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 fewer 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 fewer 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.

```
# 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()
```

```
<ipython-input-1-731a81ef93c1>:8: DtypeWarning: Columns (6,7,28) have mixed types. Specify dtype option on import or set low_memory=Fals
  df = pd.read_csv('/content/AviationData.csv', encoding='latin1')
```

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

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: 88889 entries, 0 to 88888
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                88889 non-null  object 
 1   Investigation.Type      88889 non-null  object 
 2   Accident.Number         88889 non-null  object 
 3   Event.Date              88889 non-null  object 
 4   Location                88837 non-null  object 
 5   Country                 88663 non-null  object 
 6   Latitude                34382 non-null  object 
 7   Longitude               34373 non-null  object 
 8   Airport.Code            50132 non-null  object 
 9   Airport.Name            52704 non-null  object 
 10  Injury.Severity         87889 non-null  object 
 11  Aircraft.damage         85695 non-null  object 
 12  Aircraft.Category       32287 non-null  object 
 13  Registration.Number     87507 non-null  object 
 14  Make                    88826 non-null  object 
 15  Model                   88797 non-null  object 
 16  Amateur.Built           88787 non-null  object 
 17  Number.of.Engines       82805 non-null  float64
 18  Engine.Type             81793 non-null  object 
 19  FAR.Description         32023 non-null  object 
 20  Schedule                12582 non-null  object 
 21  Purpose.of.flight       82697 non-null  object 
 22  Air.carrier             16648 non-null  object 
 23  Total.Fatal.Injuries    77488 non-null  float64
 24  Total.Serious.Injuries  76379 non-null  float64
 25  Total.Minor.Injuries    76956 non-null  float64
 26  Total.Uninjured         82977 non-null  float64
 27  Weather.Condition       84397 non-null  object 
 28  Broad.phase.of.flight   61724 non-null  object 
 29  Report.Status           82505 non-null  object 
 30  Publication.Date        75118 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

Displaying the number of rows and columns

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

```
Shape of the dataset: (88889, 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	Airpo
count	88889	88889	88889	88889	88837	88663	34382	34373	50132	
unique	87951	2	88863	14782	27758	219	25592	27156	10374	
top	20001214X45071	Accident	WPR23LA045	1982-05-16	ANCHORAGE, AK	United States	332739N	0112457W	NONE	
freq	3	85015	2	25	434	82248	19	24	1488	
mean	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
std	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
min	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
25%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
50%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
75%	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
max	NaN	NaN	NaN	NaN	NaN	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                  52
Country                  226
Latitude               54507
Longitude              54516
Airport.Code           38757
Airport.Name           36185
Injury.Severity         1000
Aircraft.damage         3194
Aircraft.Category      56602
Registration.Number     1382
Make                      63
Model                     92
Amateur.Built            102
Number.of.Engines       6084
Engine.Type             7096
FAR.Description        56866
Schedule               76307
Purpose.of.flight       6192
Air.carrier            72241
Total.Fatal.Injuries   11401
Total.Serious.Injuries 12510
Total.Minor.Injuries   11933
Total.Uninjured         5912
Weather.Condition       4492
Broad.phase.of.flight  27165
Report.Status           6384
Publication.Date       13771
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()
```

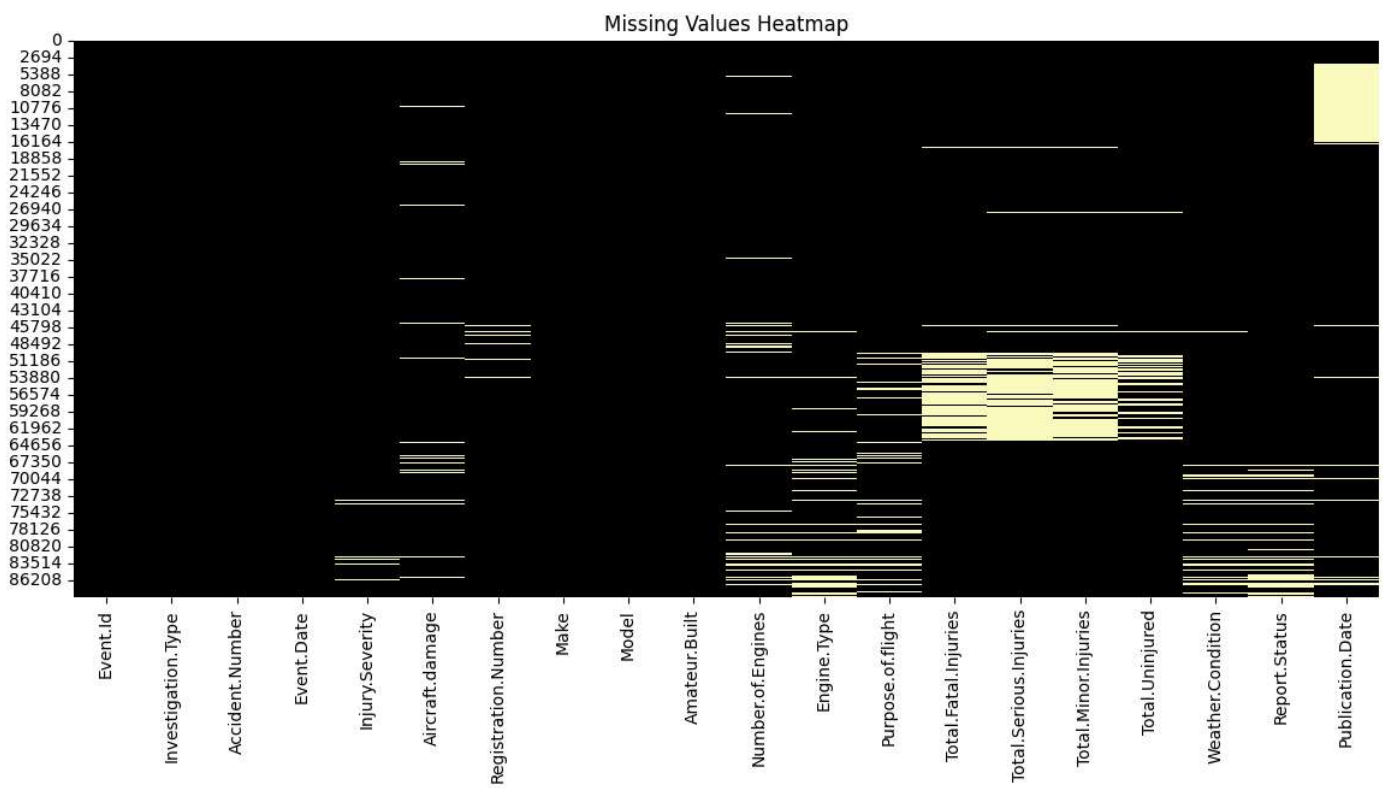
```
/usr/local/lib/python3.11/dist-packages/google/colab/_dataframe_summarizer.py:88: UserWarning: Parsing dates in %d-%m-%Y format when day
  cast_date_col = pd.to_datetime(column, errors="coerce")
```

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Injury.Severity	Aircraft.damage	Registration.Number	Make	Mode
0	20001218X45444	Accident	SEA87LA080	1948-10-24	Fatal(2)	Destroyed	NC6404	Stinson	108
1	20001218X45447	Accident	LAX94LA336	1962-07-19	Fatal(4)	Destroyed	N5069P	Piper	PA2 18
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Fatal(3)	Destroyed	N5142R	Cessna	172
3	20001218X45448	Accident	LAX96LA321	1977-06-19	Fatal(2)	Destroyed	N1168J	Rockwell	11
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Fatal(1)	Destroyed	N15NY	Cessna	50

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

Verifying missing after cleaning

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

```

Missing Values after cleaning:
 1
```

Check final data shape

```
df.shape
```

```
(88889, 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

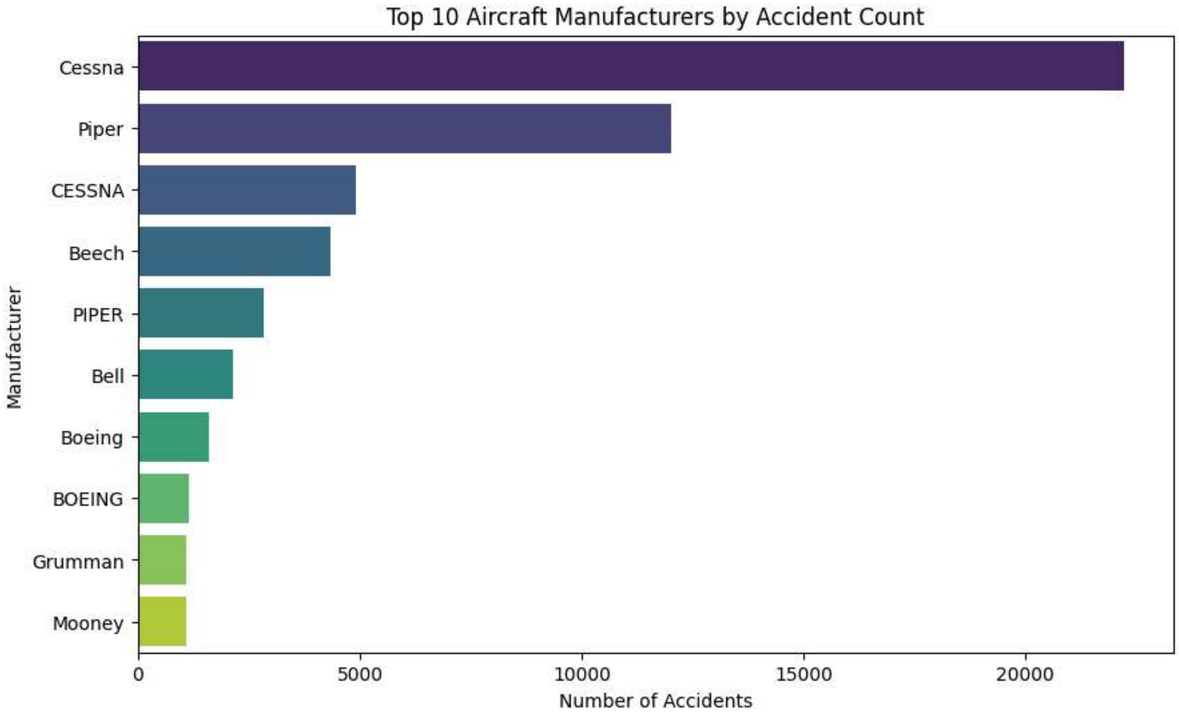
```
manufacturer_counts = df['Make'].value_counts().head(10)


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 `legenc

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



Accidents by the number of engines in the aircraft

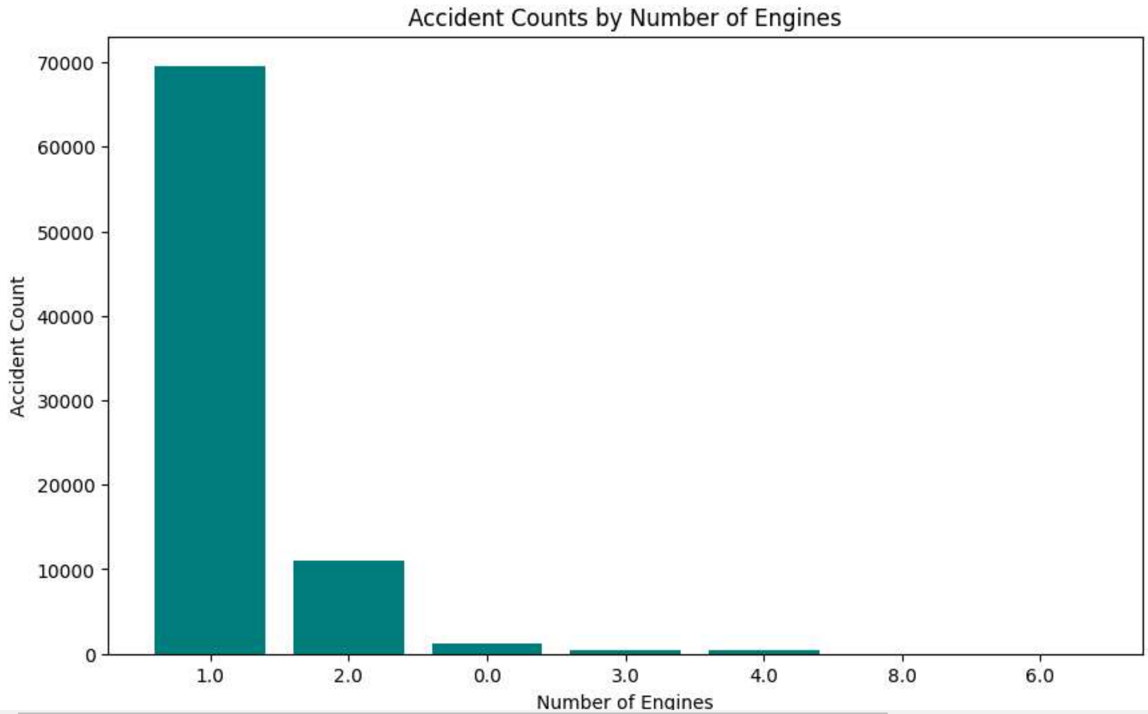
Analyze the number of engines by the aircraft

```
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           69582         High Risk
2                2.0           11079         High Risk
0                0.0            1226         High Risk
3                3.0             483         High Risk
4                4.0             431         High Risk
6                8.0               3          Low Risk
5                6.0               1          Low 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()
```



Injury Severity Distribution

Analyze injury severity

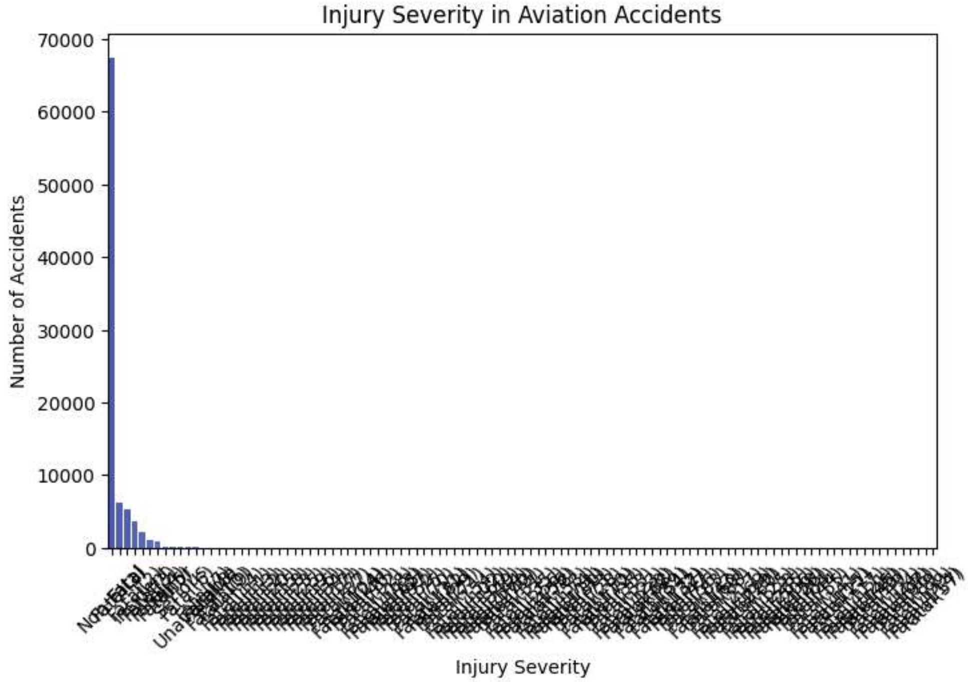
```
injury_counts = df['Injury.Severity'].value_counts()


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 `legenc

  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.")
```