A Data Analysis of Aircraft Incidents for Business Strategy Minimizing Risk

Overview

In this project, I analyzed aviation accident data from the National Transportation Safety Board (NTSB) to help guide safer aircraft purchases. Using Python and pandas, I cleaned and explored the data, focusing on trends in manufacturer safety, injury severity, and number of engines. The analysis showed that aircraft from certain manufacturers and those with more engines tend to be involved in fewer and less severe accidents. These insights informed three business recommendations to support data-driven decisions as the company enters the aviation industry.

Business Understanding

The business problem focuses on minimizing risk as the company expands into aviation by purchasing aircraft for commercial and private use. To support safe investment decisions, I analyzed historical accident data to identify manufacturers with fewer incidents, aircraft with more engines, and models linked to less severe outcomes. These factors directly impact safety, operational costs, and reputation, helping the company make informed, low-risk purchasing choices.

Data Understanding

The dataset comes from the NTSB and contains records of civil aviation accidents from 1962 to 2023, including aircraft manufacturer, model, number of engines, location, and injury severity. It reflects the safety history of different aircraft, which is critical for evaluating investment risks in aviation. The analysis focuses on accident severity as the target variable, using both categorical and numerical data to uncover safety trends.

```python
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Load dataset
df = pd.read_csv('/content/AviationData.csv', encoding='latin1')

# Preview first few rows
df.head()
```

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	Airport.Name	...	Purpose.of.flight	Air.carrier	Total.Fatal
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.922223	-81.878056	NaN	NaN	...	Personal	NaN	
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	

5 rows × 31 columns

The dataset contains accident reports from 1962 to 2023, including fields like aircraft manufacturer, model, number of engines in the aircraft, and injury severity. The target focus is on accident severity and safety trends among manufacturers and aircraft types.

Basic information about the dataset

```
print("\nData Information:")
df.info()
```

```
Data Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29623 entries, 0 to 29622
Data columns (total 31 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Event.Id               29623 non-null  object
 1   Investigation.Type     29623 non-null  object
 2   Accident.Number        29623 non-null  object
 3   Event.Date             29623 non-null  object
 4   Location               29613 non-null  object
 5   Country                29482 non-null  object
 6   Latitude               8 non-null      float64
 7   Longitude              8 non-null      float64
 8   Airport.Code           15658 non-null  object
 9   Airport.Name           17379 non-null  object
 10  Injury.Severity        29623 non-null  object
 11  Aircraft.damage        28978 non-null  object
 12  Aircraft.Category      3665 non-null   object
 13  Registration.Number    29612 non-null  object
 14  Make                   29616 non-null  object
 15  Model                  29606 non-null  object
 16  Amateur.Built          29622 non-null  object
 17  Number.of.Engines      29291 non-null  float64
 18  Engine.Type            29619 non-null  object
 19  FAR.Description        3665 non-null   object
```

```
 20  Schedule                4849 non-null   object
 21  Purpose.of.flight       29579 non-null  object
 22  Air.carrier             1584 non-null   object
 23  Total.Fatal.Injuries    29478 non-null  float64
 24  Total.Serious.Injuries  29432 non-null  float64
 25  Total.Minor.Injuries    29428 non-null  float64
 26  Total.Uninjured         29496 non-null  float64
 27  Weather.Condition       29621 non-null  object
 28  Broad.phase.of.flight   29387 non-null  object
 29  Report.Status           29623 non-null  object
 30  Publication.Date        17176 non-null  object
dtypes: float64(7), object(24)
memory usage: 7.0+ MB
```

Displaying the number of rows and columns

```
print("Shape of the dataset:", df.shape)
```

```
Shape of the dataset: (29623, 31)
```

Statistical Summary

```
print("\nSummary Statistics:")
df.describe(include='all')
```

```
Summary Statistics:
```

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	Airport.Name	...	Purpose.of.flight	Air.carrier	Total
count	29623	29623	29623	29623	29613	29482	8.000000	8.000000	15658	17379	...	29579	1584	
unique	29171	2	29623	3636	10627	59	NaN	NaN	5003	8905	...	12	1251	
top	20001214X45071	Accident	ANC92LA021	1982-05-16	ANCHORAGE, AK	United States	NaN	NaN	NONE	PRIVATE	...	Personal	United Airlines	
freq	3	28583	1	25	211	29172	NaN	NaN	617	102	...	16713	33	
mean	NaN	NaN	NaN	NaN	NaN	NaN	44.914271	-110.695764	NaN	NaN	...	NaN	NaN	
std	NaN	NaN	NaN	NaN	NaN	NaN	11.772969	36.243789	NaN	NaN	...	NaN	NaN	
min	NaN	NaN	NaN	NaN	NaN	NaN	30.757778	-173.240000	NaN	NaN	...	NaN	NaN	
25%	NaN	NaN	NaN	NaN	NaN	NaN	38.135556	-128.370625	NaN	NaN	...	NaN	NaN	
50%	NaN	NaN	NaN	NaN	NaN	NaN	44.243194	-101.121527	NaN	NaN	...	NaN	NaN	
75%	NaN	NaN	NaN	NaN	NaN	NaN	46.645833	-84.717222	NaN	NaN	...	NaN	NaN	
max	NaN	NaN	NaN	NaN	NaN	NaN	70.333333	-70.758333	NaN	NaN	...	NaN	NaN	

11 rows × 31 columns

Data Preparation

I cleaned the dataset by dropping irrelevant columns, handling missing values through removal or forward-filling, and standardizing categorical data. These steps ensured the dataset was reliable and focused on key factors related to aircraft safety and risk assessment.

Checking for missing values

```
missing_values = df.isnull().sum()
missing_values = missing_values[missing_values > 0]
print("\nMissing Values:\n", missing_values)
```

```
Missing Values:
 Location                    10
Country                    141
Latitude                 29615
Longitude                29615
Airport.Code             13965
Airport.Name             12244
Aircraft.damage            645
Aircraft.Category        25958
Registration.Number         11
Make                         7
Model                       17
Amateur.Built                1
Number.of.Engines          332
Engine.Type                  4
FAR.Description          25958
Schedule                 24774
Purpose.of.flight           44
Air.carrier              28039
Total.Fatal.Injuries       145
Total.Serious.Injuries     191
Total.Minor.Injuries       195
Total.Uninjured            127
Weather.Condition            2
Broad.phase.of.flight      236
Publication.Date         12447
dtype: int64
```

Dropping columns with more than 30% missing values

```
threshold = len(df) * 0.3
cols_to_drop = missing_values[missing_values > threshold].index
df = df.drop(columns=cols_to_drop, errors='ignore')
```

Dropping irrelevant columns manually

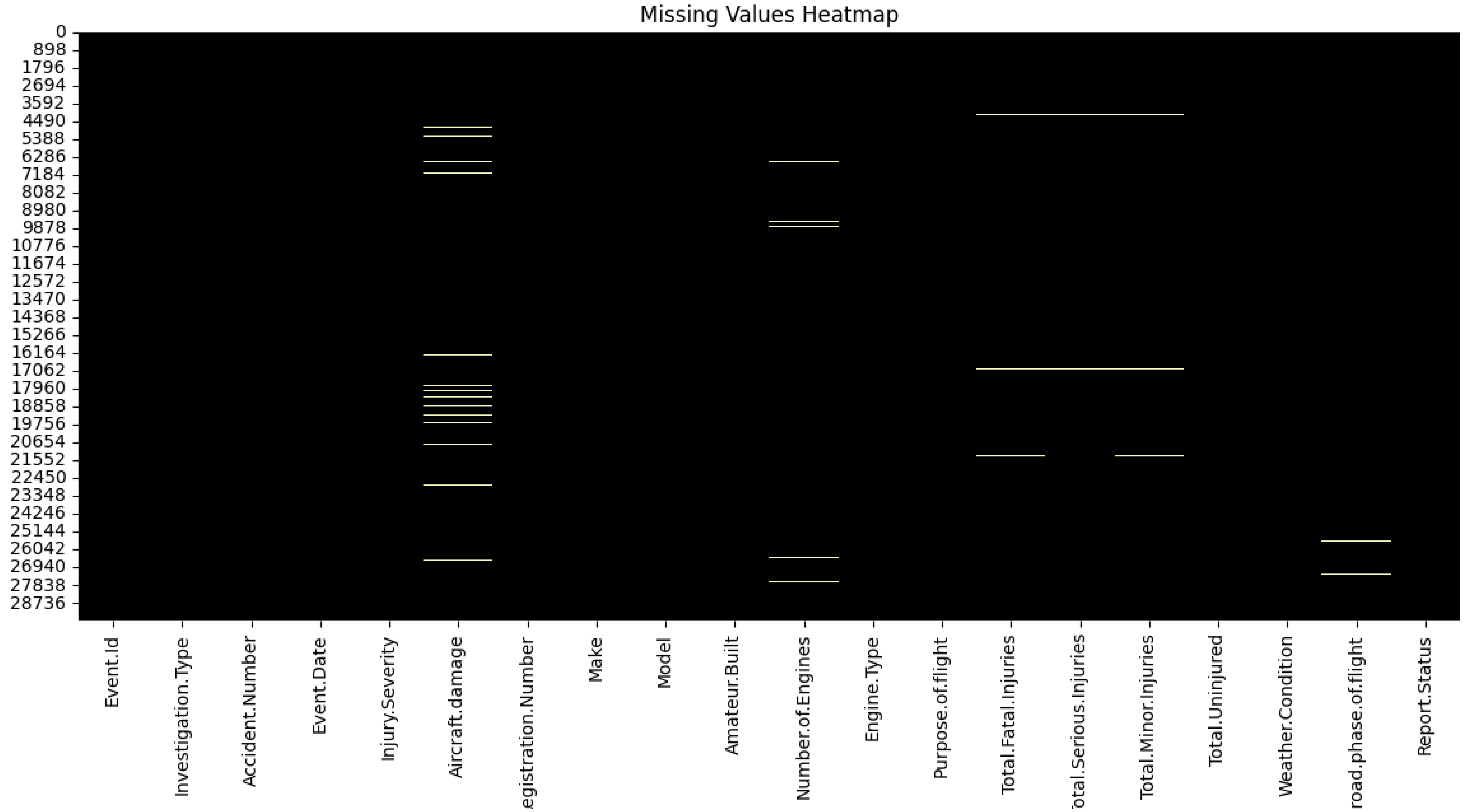
```
df = df.drop(['Location', 'Country', 'Publication_Date','Report_Status',
              'Aircraft_Category',  'Broad_phase_of_flight','Schedule', 'Air_carrier',
              'FAR_Description', 'Longitude', 'Latitude', 'Airport_Code', 'Airport_Name'], axis=1, errors='ignore')
df.head()
```

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Injury.Severity	Aircraft.damage	Registration.Number	Make	Model	Amateur.Built	Number.of.Engines	Engine.Type	Pu
0	20001218X45444	Accident	SEA87LA080	1948-10-24	Fatal(2)	Destroyed	NC6404	Stinson	108-3	No	1.0	Reciprocating	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	Fatal(4)	Destroyed	N5069P	Piper	PA24-180	No	1.0	Reciprocating	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Fatal(3)	Destroyed	N5142R	Cessna	172M	No	1.0	Reciprocating	
3	20001218X45448	Accident	LAX96LA321	1977-06-19	Fatal(2)	Destroyed	N1168J	Rockwell	112	No	1.0	Reciprocating	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Fatal(1)	Destroyed	N15NY	Cessna	501	No	NaN	NaN	

Next steps: View recommended plots New interactive sheet

Visualizing missing data

```
plt.figure(figsize=(14,6))
sns.heatmap(df.isnull(), cbar=False, cmap='magma')
plt.title('Missing Values Heatmap')
plt.show()
```



Filling remaining values with forward fill

```
data = df.fillna(method='ffill')
```

```
<ipython-input-9-8c21be8192a7>:1: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a future version. Use obj.ffill() or obj.bfill() instead.
  data = df.fillna(method='ffill')
```

Verifying missing after cleaning

```
print("\nMissing Values after cleaning:\n", data.isnull().sum().sum())
```

```
Missing Values after cleaning:
 0
```

Check final data shape

```
df.shape
```

```
(29623, 20)
```

I dropped irrelevant columns and handled missing data appropriately to maintain focus on aircraft safety factors, ensuring a clean dataset for analysis.

Exploratory Data Analysis(EDA)

I used exploratory data analysis (EDA) with groupings, aggregations, and visualizations to uncover trends related to aircraft safety. This descriptive approach was appropriate because the project focused on identifying safer aircraft models, not predictive modeling.

Top 10 Aircraft Manufacturers

Analyze aircraft manufacturer accident counts

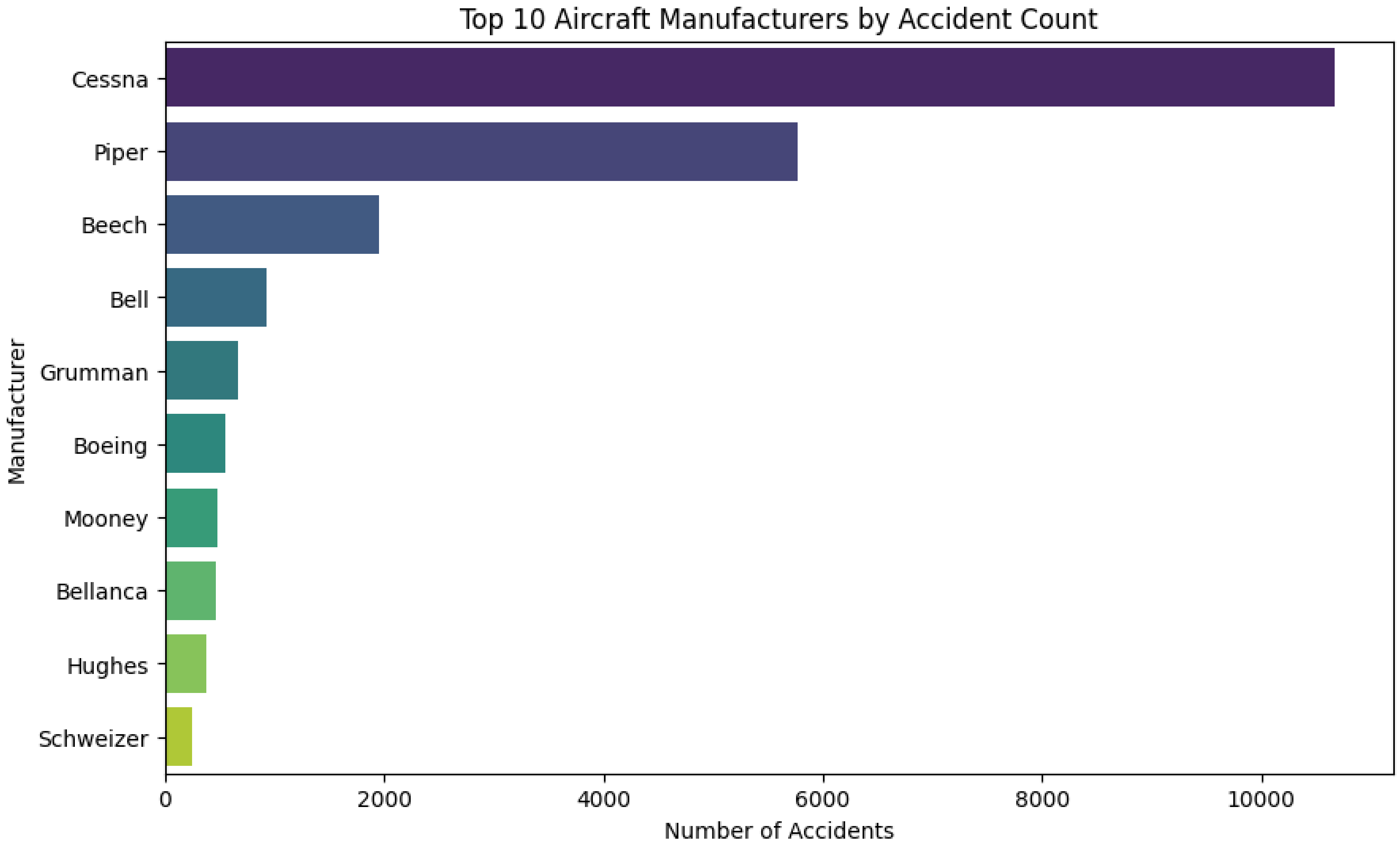
```
manufacturer_counts = df['Make'].value_counts().head(10)
```

```
plt.figure(figsize=(10,6))
sns.barplot(x=manufacturer_counts.values, y=manufacturer_counts.index, palette='viridis')
plt.title('Top 10 Aircraft Manufacturers by Accident Count')
plt.xlabel('Number of Accidents')
plt.ylabel('Manufacturer')
plt.show()
```

```
<ipython-input-13-b9eddfef0f59>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=manufacturer_counts.values, y=manufacturer_counts.index, palette='viridis')
```



Accidents by the number of engines in the aircraft

Analyze the number of engines by the aircraft

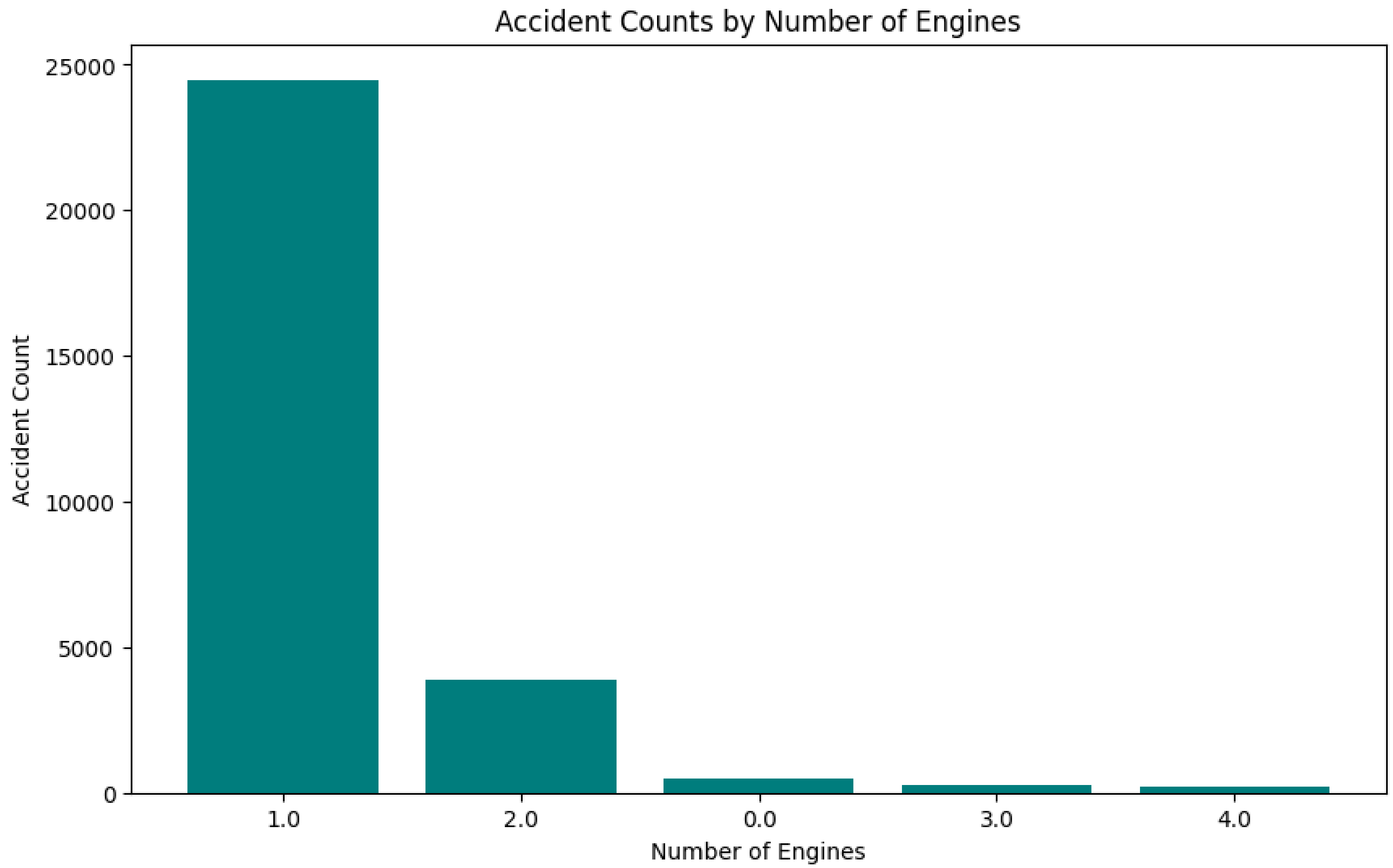
```
engine_data = df[['Number.of.Engines', 'Total.Fatal.Injuries']]
engine_accident_counts = engine_data.groupby('Number.of.Engines').size().reset_index(name='Accident_Count')
engine_accident_counts = engine_accident_counts.sort_values(by='Accident_Count', ascending=False)
engine_accident_counts['Engine_Risk_Level'] = engine_accident_counts['Accident_Count'].apply(lambda x: 'High Risk' if x > 10 else 'Low Risk')


print(engine_accident_counts)
```

```
   Number.of.Engines  Accident_Count Engine_Risk_Level
1                1.0           24485         High Risk
2                2.0            3865         High Risk
```

```
0           0.0         474       High Risk
3           3.0         283       High Risk
4           4.0         184       High Risk
```

```
plt.figure(figsize=(10,6))
plt.bar(engine_accident_counts['Number.of.Engines'].astype(str), engine_accident_counts['Accident_Count'], color='teal')
plt.xlabel('Number of Engines')
plt.ylabel('Accident Count')
plt.title('Accident Counts by Number of Engines')
plt.show()
```



I conclude that the higher the number of engines the lower the accident count.

Injury Severity Distribution

Analyze injury severity

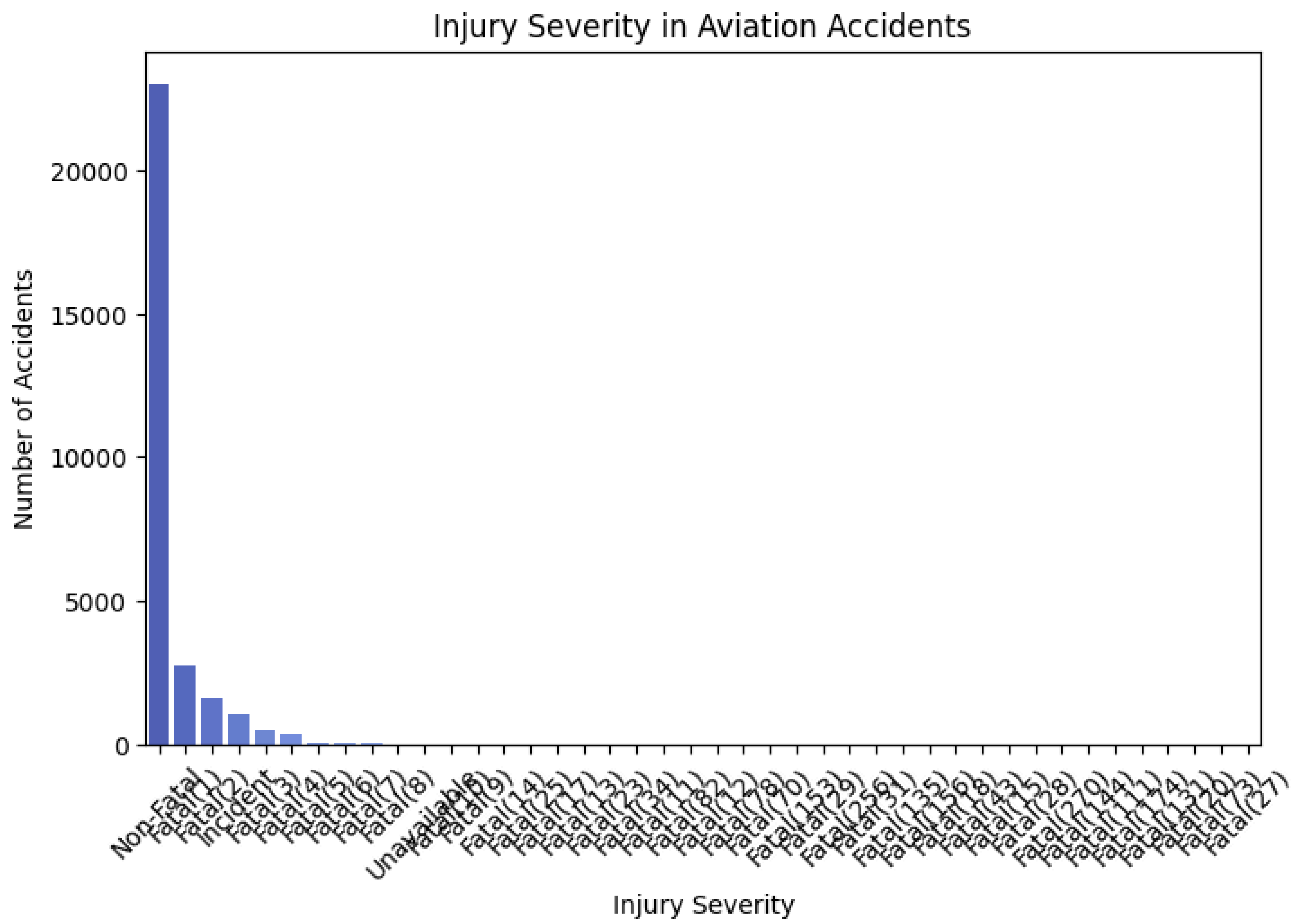
```
injury_counts = df['Injury.Severity'].value_counts()
```

```
plt.figure(figsize=(8,5))
sns.barplot(x=injury_counts.index, y=injury_counts.values, palette='coolwarm')
plt.title('Injury Severity in Aviation Accidents')
plt.xlabel('Injury Severity')
plt.ylabel('Number of Accidents')
plt.xticks(rotation=45)
plt.show()
```

```
<ipython-input-17-68a949998212>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=injury_counts.index, y=injury_counts.values, palette='coolwarm')
```

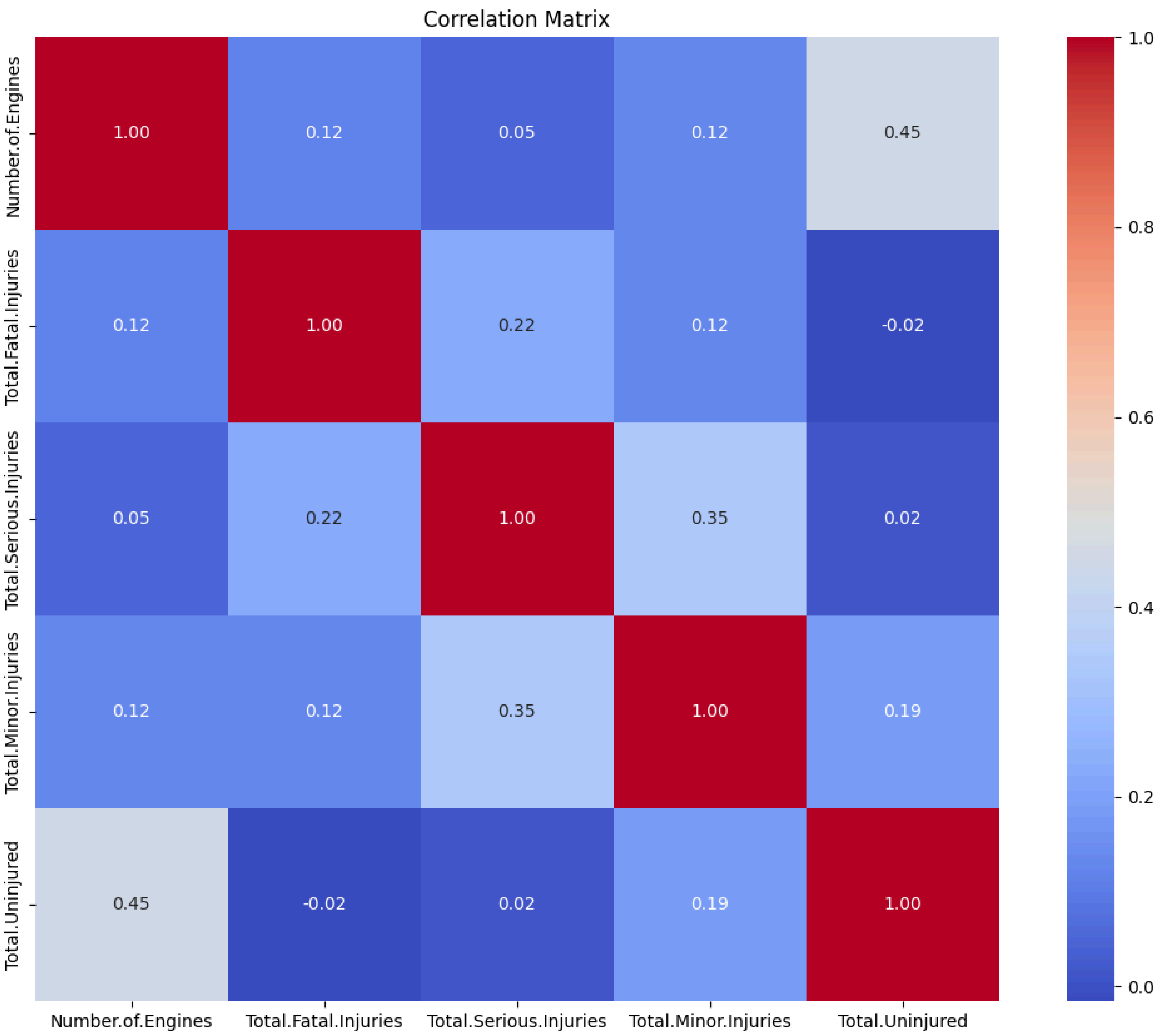


Correlation Matrix

```
# Select only numeric columns
numeric_df = df.select_dtypes(include=[np.number])

if not numeric_df.empty:
    plt.figure(figsize=(14,10))
    sns.heatmap(numeric_df.corr(), annot=True, cmap='coolwarm', fmt='.2f', square=True)
    plt.title('Correlation Matrix')
    plt.show()
```

```
else:
    print("No numeric data available for correlation heatmap.")
```



Evaluation

The analysis successfully identified safer aircraft manufacturers and revealed that planes with more engines are linked to less severe accidents. Since this was a descriptive analysis, evaluation focused on how well the insights addressed business questions and supported risk-aware decision-making.

Recommendations

1. Focus investments on aircraft models built by manufacturers who show consistently low numbers of accidents and incidents over time.

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