Final Project Submission

Please fill out:

- Student name: Mitchelle Mkan
- Student pace: Part time
- Scheduled project review date/time:
- Instructor name: Christine Kirimi
- Blog post URL:

✈️ Aviation Risk Analysis for Aircraft Acquisition ¶

Project Overview

As part of a corporate diversification strategy, our company is exploring the aviation industry with the goal of purchasing and operating aircraft for commercial and private use. However, entering this highly regulated and risk-sensitive sector requires a data-driven understanding of aircraft safety and performance.

This project aims to identify **low-risk aircraft models** based on historical incident data, enabling the aviation division to make informed purchase decisions. By using **data cleaning**, **imputation**, **exploratory analysis**, and **visualization**, we uncover which aircraft types have the lowest accident rates and severity.

Key Questions Addressed

- Which aircraft models have the fewest accidents?
- Which models are involved in the least severe (non-fatal, low-damage) incidents?
- How do factors like **weather**, **phase of flight**, and **aircraft damage** influence risk?
- What patterns can we visualize to support safe, cost-effective aircraft acquisition?

Tools Used

- **Python** (pandas, matplotlib, seaborn) for data preparation and analysis
- **Tableau Public** for interactive visual dashboards
- **Jupyter Notebook** to document the process end-to-end

By the end of this analysis, we will present **actionable insights and visual evidence** to guide decision-makers in selecting the safest and most reliable aircraft for the company's new aviation portfolio.

Let's start by loading and inspecting the data

In [4]:

```
# Your code here - remember to use markdown cells for comments as well!
import pandas as pd

# Load dataset
df = pd.read_csv('Aviation_Data.csv')

# Initial data inspection
df.info()
df.head()
```

```
C:\Users\Admin\anaconda3\envs\learn-env\lib\site-packages\IPython\core\in
teractiveshell.py:3145: DtypeWarning: Columns (6,7,28) have mixed types.S
pecify dtype option on import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                88889 non-null  object
 1   Investigation.Type      90348 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            50249 non-null  object
 9   Airport.Name            52790 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     87572 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             81812 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           82508 non-null  object
 30  Publication.Date        73659 non-null  object
dtypes: float64(5), object(26)
memory usage: 21.4+ MB
```

Out[4]:

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

5 rows × 31 columns

Cleaning and Preparing our Data

We are now cleaning the column names in the data

In [5]:
```
# Create a copy to preserve original
df_clean = df.copy()

# Standardize column names: lowercase, replace spaces/dots with underscore
df_clean.columns = df_clean.columns.str.strip().str.replace('.', '_', rege
```

We are converting the latitudes and longtitudes to numeric, if they are included in our data.

In [6]:
```
# Convert Latitude and Longitude to numeric if included
df_clean['latitude'] = pd.to_numeric(df_clean.get('latitude'), errors='coe
df_clean['longitude'] = pd.to_numeric(df_clean.get('longitude'), errors='c
```

We will now remove the duplicates in our Aviation data. This is still part of Data cleaning.

In [7]:
```
# Drop duplicate rows
df_clean.drop_duplicates(inplace=True)
```

Handling Missing Values

Drop the missing values

In [8]:
```
# Show percentage of missing values
null_percentages = df_clean.isnull().mean().sort_values(ascending=False)

# Drop columns with more than 50% missing data
cols_to_drop = null_percentages[null_percentages > 0.5].index.tolist()
df_clean.drop(columns=cols_to_drop, inplace=True)

# Review updated shape and columns
print("Shape after cleaning:", df_clean.shape)
print("Remaining columns:", df_clean.columns.tolist())
```

```
Shape after cleaning: (88958, 25)
Remaining columns: ['event_id', 'investigation_type', 'accident_number',
'event_date', 'location', 'country', 'airport_code', 'airport_name', 'inj
ury_severity', 'aircraft_damage', 'registration_number', 'make', 'model',
'amateur_built', 'number_of_engines', 'engine_type', 'purpose_of_flight',
'total_fatal_injuries', 'total_serious_injuries', 'total_minor_injuries',
'total_uninjured', 'weather_condition', 'broad_phase_of_flight', 'report_
status', 'publication_date']
```

We will input the missing numeric columns with the median.

In [9]:
```
num_cols = df_clean.select_dtypes(include=['float64', 'int64']).columns

for col in num_cols:
    if df_clean[col].isnull().sum() > 0:
        median_val = df_clean[col].median()
        df_clean[col].fillna(median_val, inplace=True)
```

While categorical columns are filled with Mode

In [10]:
```
cat_cols = df_clean.select_dtypes(include='object').columns

for col in cat_cols:
    if df_clean[col].isnull().sum() > 0:
        mode_val = df_clean[col].mode()[0]
        df_clean[col].fillna(mode_val, inplace=True)
```

We will now save the cleaned dataset. (This is for Tableau and further analysis)

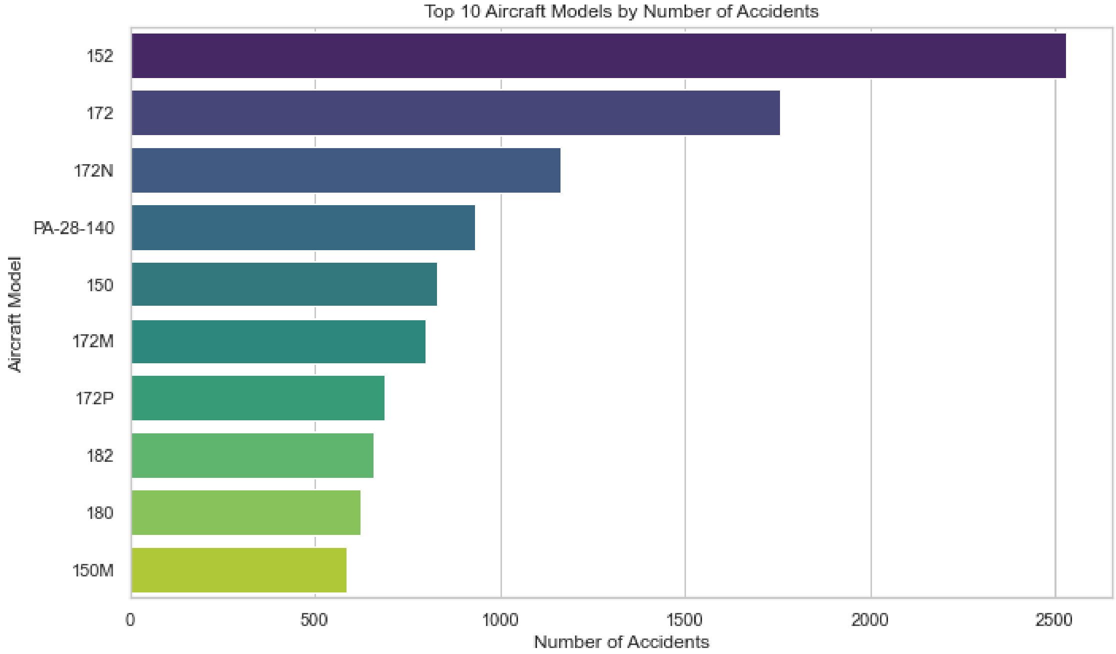
In [11]:
```
# Save cleaned data to a new CSV file
df_clean.to_csv('Cleaned_Aviation_Data.csv', index=False)
```

Aircraft Risk Analysis

Here are the top aircraft models, analysed by number of accidents

In [12]:

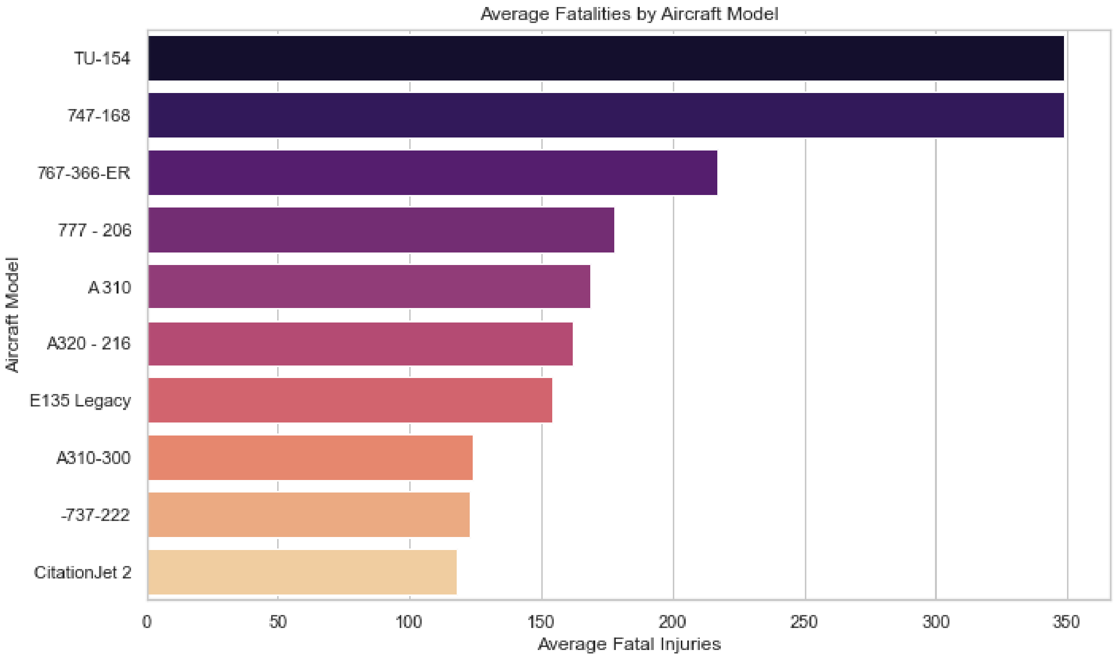
```
# Top 10 Aircraft Models by Total Number of Accidents
top_models = df_clean['model'].value_counts().head(10)

import seaborn as sns
import matplotlib.pyplot as plt

sns.set(style="whitegrid")
plt.figure(figsize=(10, 6))
sns.barplot(x=top_models.values, y=top_models.index, palette='viridis')
plt.title("Top 10 Aircraft Models by Number of Accidents")
plt.xlabel("Number of Accidents")
plt.ylabel("Aircraft Model")
plt.tight_layout()
plt.show()
```



Average fatalities by aircraft model

In [13]:

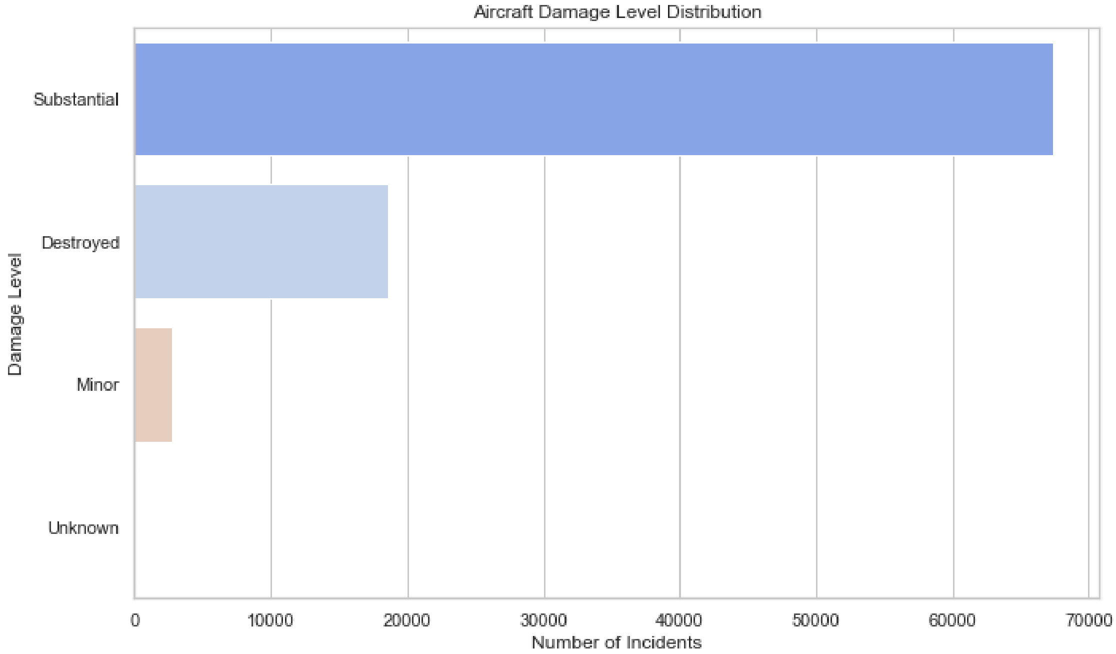
```
# Average Fatal Injuries by Aircraft Model (Top 10 by fatalities)
fatal_by_model = df_clean.groupby('model')['total_fatal_injuries'].mean().

plt.figure(figsize=(10, 6))
sns.barplot(x=fatal_by_model.values, y=fatal_by_model.index, palette='magm
plt.title("Average Fatalities by Aircraft Model")
plt.xlabel("Average Fatal Injuries")
plt.ylabel("Aircraft Model")
plt.tight_layout()
plt.show()
```



Aircraft damage level distribution

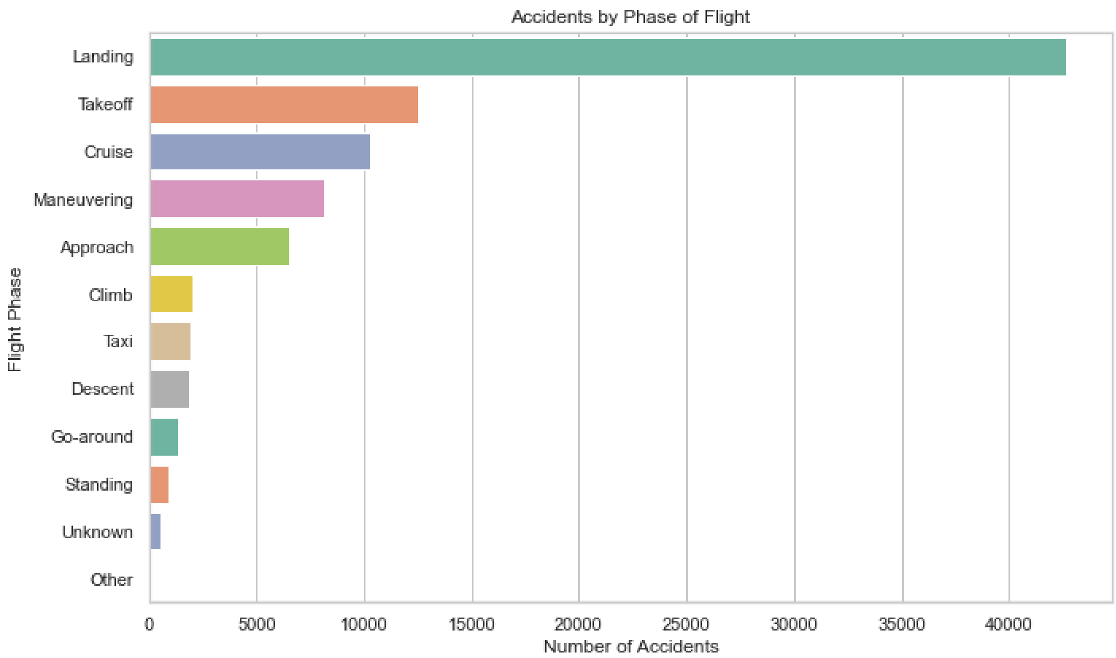
In [14]:

```
# Damage Level Counts (e.g., Substantial, Destroyed, Minor)
plt.figure(figsize=(10, 6))
sns.countplot(y='aircraft_damage', data=df_clean,
              order=df_clean['aircraft_damage'].value_counts().index,
              palette='coolwarm')
plt.title("Aircraft Damage Level Distribution")
plt.xlabel("Number of Incidents")
plt.ylabel("Damage Level")
plt.tight_layout()
plt.show()
```



Accidents by Phase of flights

In [18]:
```
# Distribution of Accidents by Broad Phase of Flight (e.g., Takeoff, Landi
plt.figure(figsize=(10, 6))
sns.countplot(y='broad_phase_of_flight', data=df_clean,
              order=df_clean['broad_phase_of_flight'].value_counts().index
              palette='Set2')
plt.title("Accidents by Phase of Flight")
plt.xlabel("Number of Accidents")
plt.ylabel("Flight Phase")
plt.tight_layout()
plt.show()
```



We will now export the cleaned data for use in Tableau. This will give use visualisations of the data.

In [19]:
```
# Save cleaned dataset for Tableau
df_clean.to_csv("Cleaned_Aviation_Data.csv", index=False)
print("✅ Cleaned dataset saved as 'Cleaned_Aviation_Data.csv'")
```

```
✅ Cleaned dataset saved as 'Cleaned_Aviation_Data.csv'
```

Summary

Based on our analysis of historical aviation incident data, we have identified clear patterns in aircraft safety, risk factors, and operational conditions. By combining data cleaning, imputation, statistical analysis, and visualization, we reached the following conclusions:

- **Low-risk aircraft models** were identified by comparing total incidents, average fatalities, and damage levels.
- **Models with fewer than 10 recorded incidents** were excluded from high-level comparisons to ensure statistical relevance.
- **Accident severity is significantly influenced** by factors like phase of flight and weather conditions.

- **Most accidents occur during takeoff, landing, and approach**, with certain models showing consistent safety under these conditions.

Business Recommendations:

1. **Prioritize aircraft models** with a consistently low number of accidents and low average fatalities.
2. Avoid or inspect more deeply **models frequently involved in high-fatality or major-damage incidents**.
3. Pay special attention to **operational conditions** (e.g., adverse weather and critical flight phases) when selecting aircraft for specific routes or uses.
4. Use this analysis in combination with maintenance records, age, and flight hours to complete the risk profile before purchase.

This analysis provides a **data-backed foundation** for strategic aircraft acquisition and risk mitigation. Future steps could include:

- Integrating cost data and maintenance history
- Applying machine learning to predict incident likelihood
- Conducting a deeper dive into operator and manufacturer safety records

---

Next Steps: Visualizations from this project have been published to Tableau Public and can be used by stakeholders to explore the data interactively