TASK_5_EXPLORATORY_DATA_ANALYSIS

In [2]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:
```python
train_data = pd.read_csv(r"C:\Users\Rakshitha K B\Documents\ELEVATE LABS INTERNSHIP\DATASETS\Titan-ML Dataset\train.csv")
test_data = pd.read_csv(r"C:\Users\Rakshitha K B\Documents\ELEVATE LABS INTERNSHIP\DATASETS\Titan-ML Dataset\test.csv")
gender_submission_data = pd.read_csv(r"C:\Users\Rakshitha K B\Documents\ELEVATE LABS INTERNSHIP\DATASETS\Titan-ML Dataset\gender_submission.csv")
```

Understanding the train data

In [12]:
```python
#to check the data structure
train_data.head()
```

Out[12]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

In [13]:
```python
train_data.tail()
```

Out[13]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.75	NaN	Q

In [6]:
```python
#to get the data types and missing values
train_data.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 [8]:
```python
train_data.describe()
```

Out[8]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

Understanding the test data

In [10]:
```python
test_data.head()
```

Out[10]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S

In [11]:
```python
test_data.tail()
```

Out[11]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
413	1305	3	Spector, Mr. Woolf	male	NaN	0	0	A.5. 3236	8.0500	NaN	S
414	1306	1	Oliva y Ocana, Dona. Fermina	female	39.0	0	0	PC 17758	108.9000	C105	C
415	1307	3	Saether, Mr. Simon Sivertsen	male	38.5	0	0	SOTON/O.Q. 3101262	7.2500	NaN	S
416	1308	3	Ware, Mr. Frederick	male	NaN	0	0	359309	8.0500	NaN	S
417	1309	3	Peter, Master. Michael J	male	NaN	1	1	2668	22.3583	NaN	C

In [14]:
```python
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 11 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  418 non-null    int64
 1   Pclass       418 non-null    int64
 2   Name         418 non-null    object
 3   Sex          418 non-null    object
 4   Age          332 non-null    float64
 5   SibSp        418 non-null    int64
 6   Parch        418 non-null    int64
 7   Ticket       418 non-null    object
 8   Fare         417 non-null    float64
 9   Cabin        91 non-null     object
 10  Embarked     418 non-null    object
dtypes: float64(2), int64(4), object(5)
memory usage: 36.1+ KB
```

In [15]:
```python
test_data.describe()
```

Out[15]:

	PassengerId	Pclass	Age	SibSp	Parch	Fare
count	418.000000	418.000000	332.000000	418.000000	418.000000	417.000000
mean	1100.500000	2.265550	30.272590	0.447368	0.392344	35.627188
std	120.810458	0.841838	14.181209	0.896760	0.981429	55.907576
min	892.000000	1.000000	0.170000	0.000000	0.000000	0.000000
25%	996.250000	1.000000	21.000000	0.000000	0.000000	7.895800
50%	1100.500000	3.000000	27.000000	0.000000	0.000000	14.454200
75%	1204.750000	3.000000	39.000000	1.000000	0.000000	31.500000
max	1309.000000	3.000000	76.000000	8.000000	9.000000	512.329200

Value counts for the categorical variable

In [16]:
```python
train_data['Pclass'].value_counts()
```

Out[16]:
```
Pclass
3    491
1    216
2    184
Name: count, dtype: int64
```

In [17]:
```python
# Check value counts for multiple categorical columns together
categorical_cols = ['Sex', 'Survived', 'Embarked', 'SibSp', 'Parch']

for col in categorical_cols:
    print(f"\nValue counts for {col}:\n")
    print(train_data[col].value_counts())
    print("-"*40)
```

```
Value counts for Sex:

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

Value counts for Survived:

Survived
0    549
1    342
Name: count, dtype: int64
----------------------------------------

Value counts for Embarked:

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

Value counts for SibSp:

SibSp
0    608
1    209
2     28
4     18
3     16
8      7
5      5
Name: count, dtype: int64
----------------------------------------

Value counts for Parch:

Parch
0    678
1    118
2     80
5      5
3      5
4      4
6      1
Name: count, dtype: int64
----------------------------------------
```

In [18]:
```python
# Check value counts for multiple categorical columns together in test data
categorical_cols = ['Sex', 'Pclass', 'Embarked', 'SibSp', 'Parch']

for col in categorical_cols:
    print(f"\nValue counts for {col}:\n")
    print(test_data[col].value_counts())
    print("-"*40)
```

```
Value counts for Sex:

Sex
male      266
female    152
Name: count, dtype: int64
----------------------------------------

Value counts for Pclass:

Pclass
3    218
1    107
2     93
Name: count, dtype: int64
----------------------------------------

Value counts for Embarked:

Embarked
S    270
C    102
Q     46
Name: count, dtype: int64
----------------------------------------

Value counts for SibSp:

SibSp
0    283
1    110
2     14
3      4
4      4
8      2
5      1
Name: count, dtype: int64
----------------------------------------

Value counts for Parch:

Parch
0    324
1     52
2     33
3      3
4      2
9      2
6      1
5      1
Name: count, dtype: int64
----------------------------------------
```

In [19]:
```python
#checking the missing values
train_data.isnull().sum()
```

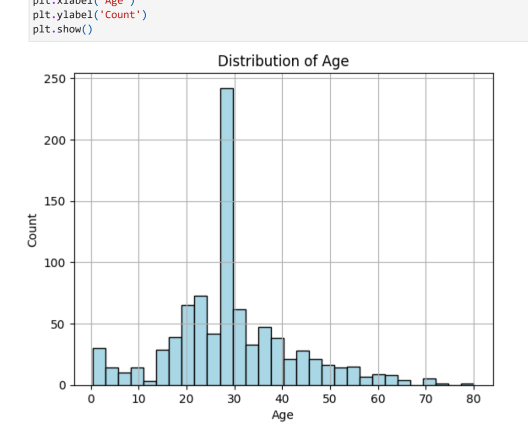
Out[19]:
```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [21]:
```python
# Filling missing 'Age' with the median
train_data['Age'] = train_data['Age'].fillna(train_data['Age'].median())

# Fill missing 'Cabin' with 'Unknown' (or any placeholder)
train_data['Cabin'] = train_data['Cabin'].fillna('Unknown')

# Fill missing 'Embarked' with the mode (most frequent value)
train_data['Embarked'] = train_data['Embarked'].fillna(train_data['Embarked'].mode()[0])
```

UNIVARIATE ANALYSIS

HISTOGRAM FOR NUMERICAL FEATURES

In [22]:
```python
train_data['Age'].hist(bins=30, color='lightblue', edgecolor='black')
plt.title('Distribution of Age')
plt.xlabel('Age')
plt.ylabel('Count')
plt.show()
```

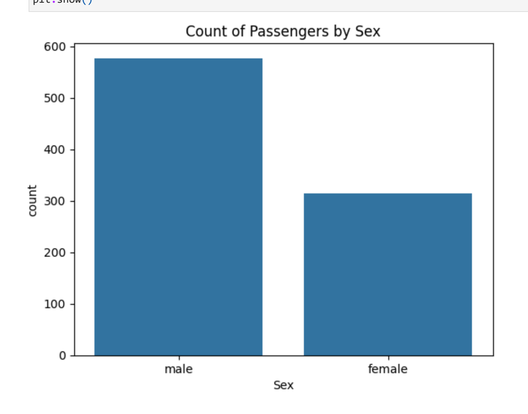


Distribution of Age

- Most passangers are between 20 to 40
- About 250 passengers are of age around 30
- Very few passangers are above 60 years

Countplot for categorical features Sex, Pclass

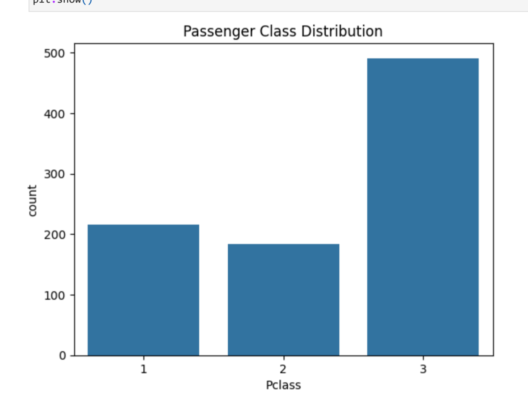
In [50]:
```python
sns.countplot(x='Sex', data=train_data)
plt.title('Count of Passengers by Sex')
plt.show()
```



Count of Passengers by Sex

- The count of male passengers is the highest, with around 550+ out of 892, showing that men made up the majority of the passengers on board.
- The count of female passengers is around 300 out of 892, indicating that women were fewer in number compared to men on the Titanic.

In [52]:
```python
#COUNTPLOT FOR PASSANGER CLASS DISTRIBUTION
sns.countplot(x='Pclass', data=train_data)
plt.title('Passenger Class Distribution')
plt.show()
```



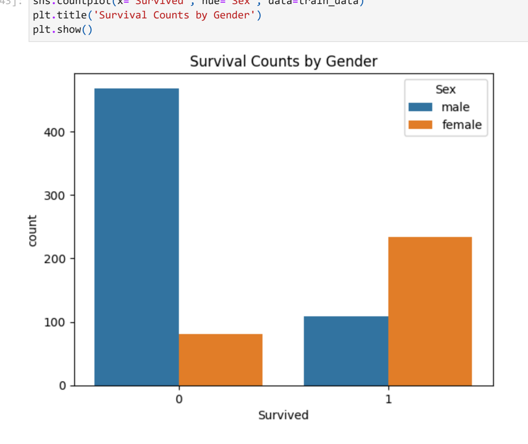
Passenger Class Distribution plot

- The 3rd class had the highest number of passengers by a large margin , shows many were lower-income passengers, including immigrants.
- Interestingly, there were more 1st class passengers than 2nd class, despite higher ticket prices.

BIVARIATE ANALYSIS

Survival rate by gender

In [43]:
```python
sns.countplot(x='Survived', hue='Sex', data=train_data)
plt.title('Survival Counts by Gender')
plt.show()
```

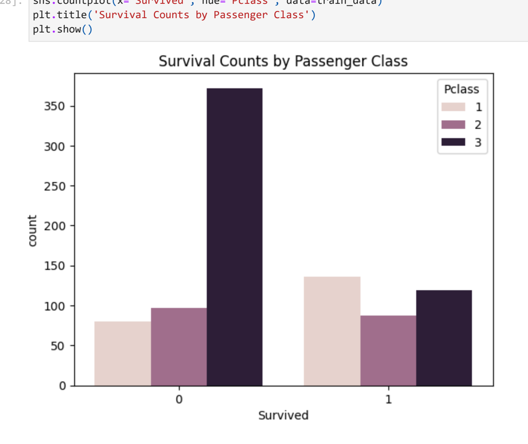


Survival Counts by Gender

- **Most deaths were male:** Over 400 of 549 who died were men, while fewer than 100 were women.
- **Most survivors were female:** Over 200 of 342 survivors were women, showing they had a higher survival rate.
- The trends are showing that **Female** passengers had a **higher survival** rate than **male** passengers. Most males did not survive.

Survival rate by Passenger Class

In [28]:
```python
sns.countplot(x='Survived', hue='Pclass', data=train_data)
plt.title('Survival Counts by Passenger Class')
plt.show()
```

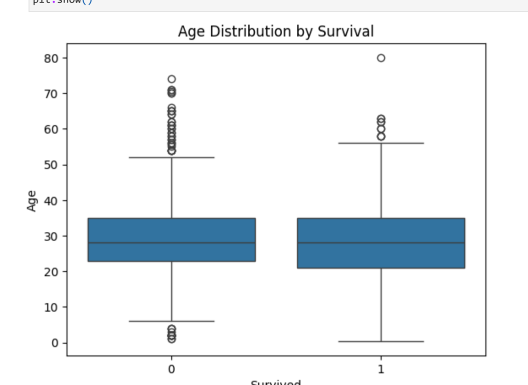


Survival by Passenger Class

- **3rd Class had the highest deaths:** Over 350 passengers in 3rd class not survived, while only 100+ survived, showing low survival rates for lower-class passengers.
- **1st Class had better survival:** Around 100+ survived and only 60–70 died, indicating higher survival chances for wealthier passengers.
- **2nd Class was in between:** Roughly 100 died and 50–70 survived, showing moderate survival rates compared to other classes.

BOXPLOT OF AGE VS SURVIVED

In [29]:
```python
sns.boxplot(x='Survived', y='Age', data=train_data)
plt.title('Age Distribution by Survival')
plt.show()
```



Age Distribution by Survival

Median Age:

- The median age (middle line inside the box) of survived passengers (Survived = 1) is slightly lower than that of non-survived passengers (Survived = 0).

Age Range:

- Survived passengers show a wider interquartile range (IQR) (the width of the box) compared to non-survived passengers, suggesting more variability in the ages of those who survived.
- Both groups have ages ranging roughly from very young children (~0–5 years) to older adults (~80 years), but outliers are present.

Outliers:

- There are many outliers on the higher age side (60+ years) in both groups, more noticeable in the non-survived group.

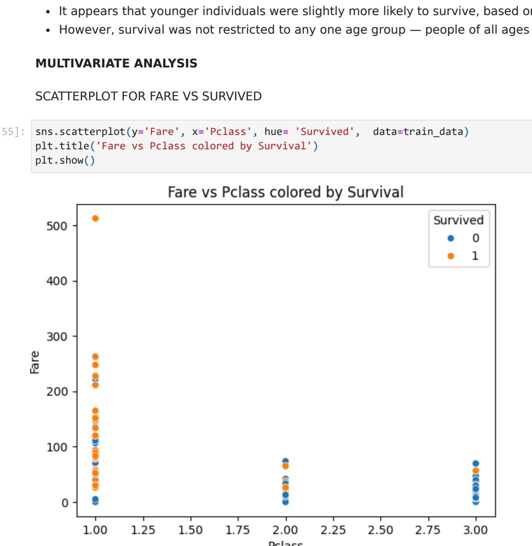
Survival Trend with Age:

- It appears that younger individuals were slightly more likely to survive, based on the lower median and slight shift in the age distribution for the survived group.
- However, survival was not restricted to any one age group — people of all ages survived and died.

MULTIVARIATE ANALYSIS

SCATTERPLOT FOR FARE VS SURVIVED

In [55]:
```python
sns.scatterplot(y='Fare', x='Pclass', hue= 'Survived',  data=train_data)
plt.title('Fare vs Pclass colored by Survival')
plt.show()
```



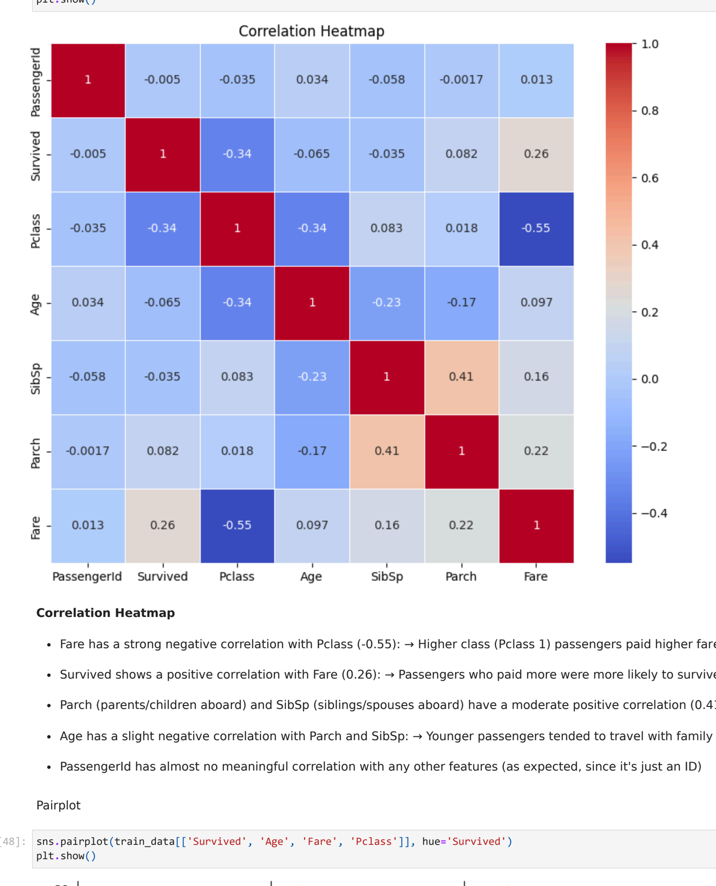
Fare vs Pclass by survival

- **Pclass 1 passengers (1st class)** paid significantly **higher fares** compared to Pclass 2 and 3.
- Most of the **high fare passengers** were from **Pclass 1**, and many of them **survived** (orange dots).
- In **Pclass 2 and Pclass 3**, fares are much lower, and a larger number of passengers did not survive (more blue dots).
- **Higher class (Pclass 1) is associated with higher survival rates**, while lower classes (Pclass 2 and 3) show lower survival rates.

MULTIVARIATE ANALYSIS

Heatmap of correlations

In [47]:
```python
numeric_data = train_data.select_dtypes(include=[np.number])

plt.figure(figsize=(10,8))
sns.heatmap(numeric_data.corr(), annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Heatmap')
plt.show()
```

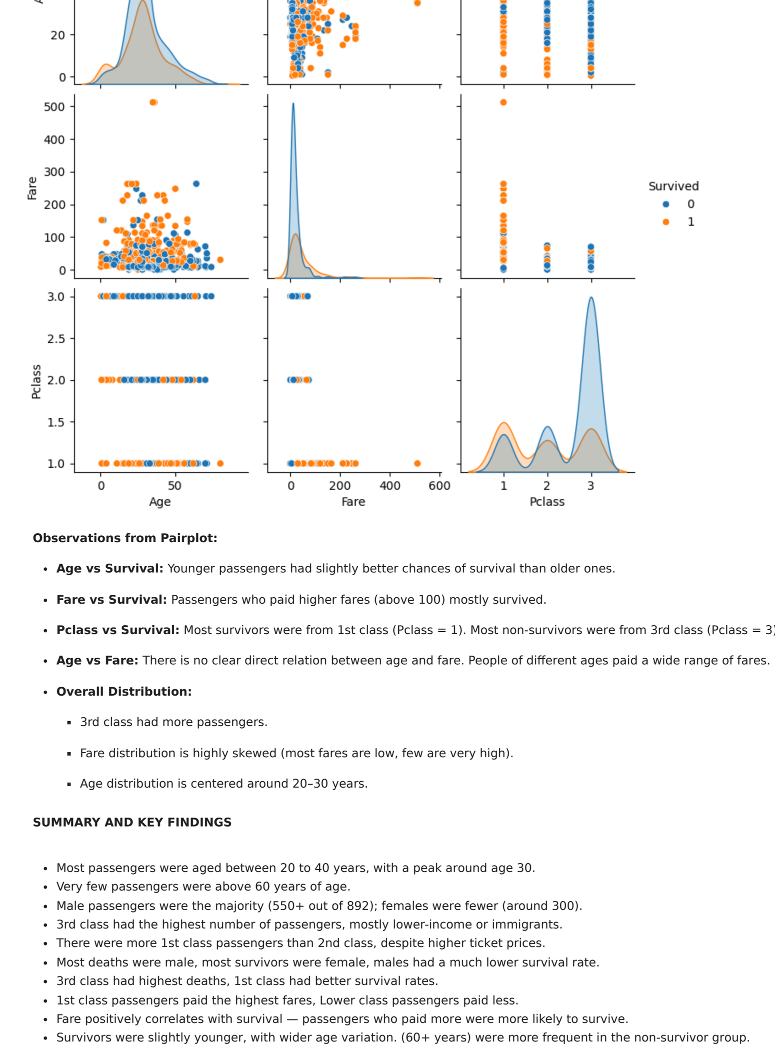


Correlation Heatmap

- Fare has a strong negative correlation with Pclass (-0.55): → Higher class (Pclass 1) passengers paid higher fares.
- Survived shows a positive correlation with Fare (0.26): → Passengers who paid more were more likely to survive.
- Parch (parents/children aboard) and SibSp (siblings/spouses aboard) have a moderate positive correlation (0.41): → People who traveled with siblings/spouses were often also traveling with parents/children.
- Age has a slight negative correlation with Parch and SibSp: → Younger passengers tended to travel with family more often.
- PassengerId has almost no meaningful correlation with any other features (as expected, since it's just an ID)

Pairplot

In [48]:
```python
sns.pairplot(train_data[['Survived', 'Age', 'Fare', 'Pclass']], hue='Survived')
plt.show()
```



Observations from Pairplot:

- **Age vs Survival:** Younger passengers had slightly better chances of survival than older ones.
- **Fare vs Survival:** Passengers who paid higher fares (above 100) mostly survived.
- **Pclass vs Survival:** Most survivors were from 1st class (Pclass = 1). Most non-survivors were from 3rd class (Pclass = 3).
- **Age vs Fare:** There is no clear direct relation between age and fare. People of different ages paid a wide range of fares.
- **Overall Distribution:**
  - 3rd class had more passengers.
  - Fare distribution is highly skewed (most fares are low, few are very high).
  - Age distribution is centered around 20–30 years.

SUMMARY AND KEY FINDINGS

- Most passengers were aged between 20 to 40 years, with a peak around age 30.
- Very few passengers were above 60 years of age.
- Male passengers were the majority (550+ out of 892); females were fewer (around 300).
- 3rd class had the highest number of passengers, mostly lower-income or immigrants.
- There were more 1st class passengers than 2nd class, despite higher ticket prices.
- Most deaths were male, most survivors were female, males had a much lower survival rate.
- 3rd class had highest deaths, 1st class had better survival rates.
- 1st class passengers paid the highest fares, Lower class passengers paid less.
- Fare positively correlates with survival — passengers who paid more were more likely to survive.
- Survivors were slightly younger, with wider age variation. (60+ years) were more frequent in the non-survivor group.
- Fare and Pclass are strongly linked (1st class paid more).
- SibSp and Parch had a moderate positive correlation — families often traveled together.
- Family members often traveled together, especially younger passengers.
- Most survivors were from 1st class, most non-survivors from 3rd class.
- Fare distribution was skewed, most fares low, few very high.
- Age mostly ranged 20–30 years.