In [217…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_style('whitegrid')
%matplotlib inline
```

In [219…

```
path = 'train.csv'
try:
    df = pd.read_csv(path)
except FileNotFoundError:
    print(f"File not found in {path}. Put file in same notebook folder")
    raise
```

In [221…

```
df.head()
```

Out[221…

	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	7.2500
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	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500

In [223…

```
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 [225…

```
df.isnull().sum()
```

Out[225…

```
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
```

In [227…

```
df.describe(include='all')
```

Out[227…

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	P
count	891.000000	891.000000	891.000000	891	891	714.000000	891.000000	891.00
unique	NaN	NaN	NaN	891	2	NaN	NaN	
top	NaN	NaN	NaN	Braund, Mr. Owen Harris	male	NaN	NaN	
freq	NaN	NaN	NaN	1	577	NaN	NaN	
mean	446.000000	0.383838	2.308642	NaN	NaN	29.699118	0.523008	0.38
std	257.353842	0.486592	0.836071	NaN	NaN	14.526497	1.102743	0.80
min	1.000000	0.000000	1.000000	NaN	NaN	0.420000	0.000000	0.00
25%	223.500000	0.000000	2.000000	NaN	NaN	20.125000	0.000000	0.00
50%	446.000000	0.000000	3.000000	NaN	NaN	28.000000	0.000000	0.00
75%	668.500000	1.000000	3.000000	NaN	NaN	38.000000	1.000000	0.00
max	891.000000	1.000000	3.000000	NaN	NaN	80.000000	8.000000	6.00

In [229…

```
survival_counts = df['Survived'].value_counts()
survival_percent = df['Survived'].value_counts(normalize=True).mul(100).round(2)
```

In [231…

```
df_clean = df.copy()
```

In [233…

```
df_clean['Age'] = df_clean['Age'].fillna(df_clean['Age'].median())
```

In [235…

```
df_clean['Embarked'] = df_clean['Embarked'].fillna(df_clean['Embarked'].mode()[0])
```

In [237…

```
df_clean['FamilySize'] = df_clean['SibSp'] + df_clean['Parch'] + 1
```

In [239…

```
df_clean['IsAlone'] = (df_clean['FamilySize'] == 1).astype(int)
```

In [241…

```
df_clean['Sex_n'] = df_clean['Sex'].map({'male':0, 'female':1})
```

In [243…

```
df_clean['Deck'] = df_clean['Cabin'].apply(lambda x: str(x)[0] if pd.notnull(x) els
```

In [245…

```
df_clean['Title'] = df_clean['Name'].str.extract(r',\s*([^\.]+)\.')[0].str.strip()
```

In [247…

```
df_clean['Title'] = df_clean['Title'].replace({'Mlle':'Miss', 'Ms':'Miss', 'Mme':'M
```

In [249…

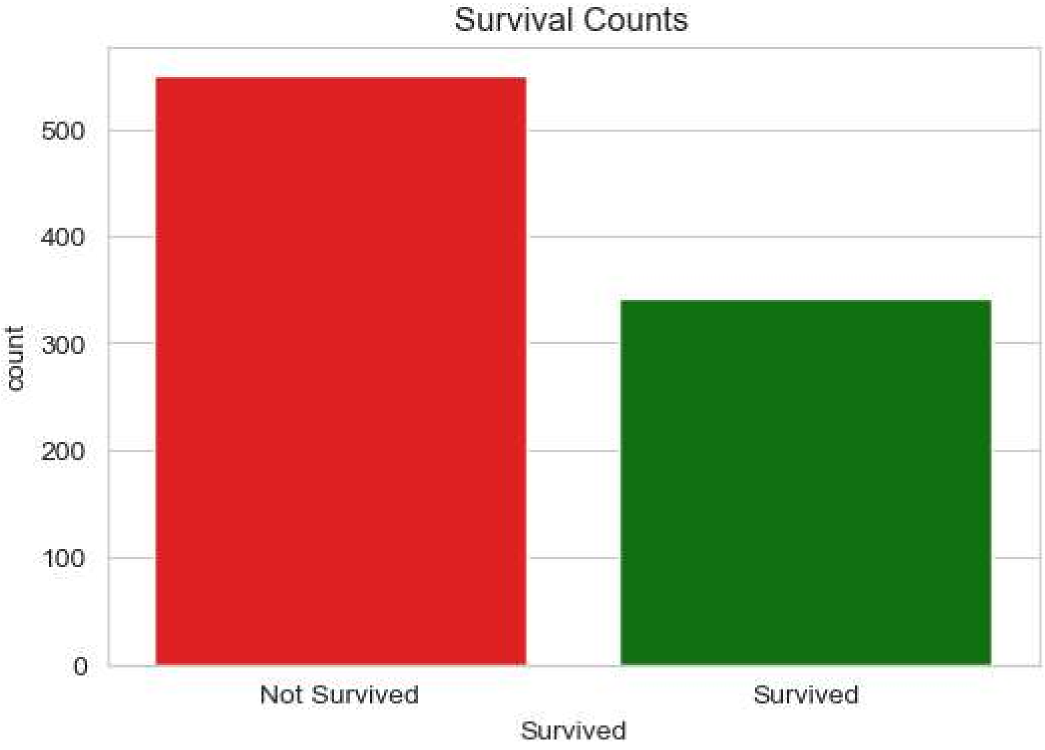
```
rare_titles = ['Lady','Countess','Capt','Col','Don','Dr','Major','Rev','Sir','Jonkh
```

In [251…

```
df_clean['Title'] = df_clean['Title'].apply(lambda t: 'Rare' if t in rare_titles el
```

In [253…

```
plt.figure(figsize=(6,4))
sns.countplot(
    x='Survived',
    data=df_clean,
    hue='Survived',
    palette={0: "red", 1: "green"},
    dodge=False,
    legend=False
)
plt.xticks([0, 1], ['Not Survived', 'Survived'])
plt.title('Survival Counts')
plt.show()
```

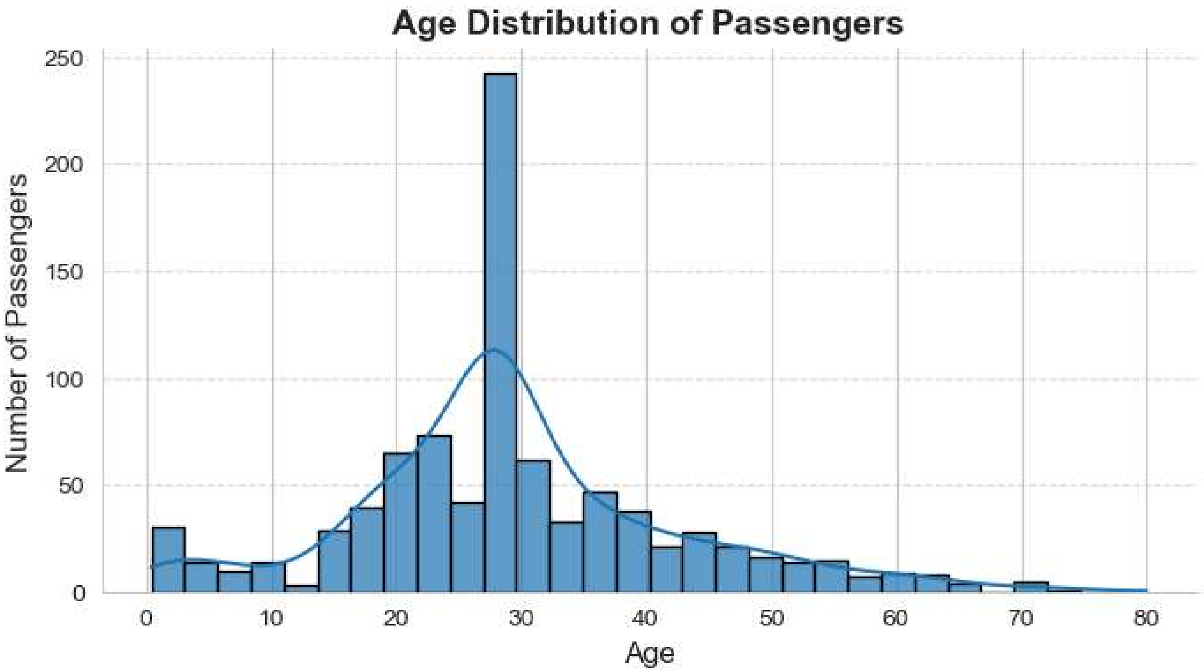


Observation: Out of 891 passengers, **38%** survived and **62%** did not. This shows a strong class imbalance, which should be considered if building predictive models.

In [256…

```
plt.figure(figsize=(8,4))
sns.histplot(
    data=df_clean,
    x='Age',
    bins=30,
    kde=True,
    color="#1f77b4",
    edgecolor="black",
    alpha=0.7
)
plt.title('Age Distribution of Passengers', fontsize=14, fontweight='bold')
plt.xlabel('Age', fontsize=12)
plt.ylabel('Number of Passengers', fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.6)
```

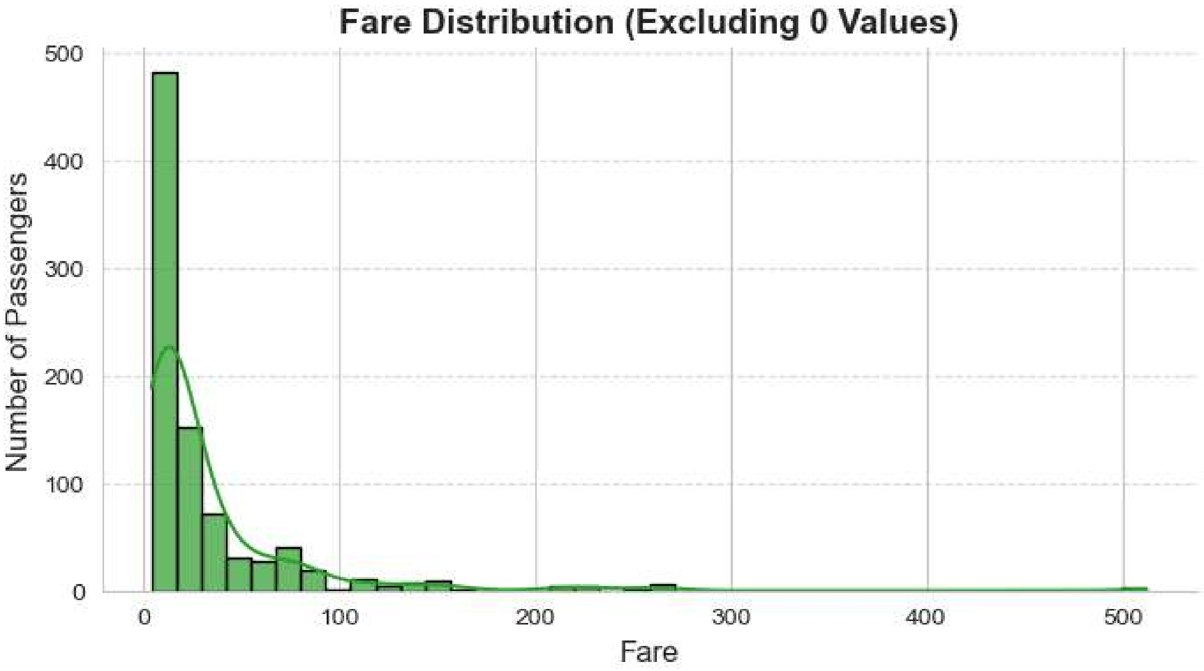
```
sns.despine()
plt.show()
```



Observation: Most passengers were between 20 and 40 years old. There is also a smaller group of children and teenagers, which could influence survival rates.

In [259…

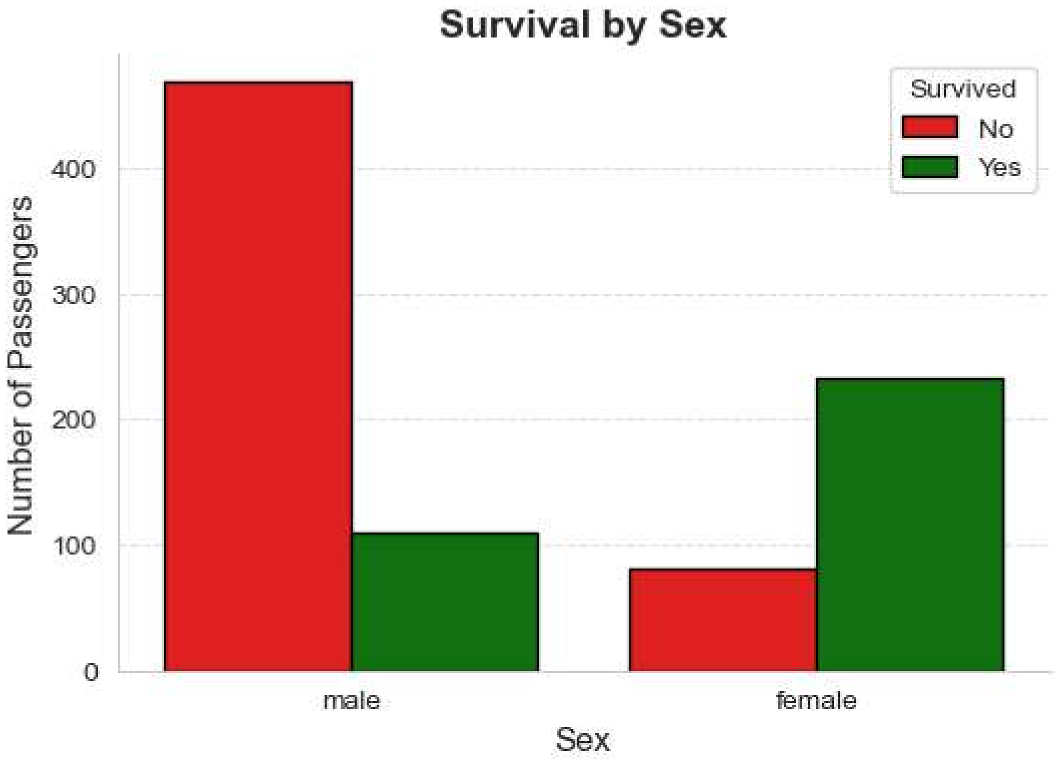
```
plt.figure(figsize=(8,4))
sns.histplot(
    data=df_clean,
    x=df_clean['Fare'].replace(0, np.nan).dropna(),
    bins=40,
    kde=True,
    color="#2ca02c",
    edgecolor="black",
    alpha=0.7
)
plt.title('Fare Distribution (Excluding 0 Values)', fontsize=14, fontweight='bold')
plt.xlabel('Fare', fontsize=12)
plt.ylabel('Number of Passengers', fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.6)
sns.despine()
plt.show()
```



Observation: Around **75%** of passengers paid less than `$50`, while a small group paid above `$200`, indicating premium or 1st Class tickets. The fare distribution is heavily right-skewed.

In [262…

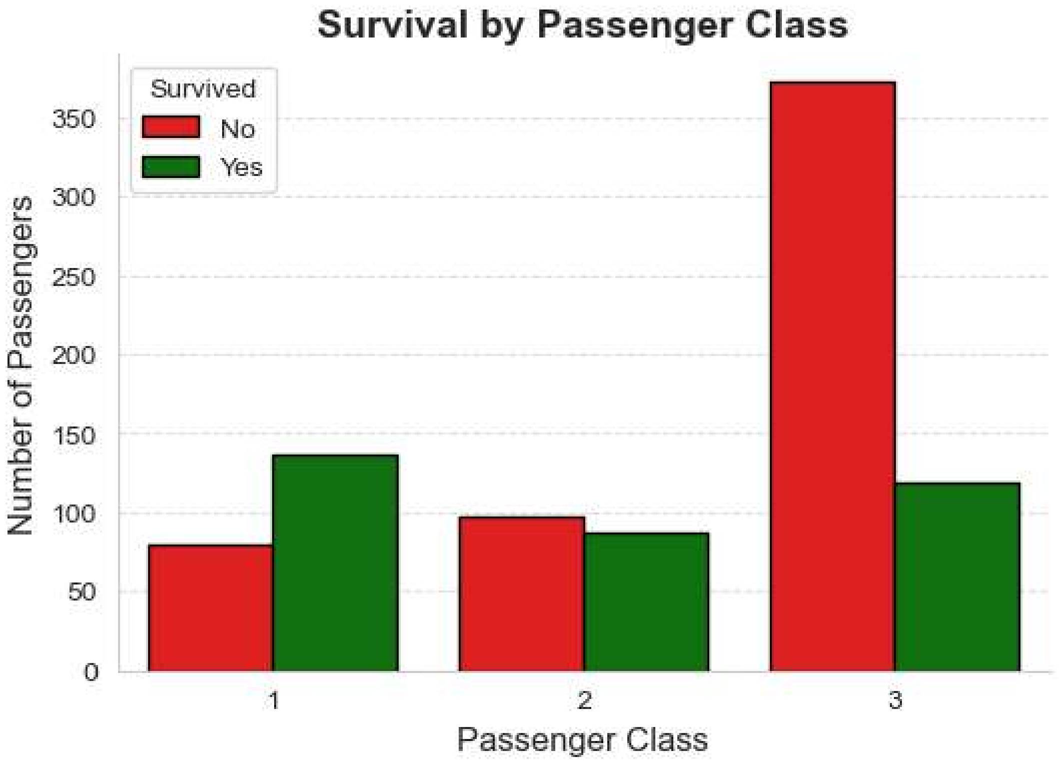
```
plt.figure(figsize=(6,4))
sns.countplot(
    x='Sex',
    hue='Survived',
    data=df_clean,
    palette={0: "red", 1: "green"},
    edgecolor="black"
)
plt.title('Survival by Sex', fontsize=14, fontweight='bold')
plt.xlabel('Sex', fontsize=12)
plt.ylabel('Number of Passengers', fontsize=12)
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.grid(axis='y', linestyle='--', alpha=0.6)
sns.despine()
plt.show()
```



Observation: Females had a survival rate of **74.2%**, compared to only **18.9%** for males. This supports the "women and children first" evacuation policy on the Titanic.

In [265…

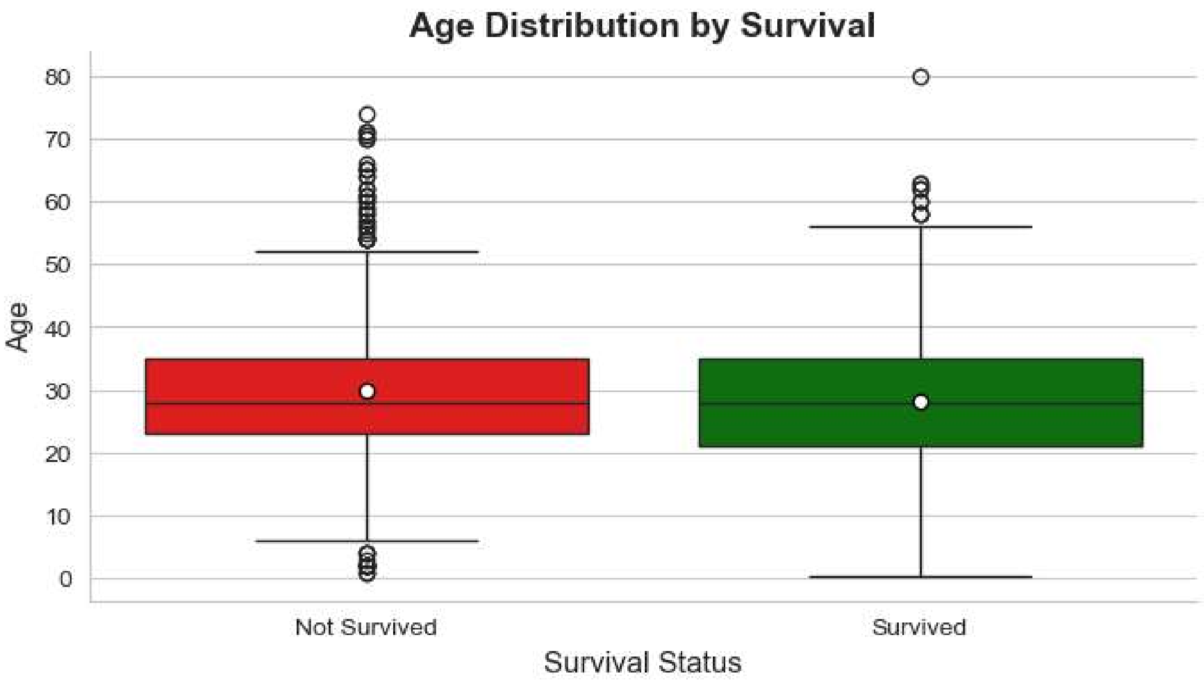
```
plt.figure(figsize=(6,4))
sns.countplot(
    x='Pclass',
    hue='Survived',
    data=df_clean,
    palette={0: "red", 1: "green"},
    edgecolor="black"
)
plt.title('Survival by Passenger Class', fontsize=14, fontweight='bold')
plt.xlabel('Passenger Class', fontsize=12)
plt.ylabel('Number of Passengers', fontsize=12)
plt.legend(title='Survived', labels=['No', 'Yes'])
plt.grid(axis='y', linestyle='--', alpha=0.6)
sns.despine()
plt.show()
```



Observation: 1st Class passengers survived at **62.9%**, while 3rd Class passengers survived at only **24.2%**. Higher-class cabins likely provided faster access to lifeboats.

In [268…

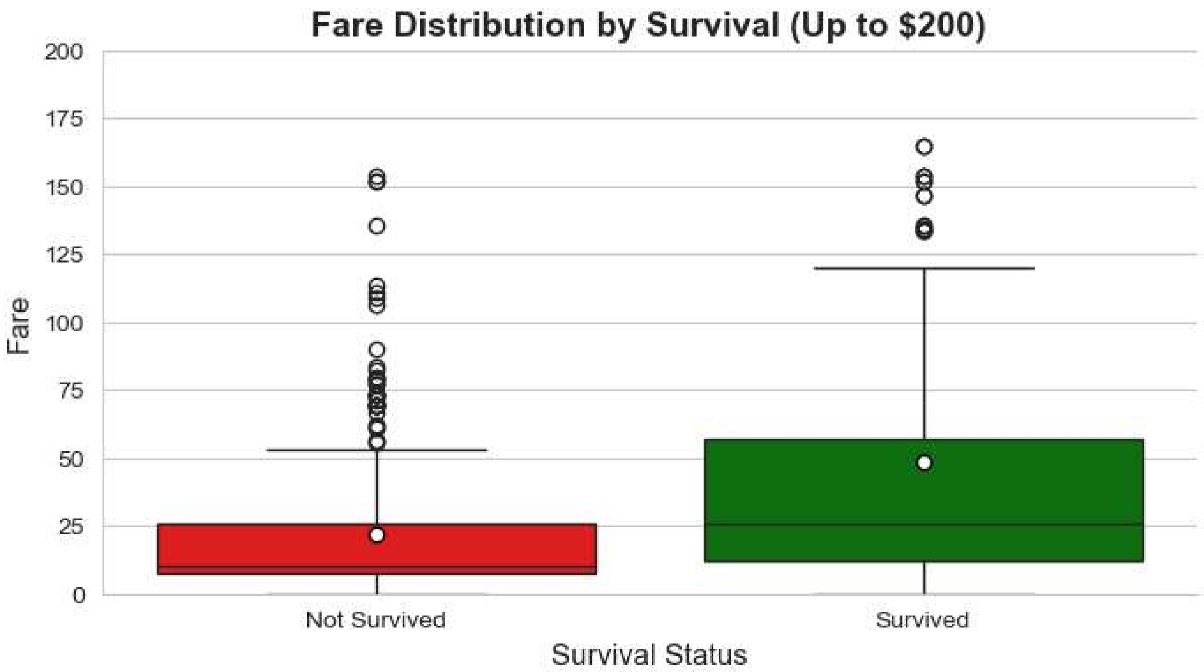
```
plt.figure(figsize=(8,4))
sns.boxplot(
    x='Survived',
    y='Age',
    hue='Survived',
    data=df_clean,
    palette={0: "red", 1: "green"},
    showmeans=True,
    meanprops={"marker":"o", "markerfacecolor":"white", "markeredgecolor":"black"},
    dodge=False
)
plt.title('Age Distribution by Survival', fontsize=14, fontweight='bold')
plt.xlabel('Survival Status', fontsize=12)
plt.ylabel('Age', fontsize=12)
plt.xticks([0,1], ['Not Survived', 'Survived'])
plt.legend([],[], frameon=False)
sns.despine()
plt.show()
```



Observation: Younger passengers, especially children, had higher survival chances. Middle-aged and elderly passengers had lower odds of survival.

In [271…

```
plt.figure(figsize=(8,4))
sns.boxplot(
    x='Survived',
    y='Fare',
    hue='Survived',
    data=df_clean,
    palette={0: "red", 1: "green"},
    showmeans=True,
    meanprops={"marker":"o", "markerfacecolor":"white", "markeredgecolor":"black"},
    dodge=False
)
plt.ylim(0,200)
plt.title('Fare Distribution by Survival (Up to $200)', fontsize=14, fontweight='bo
plt.xlabel('Survival Status', fontsize=12)
plt.ylabel('Fare', fontsize=12)
plt.xticks([0,1], ['Not Survived', 'Survived'])
plt.legend([],[], frameon=False)
sns.despine()
plt.show()
```



Observation: Survivors generally paid significantly higher fares than non-survivors on average `$48` versus `$22` . This reinforces the idea that wealthier passengers, likely in higher-class cabins, had better access to lifeboats.

In [274…

```
survival_rates = (
    df_clean.groupby('Sex')['Survived']
    .mean()
    .mul(100)
    .round(2)
    .reset_index()
    .rename(columns={'Sex': 'Gender', 'Survived': 'Survival Rate (%)'})
    .sort_values(by='Survival Rate (%)', ascending=False)
)

survival_rates
```

Out[274…

	Gender	Survival Rate (%)
0	female	74.20
1	male	18.89

In [276…

```
pclass_survival = (
    df_clean.groupby('Pclass')['Survived']
    .mean()
    .mul(100)
    .round(2)
    .reset_index()
    .rename(columns={'Pclass': 'Passenger Class', 'Survived': 'Survival Rate (%)'})
    .sort_values(by='Survival Rate (%)', ascending=False)
)

pclass_survival
```

Out[276…

	Passenger Class	Survival Rate (%)
0	1	62.96
1	2	47.28
2	3	24.24

In [278…

```
title_survival = (
    df_clean.groupby('Title')['Survived']
    .mean()
    .mul(100)
    .round(2)
    .reset_index()
    .rename(columns={'Title': 'Passenger Title', 'Survived': 'Survival Rate (%)'})
    .sort_values(by='Survival Rate (%)', ascending=False)
)

title_survival
```

Out[278…

	Passenger Title	Survival Rate (%)
5	the Countess	100.00
3	Mrs	79.37
1	Miss	70.27
0	Master	57.50
4	Rare	31.82
2	Mr	15.67

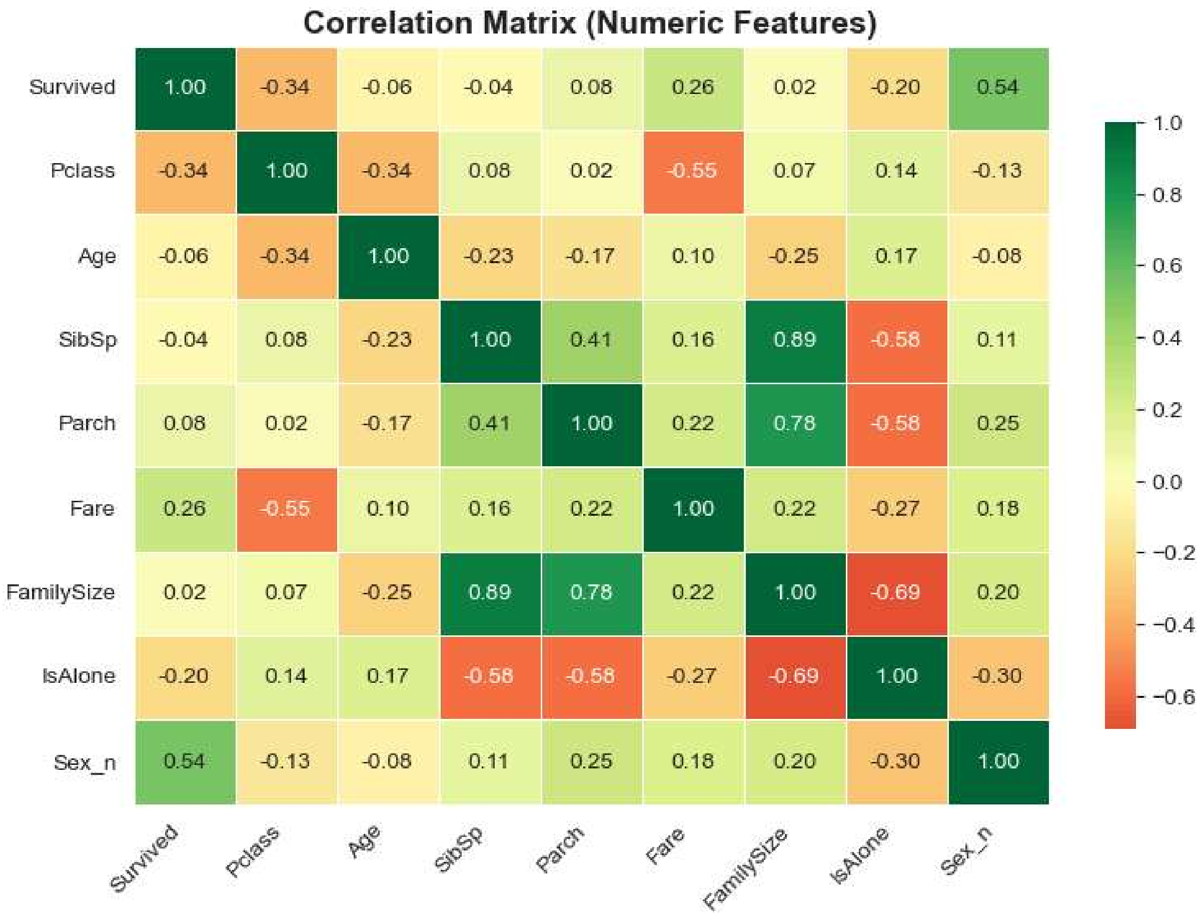
In [280…

```
num_cols = ['Survived','Pclass','Age','SibSp','Parch','Fare','FamilySize','IsAlone'
num_cols = [c for c in num_cols if c in df_clean.columns]

plt.figure(figsize=(9,6))
corr_matrix = df_clean[num_cols].corr()

sns.heatmap(
    corr_matrix,
    annot=True,
    fmt='.2f',
    cmap='RdYlGn',
    center=0,
    linewidths=0.5,
    annot_kws={"size": 10},
    cbar_kws={'shrink': 0.8}
)

plt.title('Correlation Matrix (Numeric Features)', fontsize=14, fontweight='bold')
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)
plt.show()
```



	Survived	Pclass	Age	SibSp	Parch	Fare	FamilySize	IsAlone	Sex_n
Survived	1.00	-0.34	-0.06	-0.04	0.08	0.26	0.02	-0.20	0.54
Pclass	-0.34	1.00	-0.34	0.08	0.02	-0.55	0.07	0.14	-0.13
Age	-0.06	-0.34	1.00	-0.23	-0.17	0.10	-0.25	0.17	-0.08
SibSp	-0.04	0.08	-0.23	1.00	0.41	0.16	0.89	-0.58	0.11
Parch	0.08	0.02	-0.17	0.41	1.00	0.22	0.78	-0.58	0.25
Fare	0.26	-0.55	0.10	0.16	0.22	1.00	0.22	-0.27	0.18
FamilySize	0.02	0.07	-0.25	0.89	0.78	0.22	1.00	-0.69	0.20
IsAlone	-0.20	0.14	0.17	-0.58	-0.58	-0.27	-0.69	1.00	-0.30
Sex_n	0.54	-0.13	-0.08	0.11	0.25	0.18	0.20	-0.30	1.00

Observation: Survival is positively correlated with being female (`Sex_n = 1`, correlation 0.54) and with fare (0.26). It is negatively correlated with passenger class (-0.34) and traveling alone (-0.20). These correlations align with earlier visual findings.

Executive Summary

- **Gender Effect:** Females had a much higher survival rate (**74.2%**) compared to males (**18.9%**), likely due to "women and children first" evacuation protocols.
- **Class Effect:** 1st Class passengers survived at **62.9%**, while 3rd Class survival was only **24.2%**,showing that higher-class cabins had better lifeboat access.

- **Age Effect:** Children and younger passengers had higher survival chances, while middle-aged passengers had lower odds.
- **Fare Effect:** Survivors generally paid much higher fares on average **`~$48`** compared to **`~$22`** for non-survivors.This notable gap suggests a socio-economic survival advantage.
- **Travel Group Effect:** Passengers traveling with family had slightly better survival rates than those traveling alone, supported by the negative correlation of **-0.20** for the `IsAlone` feature.
- **Correlation Insights:** Survival is positively correlated with being female (`Sex_n = 1`, **0.54**) and with fare (**0.26**),and negatively correlated with passenger class (**-0.34**) and traveling alone (**-0.20**).

Conclusion: The analysis confirms that socio-economic status,gender,age,and travel group size were key factors influencing survival on the Titanic, with wealth and cabin class playing a major role.

```
In [ ]:
```