Code and Output:

```
#  Imports and load data
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# display settings
pd.set_option('display.max_columns', 50)
sns.set(style="whitegrid")

# load Titanic dataset from seaborn
df = sns.load_dataset('titanic')
df.head()
```

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alone
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	False
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	False
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	True
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	False
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	True

```
#  Quick data inspection
df.info()
df.describe(include='all').T
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   survived     891 non-null    int64
 1   pclass       891 non-null    int64
 2   sex          891 non-null    object
 3   age          714 non-null    float64
 4   sibsp        891 non-null    int64
 5   parch        891 non-null    int64
 6   fare         891 non-null    float64
 7   embarked     889 non-null    object
 8   class        891 non-null    category
 9   who          891 non-null    object
 10  adult_male   891 non-null    bool
 11  deck         203 non-null    category
 12  embark_town  889 non-null    object
 13  alive        891 non-null    object
 14  alone        891 non-null    bool
dtypes: bool(2), category(2), float64(2), int64(4), object(5)
memory usage: 80.7+ KB
```

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
survived	891.0	NaN	NaN	NaN	0.383838	0.486592	0.0	0.0	0.0	1.0	1.0
pclass	891.0	NaN	NaN	NaN	2.308642	0.836071	1.0	2.0	3.0	3.0	3.0
sex	891	2	male	577	NaN	NaN	NaN	NaN	NaN	NaN	NaN
age	714.0	NaN	NaN	NaN	29.699118	14.526497	0.42	20.125	28.0	38.0	80.0
sibsp	891.0	NaN	NaN	NaN	0.523008	1.102743	0.0	0.0	0.0	1.0	8.0
parch	891.0	NaN	NaN	NaN	0.381594	0.806057	0.0	0.0	0.0	0.0	6.0
fare	891.0	NaN	NaN	NaN	32.204208	49.693429	0.0	7.9104	14.4542	31.0	512.3292
embarked	889	3	S	644	NaN	NaN	NaN	NaN	NaN	NaN	NaN
class	891	3	Third	491	NaN	NaN	NaN	NaN	NaN	NaN	NaN
who	891	3	man	537	NaN	NaN	NaN	NaN	NaN	NaN	NaN
adult_male	891	2	True	537	NaN	NaN	NaN	NaN	NaN	NaN	NaN
deck	203	7	C	59	NaN	NaN	NaN	NaN	NaN	NaN	NaN
embark_town	889	3	Southampton	644	NaN	NaN	NaN	NaN	NaN	NaN	NaN
alive	891	2	no	549	NaN	NaN	NaN	NaN	NaN	NaN	NaN

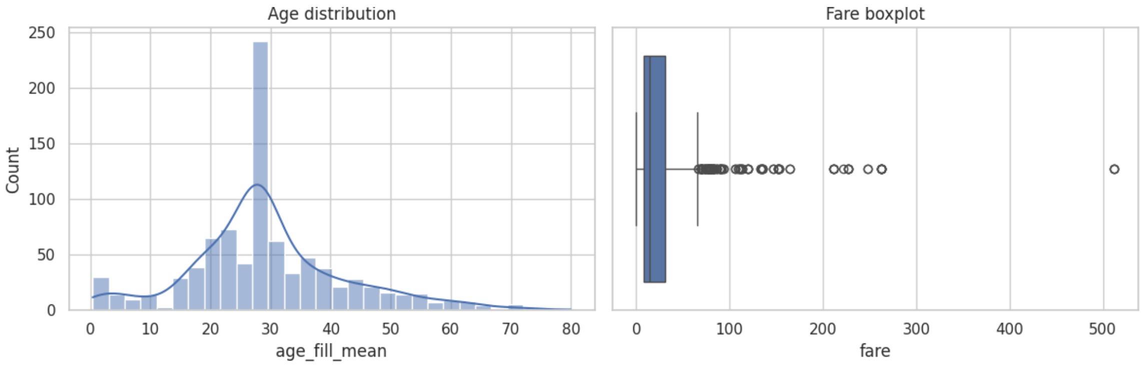
```python
# Missing values and value counts
print("Missing values per column:\n", df.isna().sum())
for col in ['survived','pclass','sex','embarked']:
    print(f"\nValue counts for {col}:\n", df[col].value_counts(dropna=False))
```

```
Missing values per column:
 survived         0
pclass         0
sex            0
age          177
sibsp          0
parch          0
fare           0
embarked       2
class          0
who            0
adult_male     0
deck         688
embark_town    2
alive          0
alone          0
dtype: int64
```

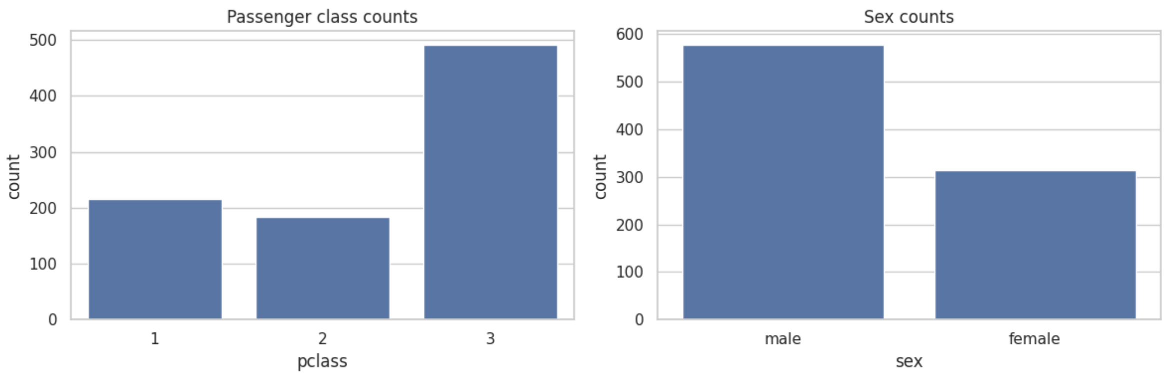
```
Value counts for survived:
 survived
0    549
1    342
Name: count, dtype: int64

Value counts for pclass:
 pclass
3    491
1    216
2    184
Name: count, dtype: int64

Value counts for sex:
 sex
male      577
female    314
Name: count, dtype: int64

Value counts for embarked:
 embarked
S      644
C      168
Q       77
NaN      2
Name: count, dtype: int64
```

```
# Cleaning / small fixes (example)
# drop rows where 'embarked' is null (small number)
df_clean = df.copy()
df_clean['age_fill_mean'] = df_clean['age'].fillna(df_clean['age'].median())
df_clean['embarked'] = df_clean['embarked'].fillna(df_clean['embarked'].mode()[0])
```

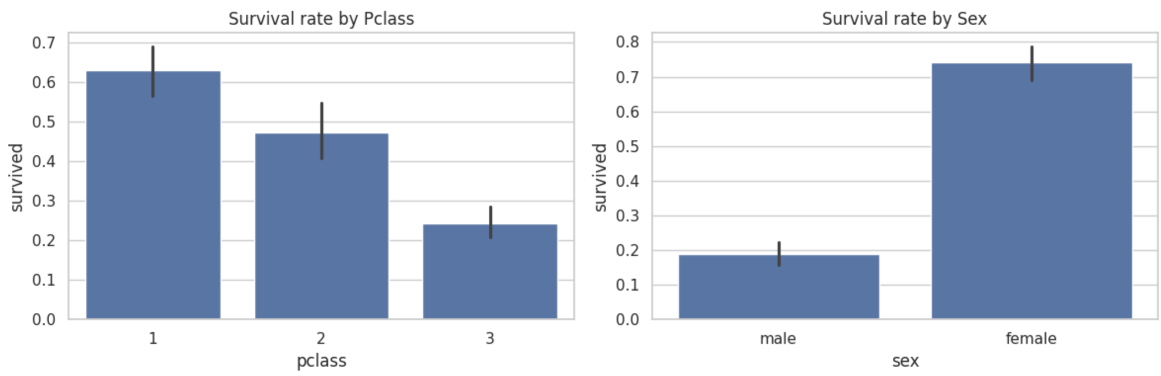
```
# Univariate plots - numeric
numeric_cols = ['age','fare']
fig, axes = plt.subplots(1,2, figsize=(12,4))
sns.histplot(df_clean['age_fill_mean'], kde=True, ax=axes[0])
axes[0].set_title('Age distribution')
sns.boxplot(x=df_clean['fare'], ax=axes[1])
axes[1].set_title('Fare boxplot')
plt.tight_layout()
```



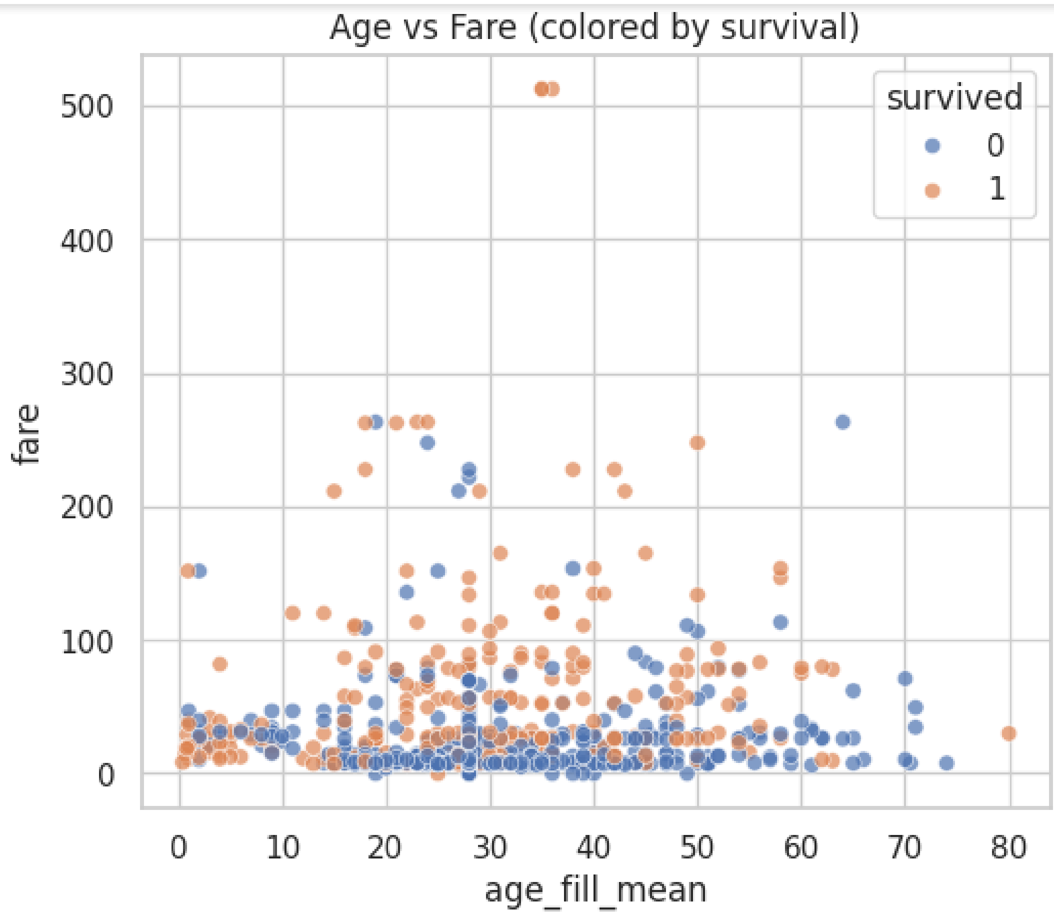

```python
# Univariate plots - categorical
fig, axes = plt.subplots(1,2, figsize=(12,4))
sns.countplot(x='pclass', data=df_clean, ax=axes[0])
axes[0].set_title('Passenger class counts')
sns.countplot(x='sex', data=df_clean, ax=axes[1])
axes[1].set_title('Sex counts')
plt.tight_layout()
```



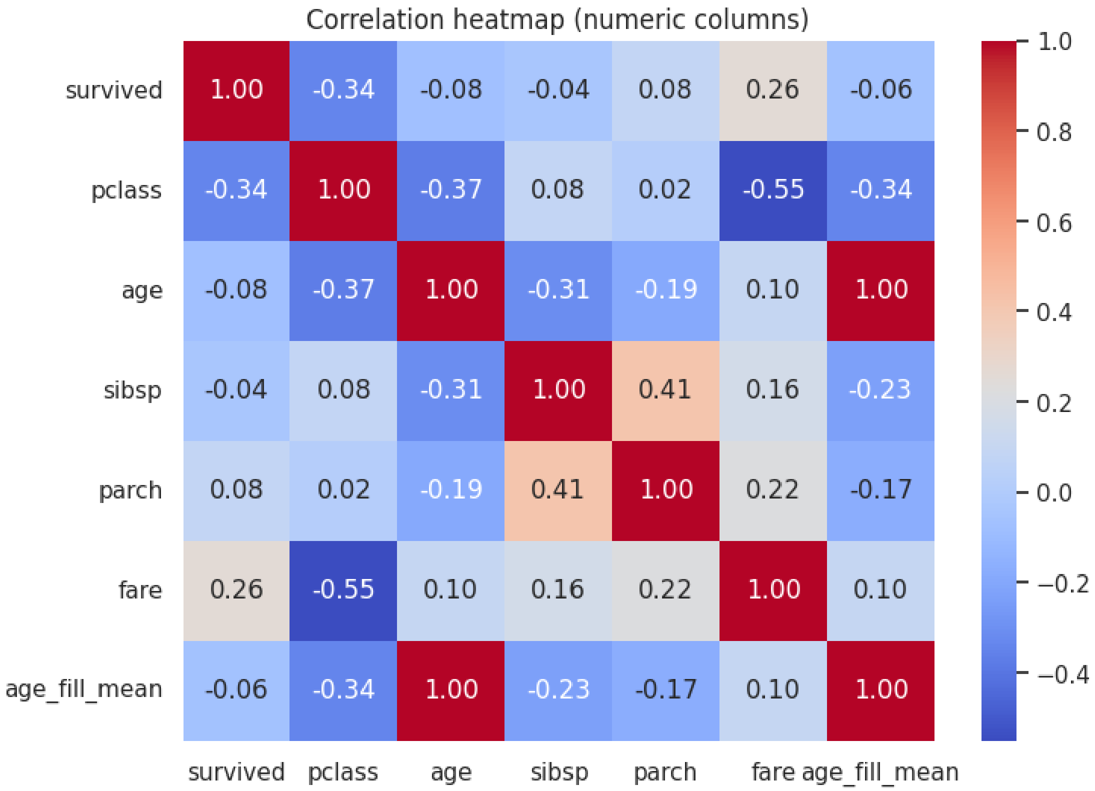

```python
# Bivariate analysis - survival vs categorical
fig, axes = plt.subplots(1,2, figsize=(12,4))
sns.barplot(x='pclass', y='survived', data=df_clean, ax=axes[0])
axes[0].set_title('Survival rate by Pclass')
sns.barplot(x='sex', y='survived', data=df_clean, ax=axes[1])
axes[1].set_title('Survival rate by Sex')
plt.tight_layout()
```



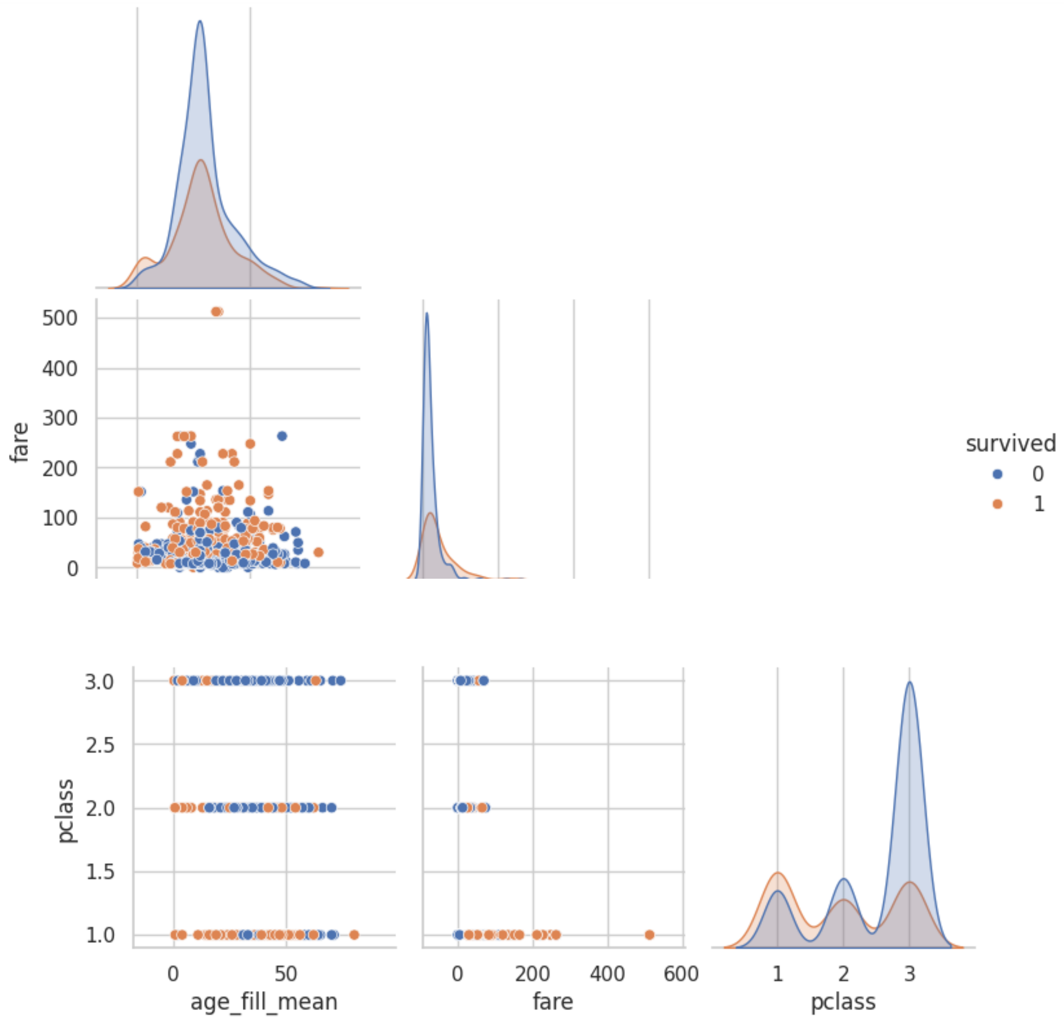

```python
# Bivariate analysis - numeric vs numeric
plt.figure(figsize=(6,5))
sns.scatterplot(x='age_fill_mean', y='fare', hue='survived', data=df_clean, alpha=0.7)
plt.title('Age vs Fare (colored by survival)')
plt.show()
```



```python
# Correlation heatmap (numeric cols)
num = df_clean.select_dtypes(include=['number'])
plt.figure(figsize=(8,6))
sns.heatmap(num.corr(), annot=True, fmt='.2f', cmap='coolwarm')
plt.title('Correlation heatmap (numeric columns)')
plt.show()
```

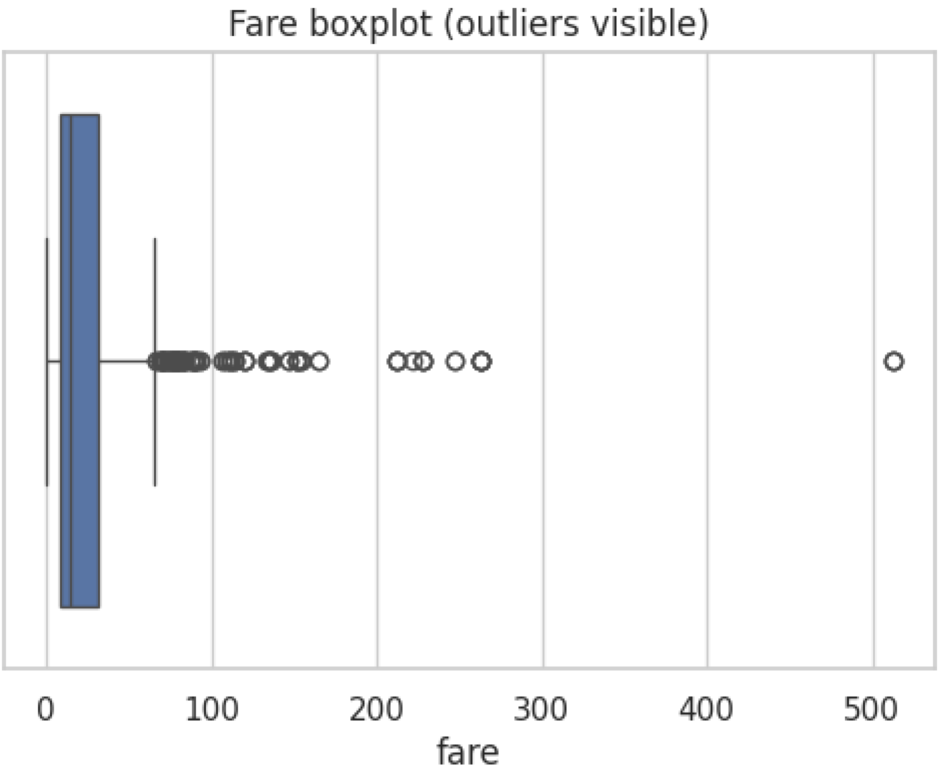



```python
# Pairplot (careful: limit columns for speed)
sns.pairplot(df_clean[['age_fill_mean','fare','survived','pclass']], hue='survived', diag_kind='kde', corner=True)
```

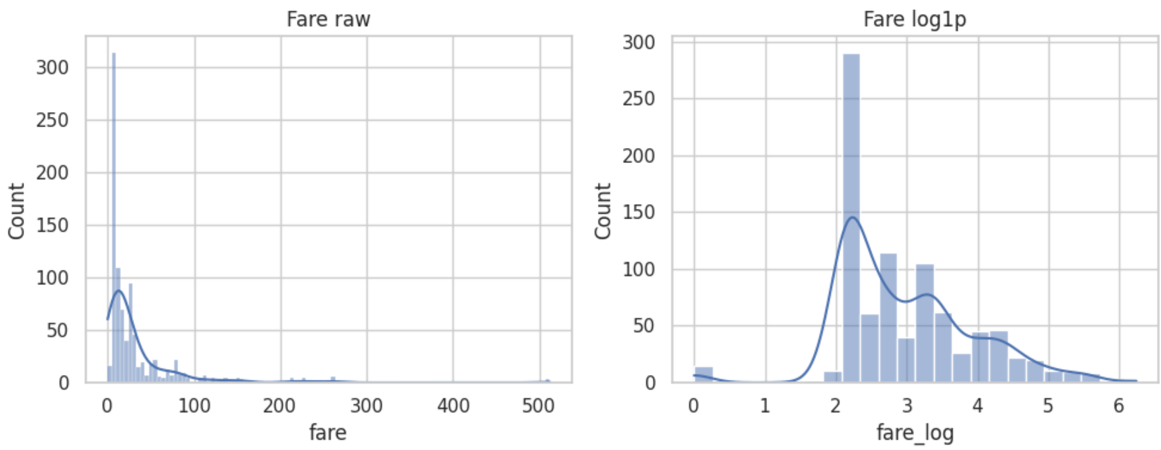


fare
pclass
age_fill_mean
fare
pclass
survived
0
1

```
# Identify outliers (example with fare)
plt.figure(figsize=(6,4))
sns.boxplot(x='fare', data=df_clean)
plt.title('Fare boxplot (outliers visible)')
plt.show()
```




```
# Handling skew (example log transform of fare)
df_clean['fare_log'] = np.log1p(df_clean['fare'])
plt.figure(figsize=(10,4))
plt.subplot(1,2,1); sns.histplot(df_clean['fare'], kde=True).set_title('Fare raw')
plt.subplot(1,2,2); sns.histplot(df_clean['fare_log'], kde=True).set_title('Fare log1p')
plt.tight_layout()
```



```python
# Multicollinearity detection (VIF)
from statsmodels.stats.outliers_influence import variance_inflation_factor
X = num.drop(columns=['survived']).dropna()  # predictors only
X = X.assign(const=1)  # add constant for VIF calc if needed
vif_data = pd.DataFrame({
    'feature': X.columns,
    'VIF': [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]
})
vif_data = vif_data[vif_data['feature']!='const']
vif_data
```

```
/usr/local/lib/python3.11/dist-packages/statsmodels/stats/outliers_influence.py:197: RuntimeWarning: divide by zero encountered in scalar divide
  vif = 1. / (1. - r_squared_i)
```

	feature	VIF
0	pclass	1.706840
1	age	inf
2	sibsp	1.273264
3	parch	1.229164
4	fare	1.581994
5	age_fill_mean	inf

```python
# Observations & summary
print("Observations:")
print("- Higher survival rate for females vs males.")
print("- Lower-class (3rd) had lower survival rate than 1st/2nd class.")
print("- Fare is highly skewed; log transform makes distribution more symmetric.")
print("- Age has missing values imputed with median; distribution shows many young passengers.")
```

```
Observations:
- Higher survival rate for females vs males.
- Lower-class (3rd) had lower survival rate than 1st/2nd class.
- Fare is highly skewed; log transform makes distribution more symmetric.
- Age has missing values imputed with median; distribution shows many young passengers.
```

```python
df_clean.to_csv('titanic_eda_cleaned.csv', index=False)
```