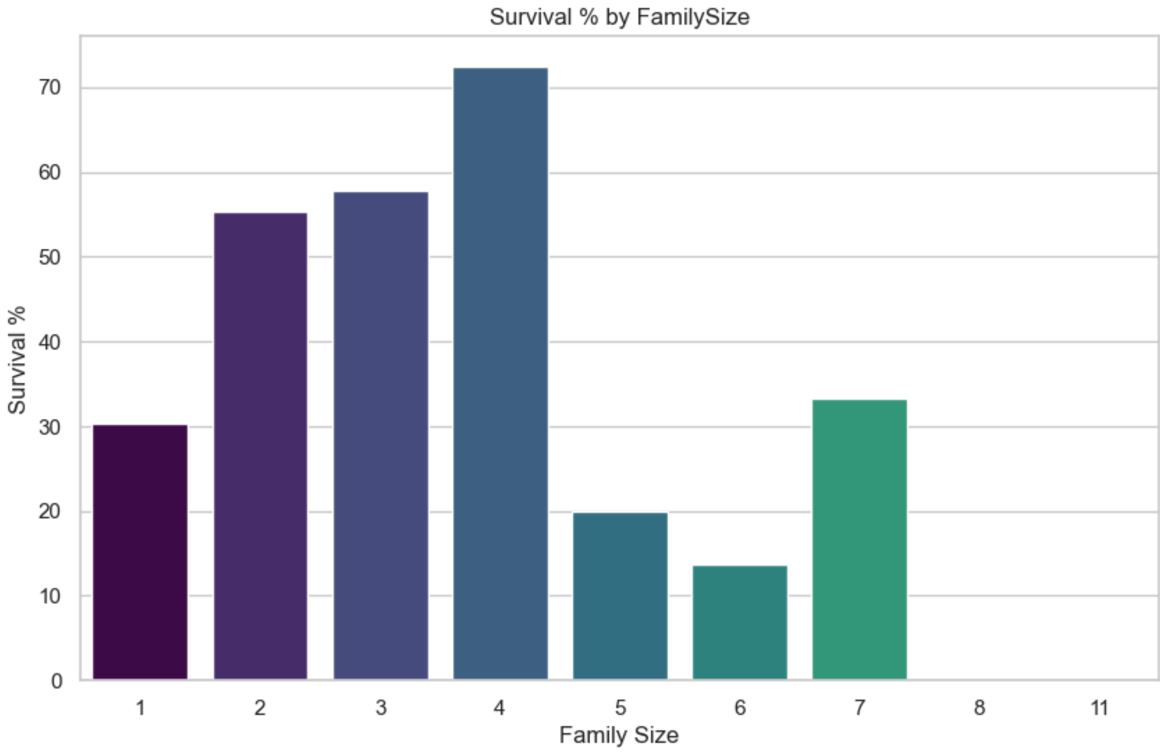
Age Observations

- Children (lower ages) appear to have higher survival densities in some ranges.
- Median age for survivors might be slightly lower than for non-survivors — check numeric stats.

In [20]:
```
# Group by FamilySize
fs_summary = data.groupby('FamilySize')['Survived'].agg(['count', 'mean']).sort_
fs_summary['mean_pct'] = fs_summary['mean'] * 100
```

```python
# Reset index so FamilySize becomes a column for plotting
fs_summary = fs_summary.reset_index()

# Show table
display(fs_summary)

# Plot FamilySize buckets (future-proof palette usage)
plt.figure()
sns.barplot(
    x='FamilySize',
    y='mean_pct',
    hue='FamilySize',
    data=fs_summary,
    palette='viridis',
    legend=False
)
plt.title('Survival % by FamilySize')
plt.ylabel('Survival %')
plt.xlabel('Family Size')
plt.show()
```

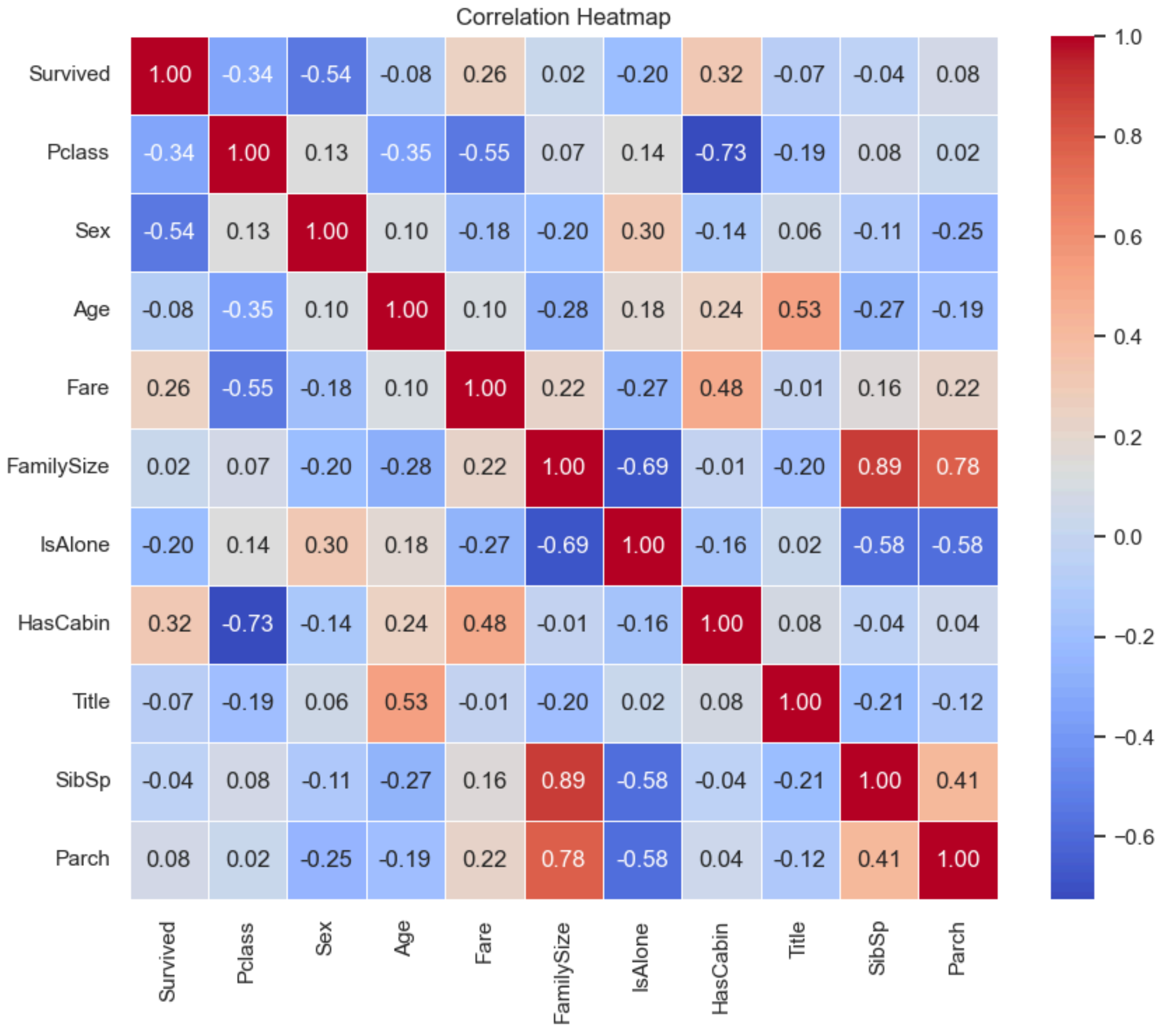
	FamilySize	count	mean	mean_pct
0	1	537	0.303538	30.353818
1	2	161	0.552795	55.279503
2	3	102	0.578431	57.843137
3	4	29	0.724138	72.413793
4	5	15	0.200000	20.000000
5	6	22	0.136364	13.636364
6	7	12	0.333333	33.333333
7	8	6	0.000000	0.000000
8	11	7	0.000000	0.000000



Family Observations

- Very small families/alone passengers often have different survival probabilities than moderate family sizes.
- Extremely large families tend to have lower survival rates.

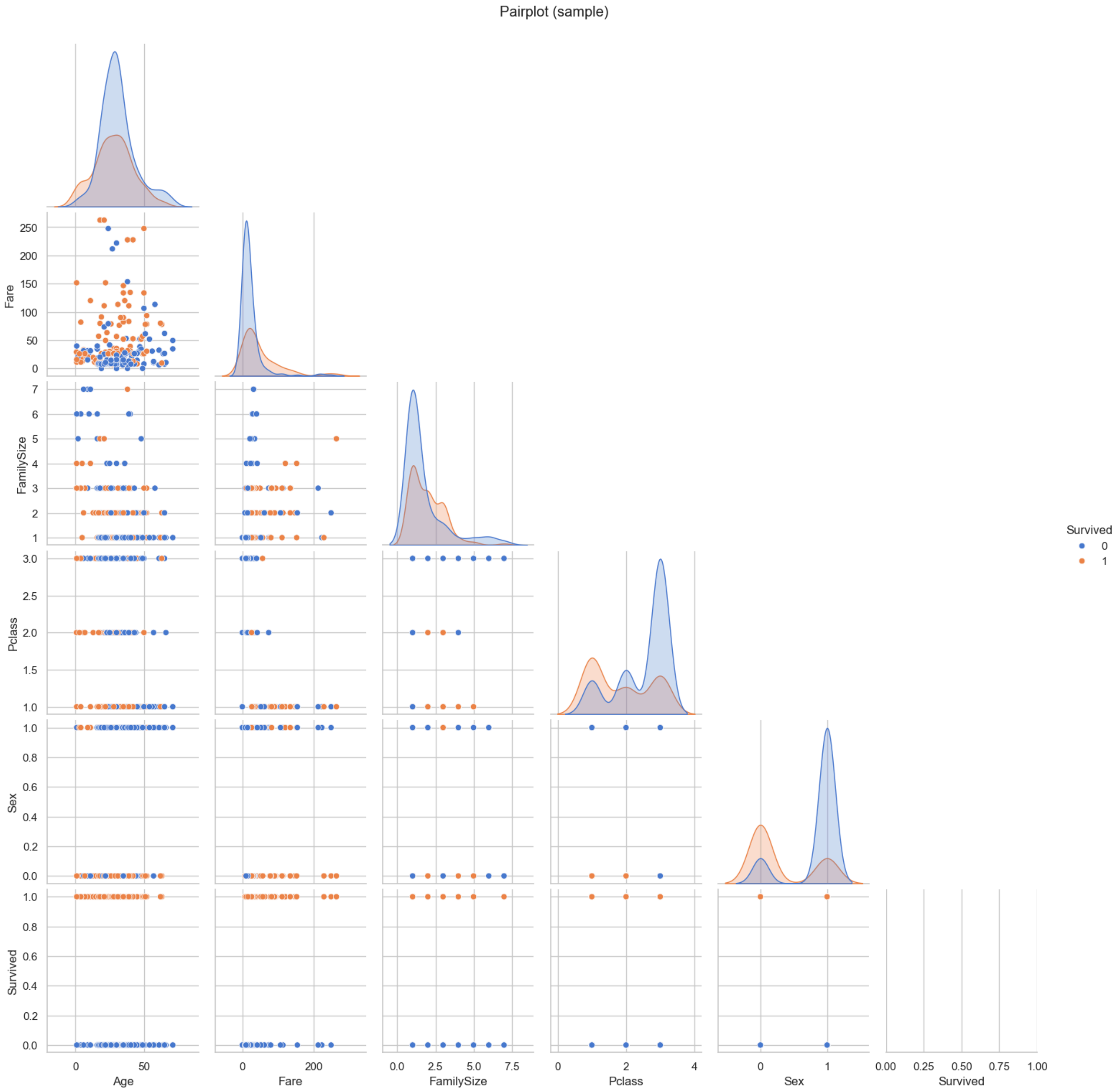
In [21]:
```
# Prepare numeric dataframe for correlation
corr_df = data.copy()
# Map categories to numbers for correlation
corr_df['Sex'] = corr_df['Sex'].cat.codes
corr_df['Embarked'] = corr_df['Embarked'].cat.codes
corr_df['Title'] = corr_df['Title'].cat.codes
corr_df['Pclass'] = corr_df['Pclass'].astype(int)

# Select columns
cols = ['Survived','Pclass','Sex','Age','Fare','FamilySize','IsAlone','HasCabin'
plt.figure(figsize=(10,8))
sns.heatmap(corr_df[cols].corr(), annot=True, fmt=".2f", cmap='coolwarm', linewi
plt.title('Correlation Heatmap')
plt.show()
```



Correlation Observations

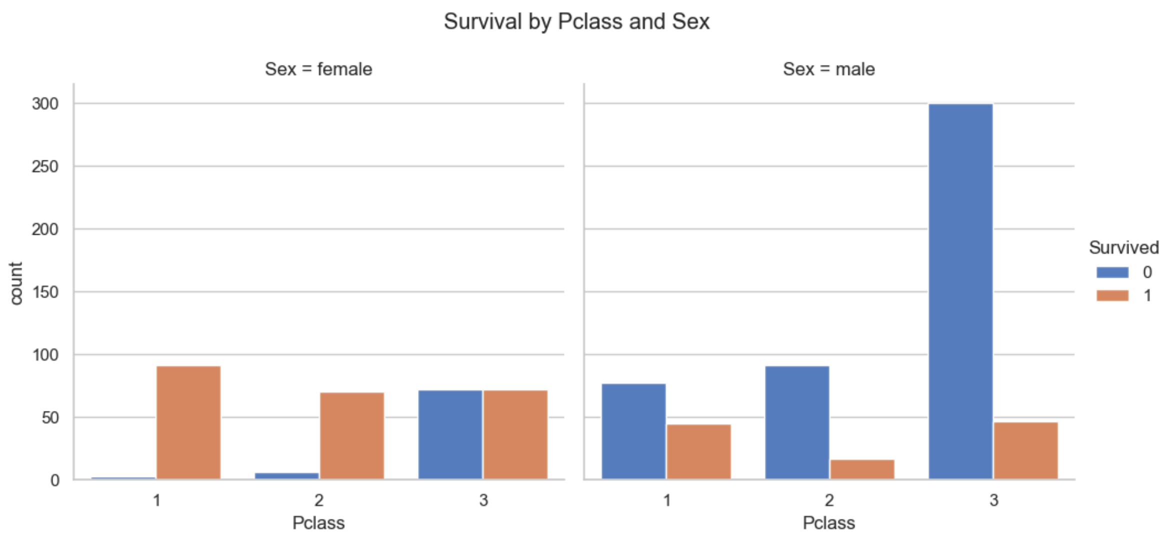
- `Sex` (encoded) and `Pclass` show moderate correlation with `Survived`.
- `Fare` correlates with `Pclass` (higher class → higher fare).
- `HasCabin` has positive correlation with survival (proxy for class).
- `Age` correlation with Survived is weaker but present.

In [23]:
```
# Pairplot on a sampled subset to avoid long render times
sample = corr_df[cols].sample(300, random_state=42)
sns.pairplot(sample, vars=['Age','Fare','FamilySize','Pclass','Sex','Survived'],
plt.suptitle('Pairplot (sample)', y=1.02)
plt.show()
```



Multivariate check: Survival by Sex and Pclass

In [24]:
```
sns.catplot(x="Pclass", hue="Survived", col="Sex", kind="count", data=data)
plt.subplots_adjust(top=0.85)
plt.suptitle('Survival by Pclass and Sex')
plt.show()
```



Final Summary of Insights

1. **Sex** is one of the strongest predictors: females had a much higher survival rate than males.
2. **Pclass** (socioeconomic status) strongly influenced survival — 1st class had higher survival than 3rd.
3. **Fare** and **HasCabin** (proxy for class) positively correlate with survival.
4. **Children** (lower ages) show a relatively higher chance of survival in some age ranges.
5. **Family size**: very small families or being alone had mixed effects; moderate family sizes sometimes had better survival percentages than very large families.
6. Feature engineering (Title, FamilySize, IsAlone, HasCabin) yields useful signals for modeling or deeper analysis.

```
In [ ]:
```