

# Exploratory Data Analysis on Titanic Dataset

Dataset source: Titanic.csv  
Number of records: 891

## Objective

- To analyze the factors that influenced passenger survival during the Titanic .
- The goal is to identify key patterns, relationships, and insights that explain survival outcomes.

## Table of Contents

- 1. Introduction
- 2. Data Loading & Preview
- 3. Missing Values & Cleaning
- 4. Feature Engineering
- 5. Univariate Analysis
- 6. Bivariate Analysis
- 7. Correlation Analysis
- 8. Insights & Conclusions
- 9. Code Appendix

## 1. Introduction

Objective: Explore the Titanic dataset to find patterns that affected passenger survival. The report includes data preview, cleaning steps, summary statistics, visualizations, and insights.

## 2. Data Loading & Preview

First 10 rows of the original dataset:

PassengerId	Survived	Pclass	Name	Sex	Age	Siblings	Par	Ticket	Fare	Cabin	Embarked
1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.25	nan	S
2	1	1	Cumings, Mrs. John Bradley	female	38.0	1	0	PC 17599	71.2833	C85	C

(Florence  
Briggs  
Thayer)

3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.925	nan	S
4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1	C123	S
5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.05	nan	S
6	0	3	Moran, Mr. James	male	nan	0	0	330877	8.4583	nan	Q
7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	E46	S
8	0	3	Palsson, Master. Gosta Leonard	male	2.0	3	1	349909	21.075	nan	S
9	1	3	Johnson, Mrs. Oscar W (Elisabe	female	27.0	0	2	347742	11.1333	nan	S

			th Vilhelm ina Berg)								
10	1	2	Nasser, Mrs. Nichola s (Adele Achem)	fema le	14. 0	1	0	237736	30.07 08	nan	C

### 3. Missing Values & Cleaning

Missing values before cleaning:

Column	MissingCount	MissingPercent
PassengerId	0	0.0
Survived	0	0.0
Pclass	0	0.0
Name	0	0.0
Sex	0	0.0
Age	177	19.87
SibSp	0	0.0
Parch	0	0.0
Ticket	0	0.0
Fare	0	0.0
Cabin	687	77.1
Embarked	2	0.22

**Cleaning steps applied:**

- Filled Age with median.

- Filled Embarked with mode.
- Dropped Cabin column due to many missing values (if present).

#### 4. Feature Engineering

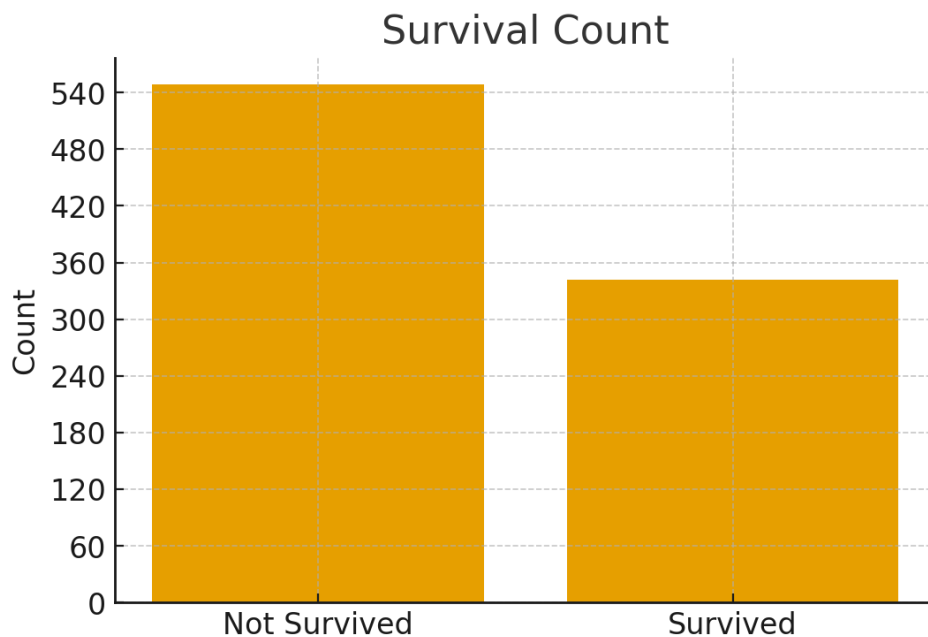
Added a 'FamilySize' column ( $\text{SibSp} + \text{Parch} + 1$ ) and a 'FamilyBucket' column (Alone / Small / Large).

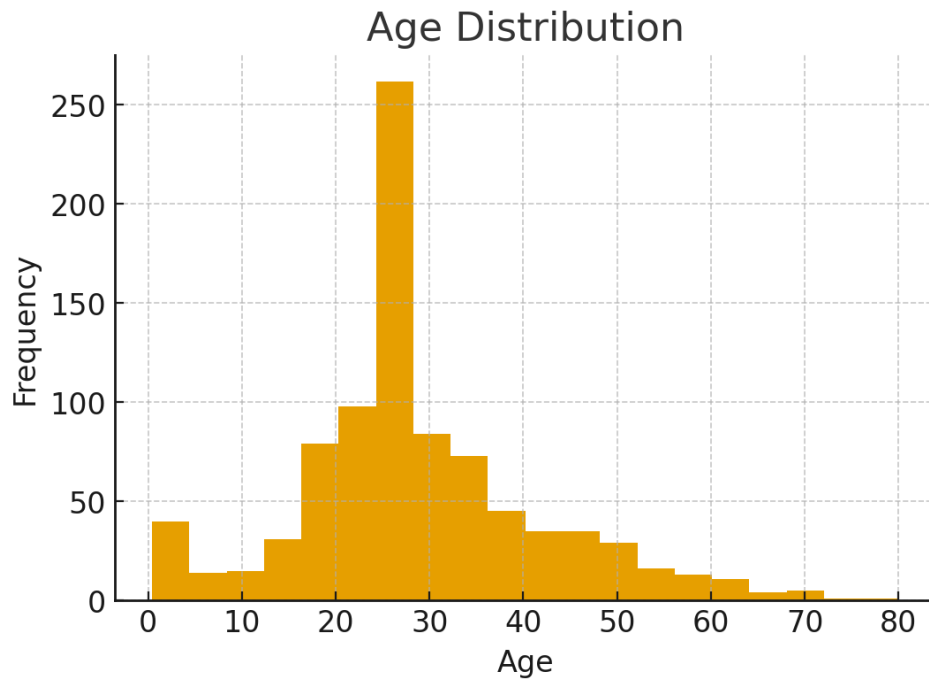
Survival rate by family bucket:

FamilyBucket	SurvivalRate
Alone	0.304
Large	0.161
Small	0.579

#### 5. Univariate Analysis

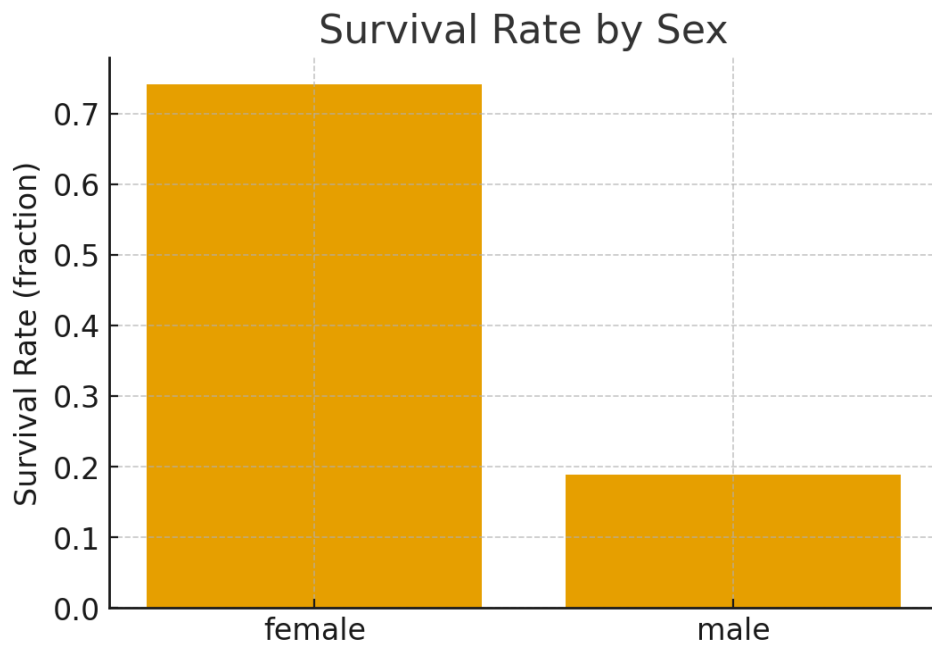
Key univariate visuals: Survival counts and Age distribution.

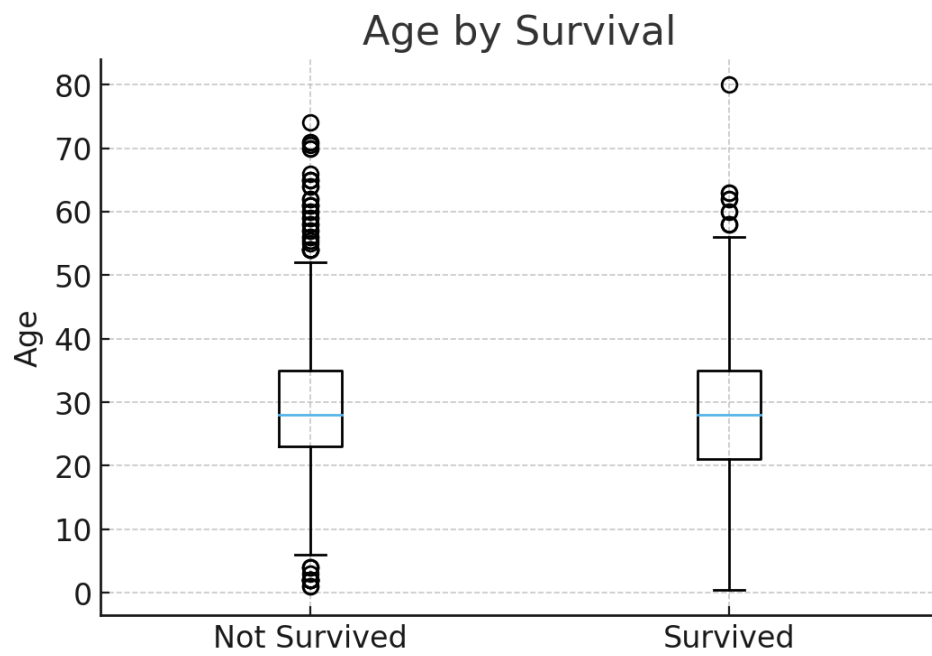
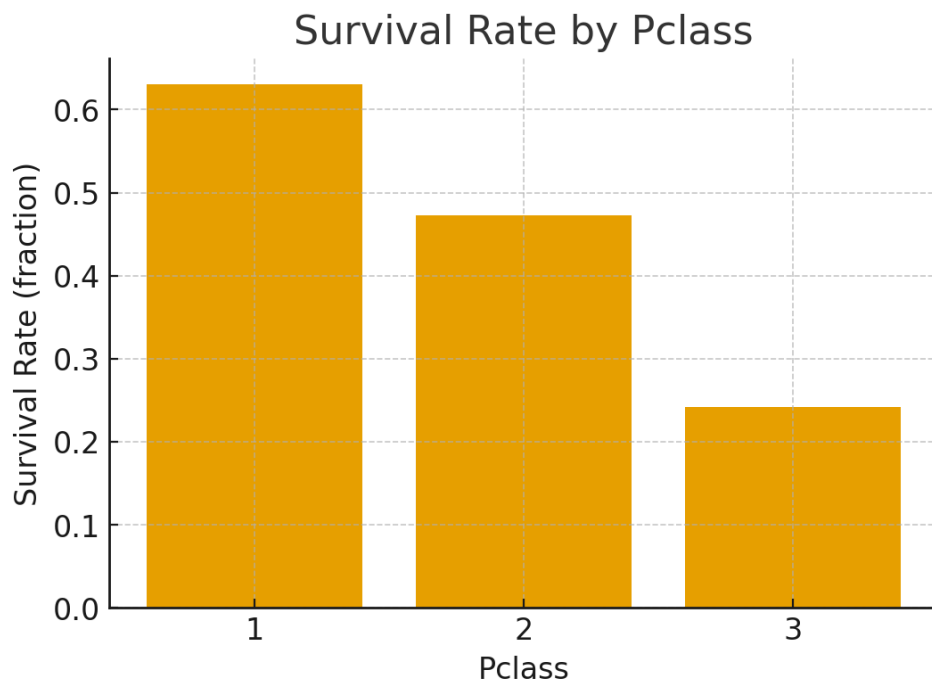




## 6. Bivariate Analysis

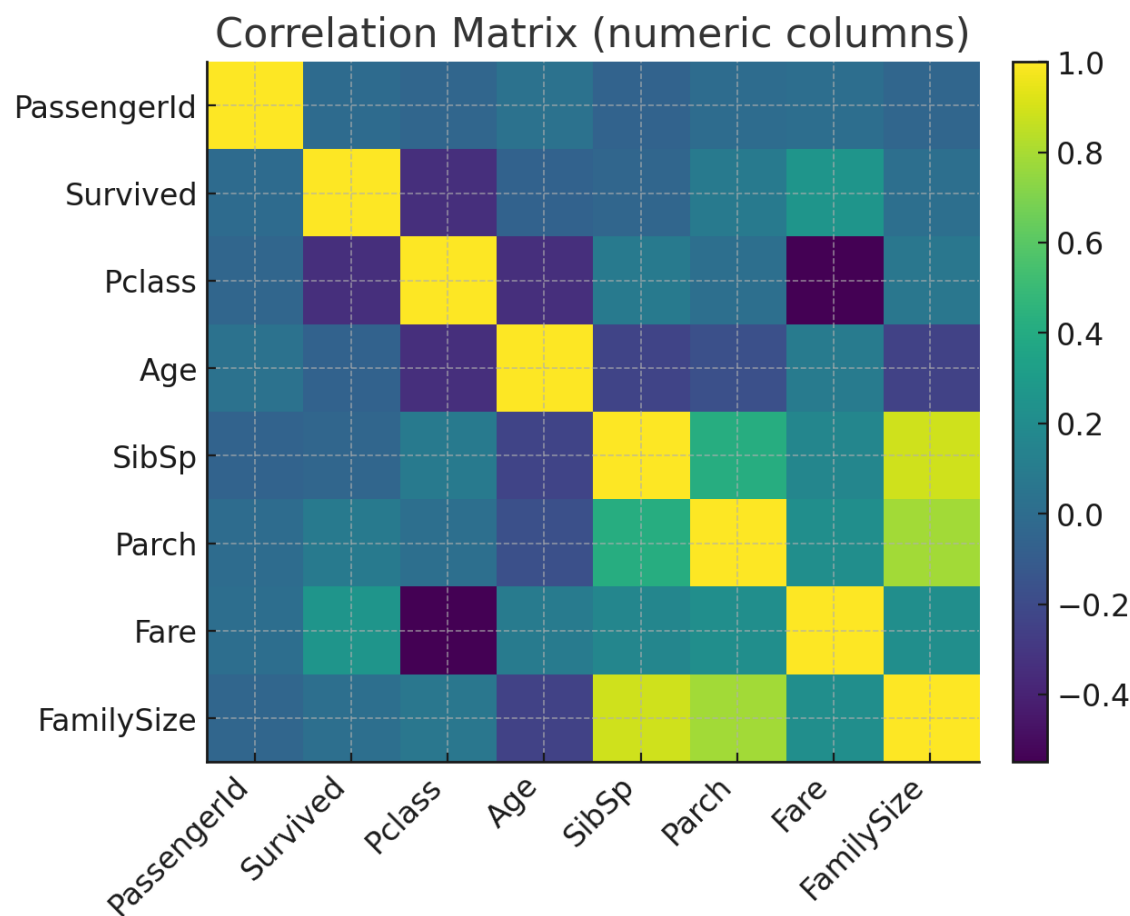
Survival rate by Sex and by Pclass, and Age distribution by survival.





### 7. Correlation Analysis

Correlation matrix of numeric columns:



Correlation (numeric) summary:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare	FamilySize
PassengerId	1.000	-0.005	-0.035	0.034	-0.058	-0.002	0.013	-0.040
Survived	-0.005	1.000	-0.338	-0.065	-0.035	0.082	0.257	0.017
Pclass	-0.035	-0.338	1.000	-0.340	0.083	0.018	-0.549	0.066
Age	0.034	-0.065	-0.340	1.000	-0.233	-0.172	0.097	-0.246
SibSp	-0.058	-0.035	0.083	-0.233	1.000	0.415	0.160	0.891

Parch	-0.002	0.082	0.018	-0.172	0.415	1.000	0.216	0.783
Fare	0.013	0.257	-0.549	0.097	0.160	0.216	1.000	0.217
FamilySize	-0.040	0.017	0.066	-0.246	0.891	0.783	0.217	1.000

## 8. Insights & Conclusions

**Gender was the strongest survival predictor** → Women had **~74% survival rate** vs only **~19% for men** (nearly 4x higher)

**Passenger class had a massive impact on survival** → 1st Class: **~63% survived** 2nd Class: **~47% survived** 3rd Class: **~24% survived** → Clear evidence of "class privilege" during evacuation

**Optimal family size dramatically increased survival odds** → Passengers with **small families (2–4 members)** had the highest survival rate: **58%** → Solo travelers: **30%** | Large families (5+): only **16%**

**Children (especially young ones) and women in 1st/2nd class were prioritized** → Supports the "Women and Children First" protocol

**Higher fare strongly correlated with survival ( $r = 0.257$ )** → Wealthier passengers (higher fare = better cabin location) had better access to lifeboats

**Pclass was the most negatively correlated feature with survival ( $r = -0.338$ )** → Lower class number (higher status) → much higher chance of survival

**Port of Embarkation (Embarked) showed indirect impact** → Passengers from Cherbourg (C) had higher survival (~55%) — likely because more 1st-class passengers boarded there more

**Age had mild influence** → Younger passengers (especially <10 years) survived more, but gender/class dominated

## 9. Code Appendix

Below are the main code snippets used to generate the analysis and visuals.

### *Loading & basic info*

---

```
import pandas as pd
df = pd.read_csv("Titanic.csv")
df.info()
df.head()
```

### *Cleaning*

---

```
df['Age'].fillna(df['Age'].median(), inplace=True)
```



```
df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)
df.drop(columns=['Cabin'], inplace=True)
```

### *Feature engineering*

---

```
df['FamilySize'] = df['SibSp'] + df['Parch'] + 1
def fam_bucket(n):
    if n == 1:
        return 'Alone'
    elif 2 <= n <= 4:
        return 'Small'
    else:
        return 'Large'
df['FamilyBucket'] = df['FamilySize'].apply(fam_bucket)
```

### *plot (survival count)*

---

```
import matplotlib.pyplot as plt
counts = df['Survived'].value_counts().sort_index()
plt.bar(['Not Survived', 'Survived'], counts.values)
plt.title('Survival Count')
plt.ylabel('Count')
plt.show()
```