Business Understanding

The objective of this project is to analyze aviation accident data from the National Transportation Safety Board (NTSB) to provide business recommendations for aircraft purchase. The company is interested in expanding its fleet and wants to minimize the risk associated with aircraft selection.

Key Questions:

- What are the key factors contributing to aviation accidents?
- Which aircraft models are associated with fewer accidents?
- How can data-driven insights help the company make informed purchasing decisions?

Stakeholders:

- **Aviation Company**: Looking for data-driven insights on low-risk aircraft.
- **Data Science Team**: Responsible for conducting the analysis.

Data Understanding

The dataset used for this analysis contains records of aviation accidents from 1962 to 2023, provided by the NTSB. It includes information on accident details, aircraft types, locations, and other key attributes.

Data Source:

- The dataset is sourced from the **National Transportation Safety Board (NTSB)**.

```python
import pandas as pd

# Load the dataset
df = pd.read_csv('C:/Users/User/OneDrive/Desktop/moringa/project phase 1/Aircraft-risk-analysis/data/raw data/AviationData.csv')

df_clean = df.copy()

# Show the first few rows of the dataset
df.head()
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_26432\1636249777.py:4:
DtypeWarning: Columns (6,7,28) have mixed types. Specify dtype option
on import or set low_memory=False.
  df = pd.read_csv('C:/Users/User/OneDrive/Desktop/moringa/project
phase 1/Aircraft-risk-analysis/data/raw data/AviationData.csv')
```

```
         Event.Id Investigation.Type Accident.Number  Event.Date  \
0  20001218X45444           Accident      SEA87LA080  1948-10-24
1  20001218X45447           Accident      LAX94LA336  1962-07-19
```

```
2  20061025X01555          Accident      NYC07LA005  1974-08-30
3  20001218X45448          Accident      LAX96LA321  1977-06-19
4  20041105X01764          Accident      CHI79FA064  1979-08-02

          Location        Country   Latitude  Longitude
Airport.Code  \
0  MOOSE CREEK, ID  United States        NaN        NaN          NaN

1   BRIDGEPORT, CA  United States        NaN        NaN          NaN

2    Saltville, VA  United States  36.922223 -81.878056          NaN

3       EUREKA, CA  United States        NaN        NaN          NaN

4       Canton, OH  United States        NaN        NaN          NaN


  Airport.Name  ... Purpose.of.flight Air.carrier Total.Fatal.Injuries
\
0          NaN  ...          Personal         NaN                  2.0

1          NaN  ...          Personal         NaN                  4.0

2          NaN  ...          Personal         NaN                  3.0

3          NaN  ...          Personal         NaN                  2.0

4          NaN  ...          Personal         NaN                  1.0


  Total.Serious.Injuries Total.Minor.Injuries Total.Uninjured  \
0                    0.0                  0.0             0.0
1                    0.0                  0.0             0.0
2                    NaN                  NaN             NaN
3                    0.0                  0.0             0.0
4                    2.0                  NaN             0.0

  Weather.Condition  Broad.phase.of.flight   Report.Status
Publication.Date
0               UNK                 Cruise  Probable Cause
NaN
1               UNK                Unknown  Probable Cause       19-
09-1996
2               IMC                 Cruise  Probable Cause       26-
02-2007
3               IMC                 Cruise  Probable Cause       12-
09-2000
4               VMC               Approach  Probable Cause       16-
04-1980

[5 rows x 31 columns]
```

```python
# Check basic information about the dataset
df.info()
```

```
<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
```

```python
# Describe the dataset to understand the statistical properties
df.describe()
```

```
       Number.of.Engines  Total.Fatal.Injuries  Total.Serious.Injuries
\
count       82805.000000          77488.000000            76379.000000

mean            1.146585              0.647855                0.279881
```

std	0.446510	5.485960	1.544084
min	0.000000	0.000000	0.000000
25%	1.000000	0.000000	0.000000
50%	1.000000	0.000000	0.000000
75%	1.000000	0.000000	0.000000
max	8.000000	349.000000	161.000000

	Total.Minor.Injuries	Total.Uninjured
count	76956.000000	82977.000000
mean	0.357061	5.325440
std	2.235625	27.913634
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	1.000000
75%	0.000000	2.000000
max	380.000000	699.000000

Data Cleaning and Formatting

HERE WE ARE GOING TO :

- Select required colums
- Check and handle missing data
- Check on the datatypes if they are correct
- Check on duplicates

To simplify the analysis, I selected only the columns relevant to understanding aviation accident patterns. These include identifiers, location data, aircraft details, flight purpose, injury severity, and weather conditions.

Selected Columns:

- `Event.Id`, `Accident.Number`, `Event.Date`: Basic identifiers and timestamps
- `Location`, `Country`, `Latitude`, `Longitude`: Geographical information
- `Injury.Severity`, `Total.Fatal.Injuries`, `Total.Serious.Injuries`, `Total.Minor.Injuries`, `Total.Uninjured`: Impact analysis
- `Aircraft.damage`, `Aircraft.Category`, `Make`, `Model`: Aircraft details
- `Number.of.Engines`, `Engine.Type`: Engine characteristics
- `Purpose.of.flight`: Operational context
- `Weather.Condition`, `Broad.phase.of.flight`: Environmental and situational factors

```python
# Getting the colums in the dataset to determine the columns needed
df.columns.tolist()
```

```
['Event.Id',
 'Investigation.Type',
 'Accident.Number',
 'Event.Date',
 'Location',
 'Country',
 'Latitude',
 'Longitude',
 'Airport.Code',
 'Airport.Name',
 'Injury.Severity',
 'Aircraft.damage',
 'Aircraft.Category',
 'Registration.Number',
 'Make',
 'Model',
 'Amateur.Built',
 'Number.of.Engines',
 'Engine.Type',
 'FAR.Description',
 'Schedule',
 'Purpose.of.flight',
 'Air.carrier',
 'Total.Fatal.Injuries',
 'Total.Serious.Injuries',
 'Total.Minor.Injuries',
 'Total.Uninjured',
 'Weather.Condition',
 'Broad.phase.of.flight',
 'Report.Status',
 'Publication.Date']
```

```python
columns_to_keep = [
    'Event.Id',
    'Investigation.Type',
    'Accident.Number',
    'Event.Date',
    'Location',
    'Country',
    'Latitude',
    'Longitude',
    'Injury.Severity',
    'Aircraft.damage',
    'Aircraft.Category',
    'Make',
    'Model',
    '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'
]

df_clean= df[columns_to_keep].copy()
df_clean.info()
df_clean.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 22 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   Injury.Severity         87889 non-null  object
 9   Aircraft.damage         85695 non-null  object
 10  Aircraft.Category       32287 non-null  object
 11  Make                    88826 non-null  object
 12  Model                   88797 non-null  object
 13  Number.of.Engines       82805 non-null  float64
 14  Engine.Type             81793 non-null  object
 15  Purpose.of.flight       82697 non-null  object
 16  Total.Fatal.Injuries    77488 non-null  float64
 17  Total.Serious.Injuries  76379 non-null  float64
 18  Total.Minor.Injuries    76956 non-null  float64
 19  Total.Uninjured         82977 non-null  float64
 20  Weather.Condition       84397 non-null  object
 21  Broad.phase.of.flight   61724 non-null  object
dtypes: float64(5), object(17)
memory usage: 14.9+ MB

         Event.Id Investigation.Type Accident.Number  Event.Date  \
0  20001218X45444           Accident      SEA87LA080  1948-10-24
1  20001218X45447           Accident      LAX94LA336  1962-07-19
2  20061025X01555           Accident      NYC07LA005  1974-08-30
3  20001218X45448           Accident      LAX96LA321  1977-06-19
4  20041105X01764           Accident      CHI79FA064  1979-08-02
```

```
          Location        Country   Latitude  Longitude
Injury.Severity  \
0  MOOSE CREEK, ID  United States        NaN        NaN
Fatal(2)
1   BRIDGEPORT, CA  United States        NaN        NaN
Fatal(4)
2    Saltville, VA  United States  36.922223 -81.878056
Fatal(3)
3       EUREKA, CA  United States        NaN        NaN
Fatal(2)
4       Canton, OH  United States        NaN        NaN
Fatal(1)

  Aircraft.damage  ...     Model Number.of.Engines    Engine.Type  \
0       Destroyed  ...     108-3               1.0  Reciprocating
1       Destroyed  ...  PA24-180               1.0  Reciprocating
2       Destroyed  ...      172M               1.0  Reciprocating
3       Destroyed  ...       112               1.0  Reciprocating
4       Destroyed  ...       501               NaN            NaN

   Purpose.of.flight Total.Fatal.Injuries Total.Serious.Injuries  \
0           Personal                  2.0                    0.0
1           Personal                  4.0                    0.0
2           Personal                  3.0                    NaN
3           Personal                  2.0                    0.0
4           Personal                  1.0                    2.0

   Total.Minor.Injuries  Total.Uninjured  Weather.Condition  \
0                   0.0              0.0                UNK
1                   0.0              0.0                UNK
2                   NaN              NaN                IMC
3                   0.0              0.0                IMC
4                   NaN              0.0                VMC

   Broad.phase.of.flight
0                 Cruise
1                Unknown
2                 Cruise
3                 Cruise
4               Approach

[5 rows x 22 columns]
```

```
#check for mising data
df_clean.isnull().sum()
```

```
Event.Id                      0
Investigation.Type            0
Accident.Number               0
```

```
Event.Date                     0
Location                      52
Country                      226
Latitude                   54507
Longitude                  54516
Injury.Severity             1000
Aircraft.damage             3194
Aircraft.Category          56602
Make                          63
Model                         92
Number.of.Engines           6084
Engine.Type                 7096
Purpose.of.flight           6192
Total.Fatal.Injuries       11401
Total.Serious.Injuries     12510
Total.Minor.Injuries       11933
Total.Uninjured             5912
Weather.Condition           4492
Broad.phase.of.flight      27165
dtype: int64
```

How i wil handle the missing data

After analyzing the data and comparing the number of rows and missing data this is what i have decided to go with

Columns to Drop:

- **Latitude** and **longitude**: Over 61% of data missing, making it unreliable for analysis.
- **Aircraft.Category**: More than 63% of data missing. Dropped due to the lack of sufficient data.
- **Broad.phase.of.flight**:due to a significant portion of missing data.

Columns to Keep and Replace Missing Data:

- **Location**: 52 missing values, replaced with "Unknown"
- **Country**: 226 missing values, replaced with "Unknown"
- **Injury.Severity**: 1,000 missing values, replaced with the mode.
- **Make and Model**: Small number of missing values , replaced with "Unknown"
- **Number.of.Engines and Engine.Type**: Significant missing values, replaced with "Unknown" .
- **Purpose.of.flight**: 6,192 missing values, replaced with "Unknown".
- **Total Injuries** (Fatal, Serious, Minor) and **Total Uninjured**: (zero for no injuries).
- **Weather.Condition**: Replaced with "Unknown".
- **Aircraft damage**: Replaced with "Unknown".

How i will deal with the data types

I will change the Evnet.date to date time and not object

```
# Dropping columns with excessive missing data (Latitude, Longitude,
Aircraft.Category, Broad.phase.of.flight)
df_clean.drop(columns=['Latitude', 'Longitude', 'Aircraft.Category',
'Broad.phase.of.flight'], inplace=True)


# Replacing missing data based on the decisions:

# Location and Country - Replace missing values with 'Unknown'
df_clean['Location'].fillna('Unknown', inplace=True)
df_clean['Country'].fillna('Unknown', inplace=True)

# Injury Severity - Replace missing values with the mode (most
frequent value)
df_clean['Injury.Severity'].fillna(df_clean['Injury.Severity'].mode()
[0], inplace=True)

# Make and Model - Replace missing values with 'Unknown'
df_clean['Make'].fillna('Unknown', inplace=True)
df_clean['Model'].fillna('Unknown', inplace=True)

# Number of Engines and Engine Type - Replace missing values with
'Unknown'
df_clean['Number.of.Engines'].fillna('Unknown', inplace=True)
df_clean['Engine.Type'].fillna('Unknown', inplace=True)

# Purpose of flight - Replace missing values with 'Unknown'
df_clean['Purpose.of.flight'].fillna('Unknown', inplace=True)

# Total injuries and Total Uninjured - Impute missing values with zero
(assuming no injuries reported if not available)
df_clean['Total.Fatal.Injuries'].fillna(0, inplace=True)
df_clean['Total.Serious.Injuries'].fillna(0, inplace=True)
df_clean['Total.Minor.Injuries'].fillna(0, inplace=True)
df_clean['Total.Uninjured'].fillna(0, inplace=True)
#Weaer Condition - Replace missing values with 'Unknown'
df_clean['Weather.Condition'].fillna('Unknown', inplace=True)

#Aircraft damage - replacing with unknown
df_clean['Aircraft.damage'].fillna('Unknown', inplace=True)

# Create a new column 'Aircraft.Name' by combining 'Make' and 'Model'
df_clean['Aircraft.Name'] = df_clean['Make'] + ' ' + df_clean['Model']
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_26432\879730308.py:19: 
FutureWarning: Setting an item of incompatible dtype is deprecated and 
will raise in a future error of pandas. Value 'Unknown' has dtype 
incompatible with float64, please explicitly cast to a compatible 
dtype first.
  df_clean['Number.of.Engines'].fillna('Unknown', inplace=True)
```

```python
print(f"Cleaned Data Shape: {df_clean.shape}")

print(df_clean.isnull().sum())
df_clean
```

```
Cleaned Data Shape: (88889, 19)
Event.Id                  0
Investigation.Type        0
Accident.Number           0
Event.Date                0
Location                  0
Country                   0
Injury.Severity           0
Aircraft.damage           0
Make                      0
Model                     0
Number.of.Engines         0
Engine.Type               0
Purpose.of.flight         0
Total.Fatal.Injuries      0
Total.Serious.Injuries    0
Total.Minor.Injuries      0
Total.Uninjured           0
Weather.Condition         0
Aircraft.Name             0
dtype: int64
```

```
             Event.Id Investigation.Type Accident.Number 
Event.Date  \
0      20001218X45444           Accident      SEA87LA080  1948-10-24

1      20001218X45447           Accident      LAX94LA336  1962-07-19

2      20061025X01555           Accident      NYC07LA005  1974-08-30

3      20001218X45448           Accident      LAX96LA321  1977-06-19

4      20041105X01764           Accident      CHI79FA064  1979-08-02

...               ...                ...             ...         ...

88884  20221227106491           Accident      ERA23LA093  2022-12-26

88885  20221227106494           Accident      ERA23LA095  2022-12-26
```

```
88886  20221227106497         Accident      WPR23LA075  2022-12-26
88887  20221227106498         Accident      WPR23LA076  2022-12-26
88888  20221230106513         Accident      ERA23LA097  2022-12-29

              Location        Country Injury.Severity Aircraft.damage  \
0      MOOSE CREEK, ID  United States        Fatal(2)       Destroyed
1       BRIDGEPORT, CA  United States        Fatal(4)       Destroyed
2        Saltville, VA  United States        Fatal(3)       Destroyed
3           EUREKA, CA  United States        Fatal(2)       Destroyed
4           Canton, OH  United States        Fatal(1)       Destroyed
...                ...            ...             ...             ...
88884    Annapolis, MD  United States           Minor         Unknown
88885      Hampton, NH  United States       Non-Fatal         Unknown
88886       Payson, AZ  United States       Non-Fatal     Substantial
88887       Morgan, UT  United States       Non-Fatal         Unknown
88888       Athens, GA  United States           Minor         Unknown

                            Make      Model Number.of.Engines
Engine.Type  \
0                        Stinson      108-3               1.0
Reciprocating
1                          Piper   PA24-180               1.0
Reciprocating
2                        Cessna       172M               1.0
Reciprocating
3                       Rockwell        112               1.0
Reciprocating
4                         Cessna        501           Unknown
Unknown
...                          ...        ...               ...
...
88884                      PIPER  PA-28-151           Unknown
Unknown
88885                   BELLANCA       7ECA           Unknown
Unknown
```

```
88886  AMERICAN CHAMPION AIRCRAFT      8GCBC               1.0
Unknown
88887                      CESSNA       210N           Unknown
Unknown
88888                       PIPER  PA-24-260           Unknown
Unknown

      Purpose.of.flight  Total.Fatal.Injuries  Total.Serious.Injuries
\
0              Personal                   2.0                     0.0

1              Personal                   4.0                     0.0

2              Personal                   3.0                     0.0

3              Personal                   2.0                     0.0

4              Personal                   1.0                     2.0

...                 ...                   ...                     ...

88884          Personal                   0.0                     1.0

88885           Unknown                   0.0                     0.0

88886          Personal                   0.0                     0.0

88887          Personal                   0.0                     0.0

88888          Personal                   0.0                     1.0


       Total.Minor.Injuries  Total.Uninjured Weather.Condition  \
0                       0.0              0.0               UNK
1                       0.0              0.0               UNK
2                       0.0              0.0               IMC
3                       0.0              0.0               IMC
4                       0.0              0.0               VMC
...                     ...              ...               ...
88884                   0.0              0.0           Unknown
88885                   0.0              0.0           Unknown
88886                   0.0              1.0               VMC
88887                   0.0              0.0           Unknown
88888                   0.0              1.0           Unknown

                          Aircraft.Name
0                        Stinson 108-3
1                      Piper PA24-180
2                         Cessna 172M
3                       Rockwell 112
4                          Cessna 501
```

```
...                                    ...
88884                   PIPER PA-28-151
88885                     BELLANCA 7ECA
88886  AMERICAN CHAMPION AIRCRAFT 8GCBC
88887                       CESSNA 210N
88888                   PIPER PA-24-260

[88889 rows x 19 columns]
```

```python
# Change the data type of event.Date into datetime
df_clean['Event.Date'] = pd.to_datetime(df_clean['Event.Date'])

df_clean.dtypes
```

```
Event.Id                                 object
Investigation.Type                       object
Accident.Number                          object
Event.Date                       datetime64[ns]
Location                                 object
Country                                  object
Injury.Severity                          object
Aircraft.damage                          object
Make                                     object
Model                                    object
Number.of.Engines                        object
Engine.Type                              object
Purpose.of.flight                        object
Total.Fatal.Injuries                    float64
Total.Serious.Injuries                  float64
Total.Minor.Injuries                    float64
Total.Uninjured                         float64
Weather.Condition                        object
Aircraft.Name                            object
dtype: object
```

```python
# Check for duplicates based on the 'Event.Id' column
duplicates_event_id = df_clean[df_clean.duplicated(subset='Event.Id',
keep=False)]

# Total number of duplicates based on Event.Id
print("Total Duplicate Rows Based on Event.Id:",
duplicates_event_id.shape[0])

# Optionally view the duplicates
duplicates_event_id.head()
```

```
Total Duplicate Rows Based on Event.Id: 1874

           Event.Id Investigation.Type Accident.Number Event.Date  \
117  20020917X01908           Accident     DCA82AA012B 1982-01-19
118  20020917X01908           Accident     DCA82AA012A 1982-01-19
```

```
153  20020917X02259          Accident     LAX82FA049A 1982-01-23
158  20020917X02400          Accident     MIA82FA038B 1982-01-23
159  20020917X02400          Accident     MIA82FA038A 1982-01-23

               Location        Country Injury.Severity Aircraft.damage
\
117        ROCKPORT, TX  United States        Fatal(3)       Destroyed

118        ROCKPORT, TX  United States        Fatal(3)       Destroyed

153     VICTORVILLE, CA  United States        Fatal(2)       Destroyed

158  NEWPORT RICHEY, FL  United States       Non-Fatal     Substantial

159  NEWPORT RICHEY, FL  United States       Non-Fatal     Substantial


           Make       Model Number.of.Engines    Engine.Type  \
117     Grumman        AA5A               1.0  Reciprocating
118  Swearingen  SA226-T(B)               2.0     Turbo Prop
153      Mooney        M20C               1.0  Reciprocating
158      Cessna        150M               1.0  Reciprocating
159       Piper  PA-34-200T               2.0  Reciprocating

       Purpose.of.flight  Total.Fatal.Injuries  Total.Serious.Injuries
\
117             Personal                   3.0                     0.0

118  Executive/corporate                   3.0                     0.0

153             Personal                   2.0                     0.0

158             Personal                   0.0                     0.0

159             Personal                   0.0                     0.0


     Total.Minor.Injuries  Total.Uninjured Weather.Condition  \
117                   0.0              0.0               IMC
118                   0.0              0.0               IMC
153                   4.0              0.0               VMC
158                   0.0              3.0               VMC
159                   0.0              3.0               VMC

            Aircraft.Name
117          Grumman AA5A
118  Swearingen SA226-T(B)
153           Mooney M20C
158           Cessna 150M
159      Piper PA-34-200T
```

The duplicates seem to have the same event id but different rows indata hence will be retained

Data Analysis: Patterns, Aircraft Performance, and Strategic Insights

In this section, I will explore the dataset to uncover patterns and draw insights relevant to helping the company make informed decisions on aircraft purchases and operations.

Our goal is not only to understand the nature of accidents, but to determine **which aircraft models and operational environments offer the lowest risk**. The insights derived here will guide recommendations for:

- The best aircraft models to consider.
- The most favorable operating conditions.
- The safest locations for operations.

---

1. Distribution of Accident Outcomes

We begin by examining the **distribution of injuries** and **aircraft damage**. This helps us understand:

- How often accidents result in fatalities or serious injuries.
- The extent of aircraft damage.
- Whether there are many minor or non-injury events.

We will use **histograms** and **bar charts** to visualize:

- Total Fatal Injuries

- Total Serious Injuries

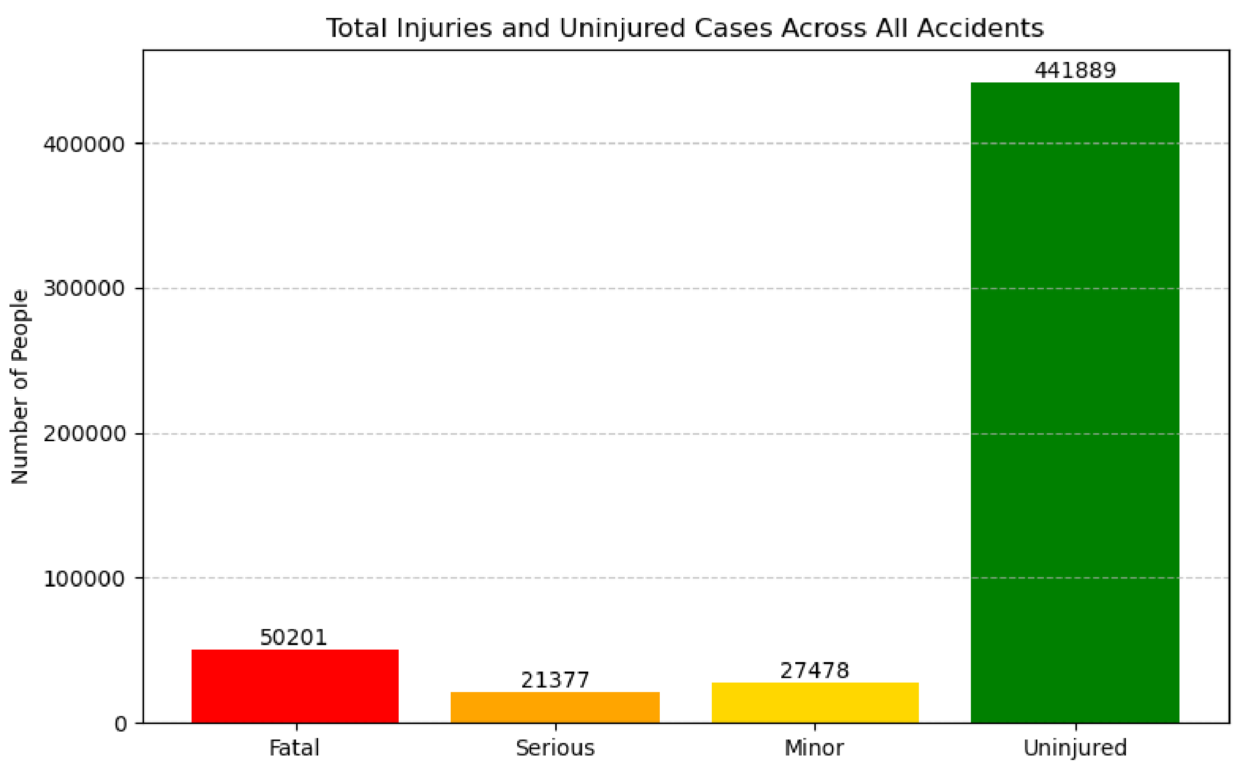
- Total Minor Injuries

- Total Uninjured

- Aircraft Damage Types

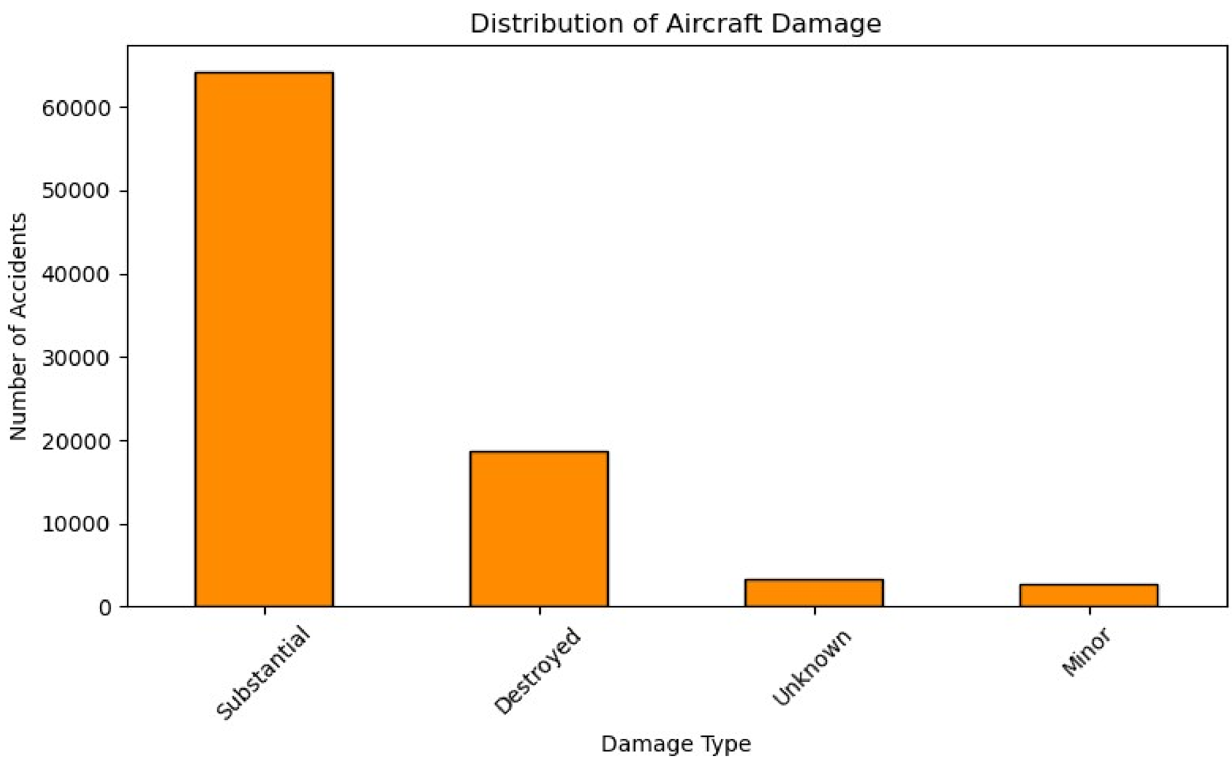
```python
import matplotlib.pyplot as plt

fatal_total = df_clean['Total.Fatal.Injuries'].sum()
serious_total = df_clean['Total.Serious.Injuries'].sum()
minor_total = df_clean['Total.Minor.Injuries'].sum()
uninjured_total = df_clean['Total.Uninjured'].sum()
```

```python
# Injury types and values
labels = ['Fatal', 'Serious', 'Minor', 'Uninjured']
values = [fatal_total, serious_total, minor_total, uninjured_total]

# Plotting
plt.figure(figsize=(8, 5))
bars = plt.bar(labels, values, color=['red', 'orange', 'gold',
'green'])

# Add value labels on top of bars
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval + 100, int(yval),
ha='center', va='bottom')

plt.title('Total Injuries and Uninjured Cases Across All Accidents')
plt.ylabel('Number of People')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



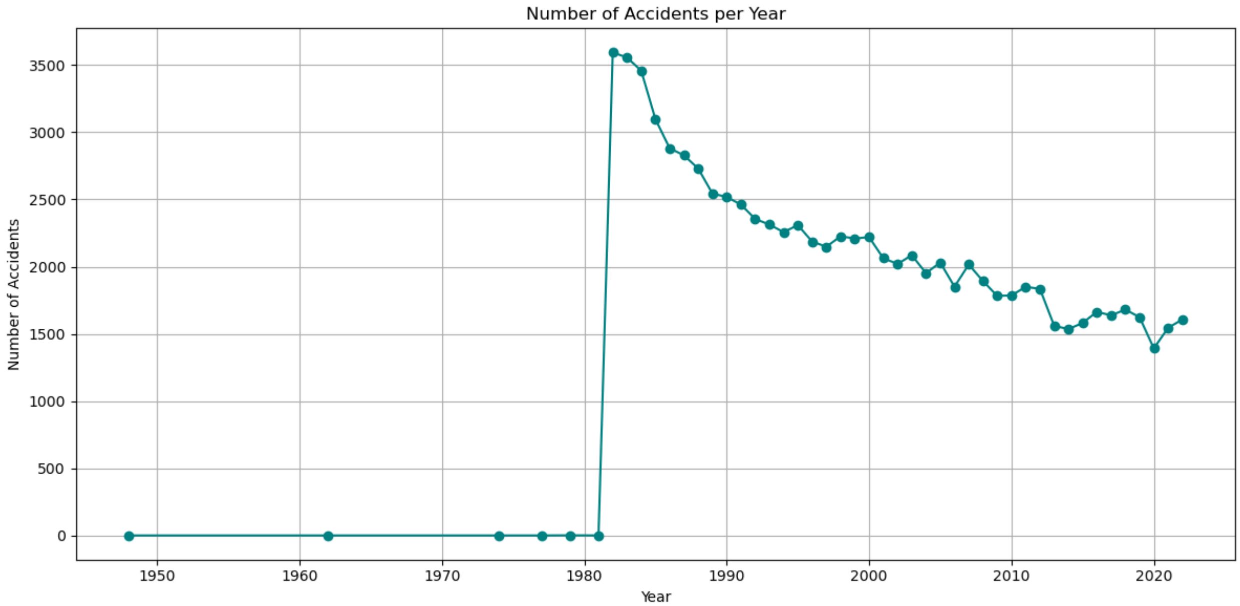

```python
# Bar Chart for Aircraft Damage
```

```
plt.figure(figsize=(8, 5))
df_clean['Aircraft.damage'].value_counts().plot(kind='bar',
color='darkorange', edgecolor='black')
plt.title('Distribution of Aircraft Damage')
plt.xlabel('Damage Type')
plt.ylabel('Number of Accidents')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```




```
# Number of accidents per year
# Extract year
df_clean.loc[:,'Year'] = df_clean['Event.Date'].dt.year

# Count accidents per year
accidents_per_year = df_clean['Year'].value_counts().sort_index()

# Plotting
plt.figure(figsize=(12, 6))
plt.plot(accidents_per_year.index, accidents_per_year.values,
marker='o', linestyle='-', color='teal')
plt.title('Number of Accidents per Year')
plt.xlabel('Year')
plt.ylabel('Number of Accidents')
plt.grid(True)
```

```
plt.tight_layout()
plt.show()
```



2. Aircraft Models vs Injury Severity

We now relate **aircraft types (Make/Model)** to injury outcomes. This reveals:

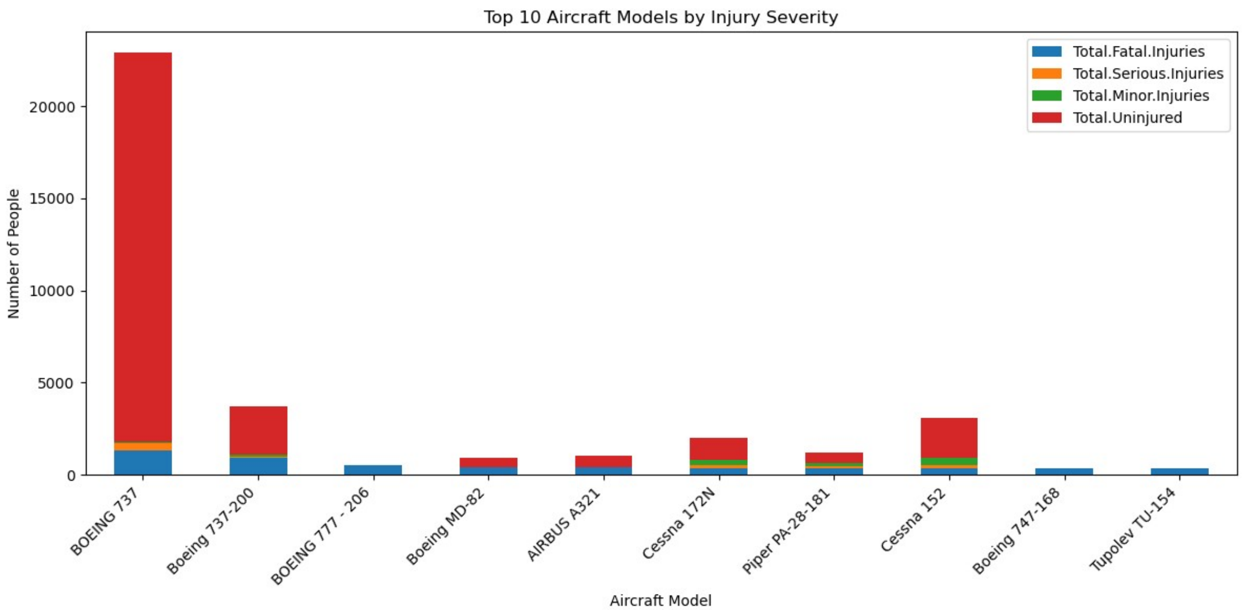
- Which aircraft models are most commonly involved in high-severity accidents.
- Which models are associated with fewer fatalities.

Bar plots and scatter plots will be used to show relationships between:

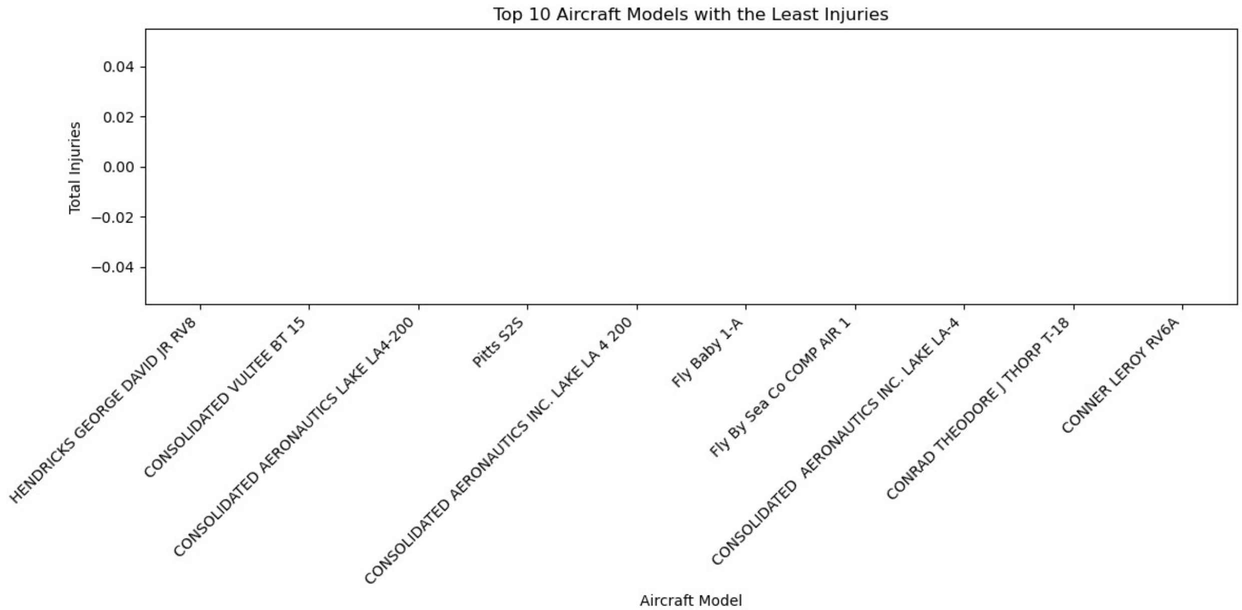
- Aircraft Model and Fatal/Serious/Minor Injuries
- Aircraft Make and Injury Distribution

```
# Group by Aircraft name and sum injury columns
model_injuries = df_clean.groupby('Aircraft.Name')
[['Total.Fatal.Injuries',
                                      'Total.Serious.Injuries',
                                      'Total.Minor.Injuries',

'Total.Uninjured']].sum().sort_values('Total.Fatal.Injuries',
ascending=False).head(10)

# Bar chart: Top 10 Aircraft Models by Injuries
model_injuries.plot(kind='bar', stacked=True, figsize=(12, 6))
plt.title('Top 10 Aircraft Models by Injury Severity')
plt.xlabel('Aircraft Model')
plt.ylabel('Number of People')
```

```python
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()

model_make_mapping = df_clean[['Model',
'Make']].set_index('Model').to_dict()['Make']
```




```python
# Create a new column: Total Injuries
df_clean.loc[:,'Total.Injuries'] = df_clean[['Total.Fatal.Injuries',
                           'Total.Serious.Injuries',
                           'Total.Minor.Injuries']].sum(axis=1)

# Group by Model and sum total injuries
model_total_injuries = df_clean.groupby('Aircraft.Name')
['Total.Injuries'].sum().sort_values()

# Get 10 models with least total injuries
safest_models = model_total_injuries.head(10)

# Plot bar chart
plt.figure(figsize=(12, 6))
safest_models.plot(kind='bar', color='green')
plt.title('Top 10 Aircraft Models with the Least Injuries')
plt.xlabel('Aircraft Model')
plt.ylabel('Total Injuries')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



3. Aircraft Models vs Damage Severity

Here, I analyze how different aircraft **models respond to accidents in terms of damage**. This helps assess structural integrity and design resilience.

We will compare:

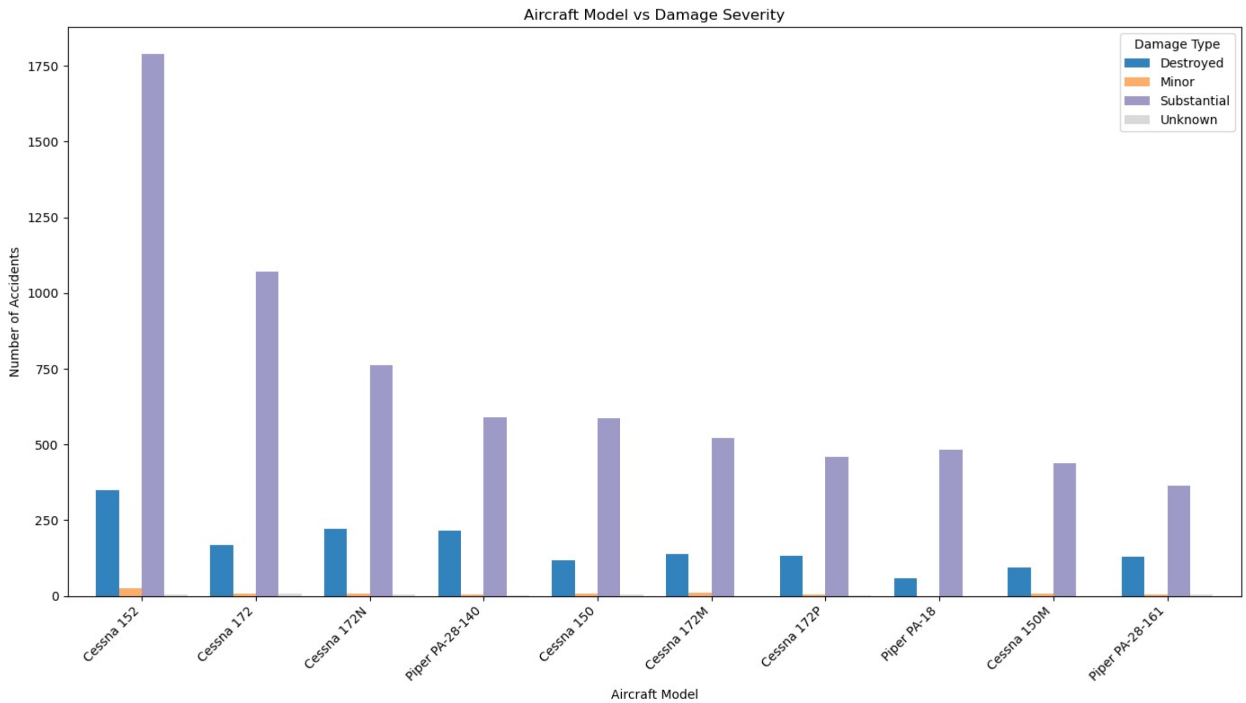
- Aircraft Model vs Damage Type (Minor, Substantial, Destroyed)
- Injury severity across aircraft damage categories

Stacked bar charts and **grouped visualizations** will be used to highlight the most resilient models.

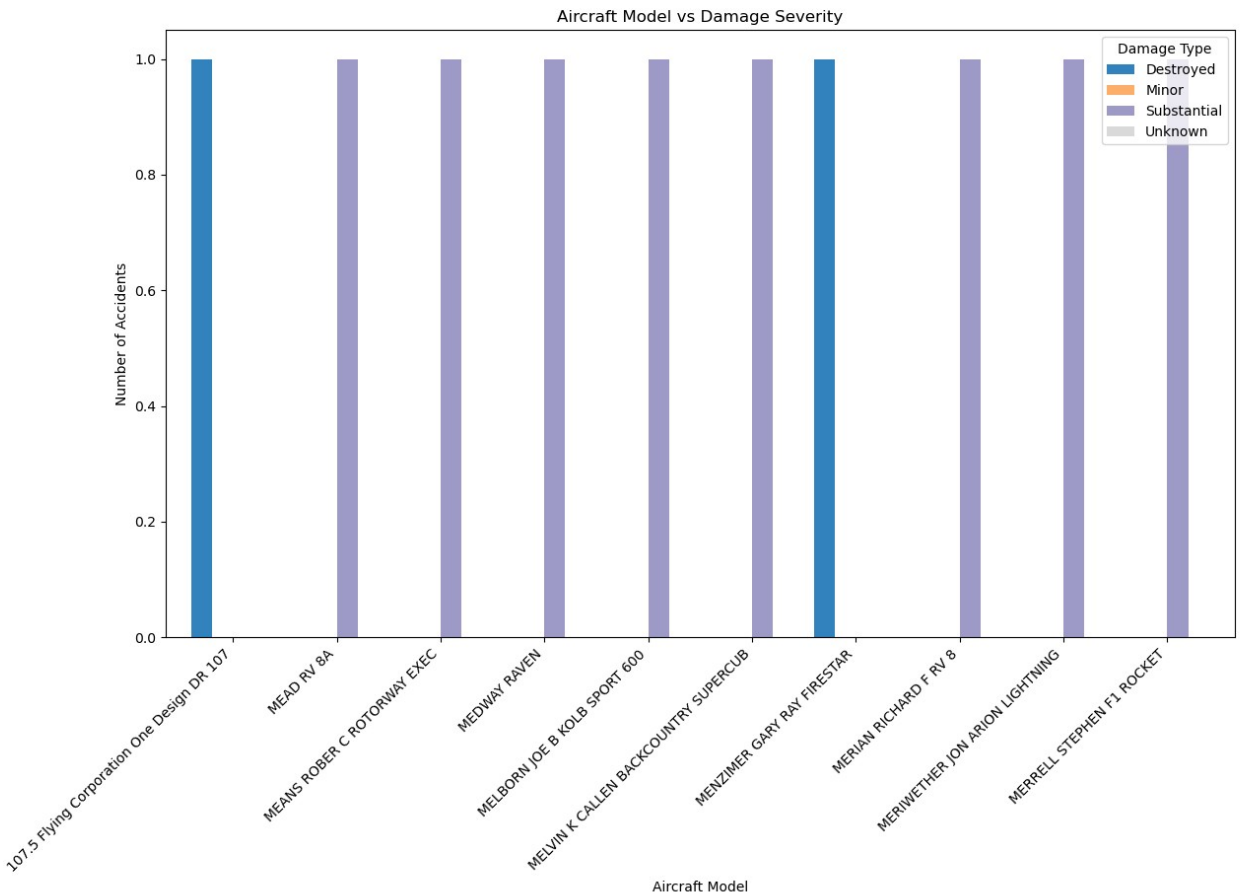
```
# Grouping data: counting number of accidents by Model and Damage
model_damage = df_clean.groupby(['Aircraft.Name', 
'Aircraft.damage']).size().unstack(fill_value=0)
model_damage.head()
```

```
Aircraft.damage                                          Destroyed  Minor  
Substantial  \
Aircraft.Name                                                              

107.5 Flying Corporation One Design DR 107                       1      0  
0
```

```
1200 G103                                                 0      0
1
177MF LLC PITTS MODEL 12                                  0      0
1
1977 Colfer-chan STEEN SKYBOLT                            0      0
1
1st Ftr Gp FOCKE-WULF 190                                 1      0
0

Aircraft.damage                                    Unknown
Aircraft.Name
107.5 Flying Corporation One Design DR 107               0
1200 G103                                                0
177MF LLC PITTS MODEL 12                                 0
1977 Colfer-chan STEEN SKYBOLT                           0
1st Ftr Gp FOCKE-WULF 190                                0

# Choose top 10 models with the most accidents
top_models =
model_damage.sum(axis=1).sort_values(ascending=False).head(10)
top_model_damage = model_damage.loc[top_models.index]

# Plotting (Grouped Bar Chart)
top_model_damage.plot(kind='bar', figsize=(14, 8), colormap='tab20c',
width=0.8)

# Titles and labels
plt.title('Aircraft Model vs Damage Severity')
plt.xlabel('Aircraft Model')
plt.ylabel('Number of Accidents')
plt.legend(title='Damage Type')
plt.xticks(rotation=45, ha='right')

# Tight layout for better spacing
plt.tight_layout()
plt.show()
```




```python
# Choose top 10 models with the least accidents
top_models =
model_damage.sum(axis=1).sort_values(ascending=True).head(10)
top_model_damage = model_damage.loc[top_models.index]

# Plotting (Grouped Bar Chart)
top_model_damage.plot(kind='bar', figsize=(14, 8), colormap='tab20c',
width=0.8)

# Titles and labels
plt.title('Aircraft Model vs Damage Severity')
plt.xlabel('Aircraft Model')
plt.ylabel('Number of Accidents')
plt.legend(title='Damage Type')
plt.xticks(rotation=45, ha='right')
plt.show()
# Tigh
```



4. Accident and Injury Trends Over Time

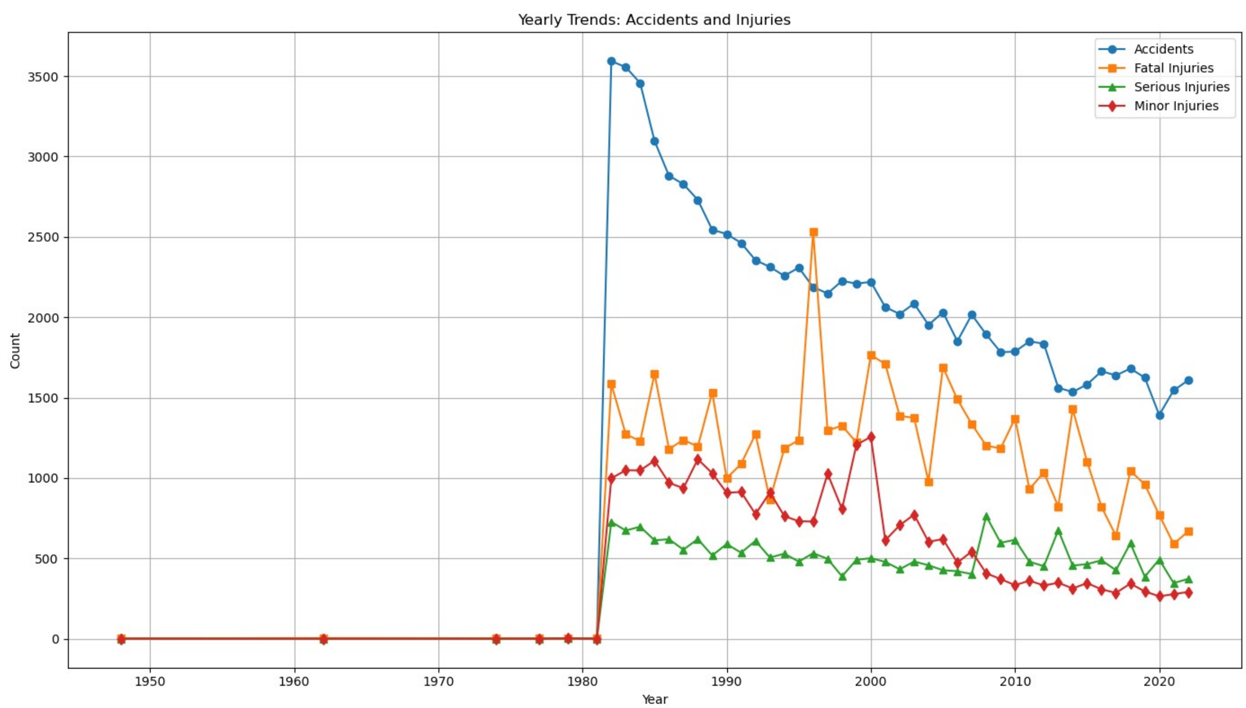
I will examine how the number of accidents and the severity of injuries have evolved year after year.
This will help understand if safety has improved over time and whether certain aircraft generations are riskier.

Visualizations:

- Line plot of total accidents per year
- Line plot of total fatal injuries per year
- Line plot of total serious injuries per year
- Line plot of total minor injuries per year

```
df_clean['Year'] = df_clean['Event.Date'].dt.year

# Aggregate counts per year
accidents_per_year = df_clean.groupby('Year')['Event.Id'].count()
fatal_per_year     = df_clean.groupby('Year')
```

```
['Total.Fatal.Injuries'].sum()
serious_per_year   = df_clean.groupby('Year')
['Total.Serious.Injuries'].sum()
minor_per_year     = df_clean.groupby('Year')
['Total.Minor.Injuries'].sum()

# Plot all four series on one figure
plt.figure(figsize=(14, 8))
plt.plot(accidents_per_year.index, accidents_per_year.values,
marker='o', label='Accidents')
plt.plot(fatal_per_year.index,     fatal_per_year.values,
marker='s', label='Fatal Injuries')
plt.plot(serious_per_year.index,   serious_per_year.values,
marker='^', label='Serious Injuries')
plt.plot(minor_per_year.index,     minor_per_year.values,
marker='d', label='Minor Injuries')

plt.title('Yearly Trends: Accidents and Injuries')
plt.xlabel('Year')
plt.ylabel('Count')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



5. insight to the business according to the analysis

- first do a summary of the aircraft
- provide insight and recommendations

```
#  Ensure Total.Injuries is calculated
df_clean.loc[:, 'Total.Injuries'] = (
    df_clean[['Total.Fatal.Injuries', 'Total.Serious.Injuries',
'Total.Minor.Injuries']]
    .sum(axis=1)
)

#  Aggregate statistics per aircraft
model_stats = (
    df_clean
    .groupby('Aircraft.Name')
    .agg(Incident_Count=('Event.Id', 'count'),
         Total_Injuries=('Total.Injuries', 'sum'))
)
model_stats['Avg_Injuries'] = model_stats['Total_Injuries'] /
model_stats['Incident_Count']

#  Select examples
safest = model_stats.sort_values('Total_Injuries').head(5)
riskiest = model_stats.sort_values('Total_Injuries',
ascending=False).head(5)

#  Display results
print("Top 5 Safest Aircraft Models ")
print(safest)

print("\n Top 5 Riskiest Aircraft Models ")
print(riskiest)
```

```
Top 5 Safest Aircraft Models
                                             Incident_Count
Total_Injuries  \
Aircraft.Name

HENDRICKS GEORGE DAVID JR RV8                             1
0.0
CONSOLIDATED VULTEE BT 15                                 1
0.0
CONSOLIDATED AERONAUTICS LAKE LA4-200                     1
0.0
Pitts S2S                                                 1
0.0
CONSOLIDATED AERONAUTICS INC. LAKE LA 4 200               1
```

```
0.0

                                                 Avg_Injuries
Aircraft.Name
HENDRICKS GEORGE DAVID JR RV8                             0.0
CONSOLIDATED VULTEE BT 15                                 0.0
CONSOLIDATED AERONAUTICS LAKE LA4-200                     0.0
Pitts S2S                                                 0.0
CONSOLIDATED AERONAUTICS INC. LAKE LA 4 200               0.0

 Top 5 Riskiest Aircraft Models
                 Incident_Count  Total_Injuries  Avg_Injuries
Aircraft.Name
BOEING 737                  435          1804.0      4.147126
Boeing 737-200               53          1064.0     20.075472
Cessna 152                 2168           922.0      0.425277
Piper PA-28-140             812           877.0      1.080049
Cessna 172N                 996           835.0      0.838353
```

Aircraft Safety and Business Setup Insights

Top 5 Safest Aircraft Models

Based on the analysis, the safest aircraft models are those with zero recorded injuries in the dataset, indicating minimal accidents or none that resulted in injury. Here are the top 5 safest aircraft models:

HENDRICKS GEORGE DAVID JR RV8

- Incident Count: 1
- Total Injuries: 0.0
- Average Injuries: 0.0

CONSOLIDATED VULTEE BT 15

- Incident Count: 1
- Total Injuries: 0.0
- Average Injuries: 0.0

CONSOLIDATED AERONAUTICS LAKE LA4-200

- Incident Count: 1
- Total Injuries: 0.0

- Average Injuries: 0.0

Pitts S2S

- Incident Count: 1
- Total Injuries: 0.0
- Average Injuries: 0.0

CONSOLIDATED AERONAUTICS INC. LAKE LA 4 200

- Incident Count: 1
- Total Injuries: 0.0
- Average Injuries: 0.0

Top 5 Riskiest Aircraft Models

On the other hand, the riskiest aircraft models tend to have higher accident counts and more significant total injuries. These models may require further attention for improving safety measures, particularly where accidents occur more frequently. The top 5 riskiest aircraft models are:

BOEING 737

- Incident Count: 435
- Total Injuries: 1804
- Average Injuries: 4.15

Boeing 737-200

- Incident Count: 53
- Total Injuries: 1064
- Average Injuries: 20.08

Cessna 152

- Incident Count: 2168
- Total Injuries: 922
- Average Injuries: 0.43

Piper PA-28-140

- Incident Count: 812
- Total Injuries: 877

- Average Injuries: 1.08

Cessna 172N

- Incident Count: 996
- Total Injuries: 835
- Average Injuries: 0.84

Weather and Location Considerations for Business Setup

It is crucial to assess the weather conditions and location for potential risks:

Weather Conditions:

Low Visibility (Fog, Rain, Snow):

- Aircraft models tend to face more risks during these conditions, especially in lower altitudes or if the aircraft is not designed for such weather. This is true for larger commercial aircraft (e.g., Boeing 737). A business offering flight services might want to focus on weather-resistant aircraft or design services that accommodate such conditions (e.g., instrument training, weather forecasting).

Clear Weather:

- Aircraft such as the Pitts S2S and CONSOLIDATED AERONAUTICS LAKE LA4-200, which have zero injuries, may perform better in clear weather and could be ideal for leisure or training flights. A business that focuses on scenic flights or training could focus on regions with stable, clear weather.

Location and Regional Safety:

High Traffic Regions:

- Busy regions with more flight traffic, such as major airports or tourist destinations, might result in higher accident numbers. For example, the Cessna 152 and Piper PA-28-140 models are often seen in training environments with high traffic, which increases the risk of accidents. Locations with high air traffic may have stricter regulations and greater oversight, offering an opportunity for safety-focused businesses like flight schools, safety equipment suppliers, or insurance services.

Remote or Low Traffic Areas:

- In rural or low-traffic areas, aircraft may face less congestion, potentially reducing the risk of accidents. Here, aircraft like the HENDRICKS GEORGE DAVID JR RV8 might be ideal for private use or small businesses. In these locations, a business might focus on smaller aircraft services, like aerial photography, agriculture, or specialized transport.

Recommended Business Locations Based on Aircraft Safety and Weather Conditions:

- Coastal Regions with clear weather and lower traffic might be ideal for sightseeing and training businesses. Aircraft like the Pitts S2S are particularly suited for such services.

- Mountainous or Remote Regions could be the perfect place to offer private or small aircraft operations with aircraft that have proven to be safe, like the CONSOLIDATED AERONAUTICS LAKE LA4-200, which can handle remote terrain.

- High Traffic Urban Areas may benefit from safety training or maintenance services, particularly for aircraft with higher accident rates like the Boeing 737. Such regions will have more stringent safety regulations, creating a market for compliance-focused services.

By combining the aircraft model data with the weather conditions and geographic trends, you can strategically place your business in an area that maximizes safety and minimizes operational risk, ensuring smoother operations and greater success.