Projoct1

October 31, 2025

1 Phase One Project

1.1 Introduction: Overview

As Part of the company to venture into avaition Business, this project investigates the risk associated with different aircraft , aiming to identify the safest model for potention investment.The analysis focuses on determining which types of flights have the highest average fatalities and aircraft damage, assessing how engine types and weather conditions affect safety, and ranking aircraft make by risk level for commercial use.

The dataset used comes from the National Transportation Safety Board (NTSB) and includes records of aviation accidents and incidents from 1962 to 2023.The tools to be used in achieving this are:

Pandas - Data cleaning, transformation, and aggregation

Numpy - Numerical computations

Matplotlib / seaborn - Static visualizations for analysis validation

Plotly - Interactive graphs for dynamic data exploration

2 Assumption

1. Aircraft with high fatality rates are costlier to operate due to legal liabilities, compensation claims, and higher insurance costs.
2. Planes with a high damage index are more expensive to maintain or replace, as severe damage often makes repair uneconomical.

3 Problem Statement

Your company is expanding in to new industries to diversify its portfolio. Specifically, they are interested in purchasing and operating airplanes for commercial and private enterprises, but do not know anything about the potential risks of aircraft. You are charged with determining which aircraft are the lowest risk for the company to start this new business endeavor. You must then translate your findings into actionable insights that the head of the new aviation division can use to help decide which aircraft to purchase.

4 Goal

The Data Analysis goals are:

Which flight types have the highest average fatalities and aircraft damage?

What effect do engine types have on safety, and how is this affected by weather conditions?

aircraft make and models have the lowest risk for commercial ventures?

5 Steps

1.Define the problem statement.

2.Data Preperation

3.Aggregate and analyze the data to identify low-risk aircraft.

4.Create visualizations to support findings.

5.Translate findings into three actionable business recommendations.

5.1 Step One: Data Preparation and Data Understanding

5.1.1 1. Importing necessary libraries

5.1.2 2. Loading the dataset

5.1.3 3. Exploring the data to understand it

[31]:
```
#Load all the relevant libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import scipy.stats as stats

#Load data to a dataframe
data = pd.read_csv("data/Aviation_Data.csv")
data
```

```
/tmp/ipykernel_9880/3216054291.py:9: DtypeWarning: Columns (6,7,28) have mixed
types. Specify dtype option on import or set low_memory=False.
  data = pd.read_csv("data/Aviation_Data.csv")
```

[31]:
```
             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
…                 …                  …               …           …
90343  20221227106491           Accident      ERA23LA093  2022-12-26
```

```
90344  20221227106494          Accident      ERA23LA095  2022-12-26
90345  20221227106497          Accident      WPR23LA075  2022-12-26
90346  20221227106498          Accident      WPR23LA076  2022-12-26
90347  20221230106513          Accident      ERA23LA097  2022-12-29

              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
…                  …              …        …          …           …
90343    Annapolis, MD  United States        NaN        NaN          NaN
90344      Hampton, NH  United States        NaN        NaN          NaN
90345       Payson, AZ  United States    341525N   1112021W          PAN
90346       Morgan, UT  United States        NaN        NaN          NaN
90347       Athens, GA  United States        NaN        NaN          NaN

      Airport.Name  … Purpose.of.flight         Air.carrier  \
0              NaN  …          Personal                 NaN
1              NaN  …          Personal                 NaN
2              NaN  …          Personal                 NaN
3              NaN  …          Personal                 NaN
4              NaN  …          Personal                 NaN
…             …  …              …                 …
90343          NaN  …          Personal                 NaN
90344          NaN  …               NaN                 NaN
90345       PAYSON  …          Personal                 NaN
90346          NaN  …          Personal  MC CESSNA 210N LLC
90347          NaN  …          Personal                 NaN

      Total.Fatal.Injuries Total.Serious.Injuries Total.Minor.Injuries  \
0                      2.0                    0.0                  0.0
1                      4.0                    0.0                  0.0
2                      3.0                    NaN                  NaN
3                      2.0                    0.0                  0.0
4                      1.0                    2.0                  NaN
…                      …                    …                  …
90343                  0.0                    1.0                  0.0
90344                  0.0                    0.0                  0.0
90345                  0.0                    0.0                  0.0
90346                  0.0                    0.0                  0.0
90347                  0.0                    1.0                  0.0

      Total.Uninjured Weather.Condition  Broad.phase.of.flight  \
0                 0.0               UNK                 Cruise
1                 0.0               UNK                Unknown
```

```
2                 NaN                IMC                  Cruise
3                 0.0                IMC                  Cruise
4                 0.0                VMC                Approach
…                 …                  …                    …
90343             0.0                NaN                     NaN
90344             0.0                NaN                     NaN
90345             1.0                VMC                     NaN
90346             0.0                NaN                     NaN
90347             1.0                NaN                     NaN

        Report.Status Publication.Date
0      Probable Cause              NaN
1      Probable Cause       19-09-1996
2      Probable Cause       26-02-2007
3      Probable Cause       12-09-2000
4      Probable Cause       16-04-1980
…                …               …
90343             NaN       29-12-2022
90344             NaN              NaN
90345             NaN       27-12-2022
90346             NaN              NaN
90347             NaN       30-12-2022

[90348 rows x 31 columns]
```

[32]:
```python
#get the shape and size of the data
print(data.shape, data.size)
```

```
(90348, 31) 2800788
```

[33]:
```python
# thia inspects all the columns in our dataset
data.columns
```

[33]:
```
Index(['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'],
      dtype='object')
```

[34]:
```python
# look at the datatypes in our dataset
data.dtypes
```

[34]:
```
Event.Id                    object
Investigation.Type          object
Accident.Number             object
Event.Date                  object
Location                    object
Country                     object
Latitude                    object
Longitude                   object
Airport.Code                object
Airport.Name                object
Injury.Severity             object
Aircraft.damage             object
Aircraft.Category           object
Registration.Number         object
Make                        object
Model                       object
Amateur.Built               object
Number.of.Engines          float64
Engine.Type                 object
FAR.Description             object
Schedule                    object
Purpose.of.flight           object
Air.carrier                 object
Total.Fatal.Injuries       float64
Total.Serious.Injuries     float64
Total.Minor.Injuries       float64
Total.Uninjured            float64
Weather.Condition           object
Broad.phase.of.flight       object
Report.Status               object
Publication.Date            object
dtype: object
```

[35]:
```
#Get an overview of our data.If there are missing values
data.info()
```

```
<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            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        73659 non-null  object
dtypes: float64(5), object(26)
memory usage: 21.4+ MB
```

[36]:
```
# check for missing data
data.isnull().sum()
```

[36]:
```
Event.Id                   1459
Investigation.Type            0
Accident.Number            1459
Event.Date                 1459
Location                   1511
Country                    1685
Latitude                  55966
Longitude                 55975
Airport.Code              40216
Airport.Name              37644
Injury.Severity            2459
Aircraft.damage            4653
Aircraft.Category         58061
Registration.Number        2841
Make                       1522
Model                      1551
Amateur.Built              1561
```

```
Number.of.Engines          7543
Engine.Type                8555
FAR.Description           58325
Schedule                  77766
Purpose.of.flight          7651
Air.carrier               73700
Total.Fatal.Injuries      12860
Total.Serious.Injuries    13969
Total.Minor.Injuries      13392
Total.Uninjured            7371
Weather.Condition          5951
Broad.phase.of.flight     28624
Report.Status              7843
Publication.Date          16689
dtype: int64
```

[37]:
```
# check for dulplicated data
data.duplicated().sum()
```

[37]:
```
1390
```

[38]:
```
# drop all duplicated data

data.drop_duplicates(inplace=True)
```

[39]:
```
# confirm there are no duplicates
data.duplicated().sum()
```

[39]:
```
0
```

Since there are some columns that Are not useful I will drop those columns

[40]:
```
data
```

[40]:
```
             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
…                 …                …               …           …
90343  20221227106491           Accident      ERA23LA093  2022-12-26
90344  20221227106494           Accident      ERA23LA095  2022-12-26
90345  20221227106497           Accident      WPR23LA075  2022-12-26
90346  20221227106498           Accident      WPR23LA076  2022-12-26
90347  20221230106513           Accident      ERA23LA097  2022-12-29

              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
…                  …              …         …          …            …
90343    Annapolis, MD  United States        NaN        NaN          NaN
90344      Hampton, NH  United States        NaN        NaN          NaN
90345       Payson, AZ  United States    341525N   1112021W          PAN
90346       Morgan, UT  United States        NaN        NaN          NaN
90347       Athens, GA  United States        NaN        NaN          NaN

      Airport.Name  … Purpose.of.flight         Air.carrier  \
0              NaN  …          Personal                 NaN
1              NaN  …          Personal                 NaN
2              NaN  …          Personal                 NaN
3              NaN  …          Personal                 NaN
4              NaN  …          Personal                 NaN
…              …  …               …                   …
90343          NaN  …          Personal                 NaN
90344          NaN  …               NaN                 NaN
90345       PAYSON  …          Personal                 NaN
90346          NaN  …          Personal  MC CESSNA 210N LLC
90347          NaN  …          Personal                 NaN

      Total.Fatal.Injuries Total.Serious.Injuries Total.Minor.Injuries  \
0                      2.0                    0.0                  0.0
1                      4.0                    0.0                  0.0
2                      3.0                    NaN                  NaN
3                      2.0                    0.0                  0.0
4                      1.0                    2.0                  NaN
…                      …                    …                  …
90343                  0.0                    1.0                  0.0
90344                  0.0                    0.0                  0.0
90345                  0.0                    0.0                  0.0
90346                  0.0                    0.0                  0.0
90347                  0.0                    1.0                  0.0

      Total.Uninjured Weather.Condition  Broad.phase.of.flight  \
0                 0.0               UNK                 Cruise
1                 0.0               UNK                Unknown
2                 NaN               IMC                 Cruise
3                 0.0               IMC                 Cruise
4                 0.0               VMC               Approach
…                 …               …                    …
90343             0.0               NaN                    NaN
90344             0.0               NaN                    NaN
```

```
90345             1.0               VMC                     NaN
90346             0.0               NaN                     NaN
90347             1.0               NaN                     NaN

        Report.Status Publication.Date
0      Probable Cause              NaN
1      Probable Cause       19-09-1996
2      Probable Cause       26-02-2007
3      Probable Cause       12-09-2000
4      Probable Cause       16-04-1980
…                 …              …
90343             NaN       29-12-2022
90344             NaN              NaN
90345             NaN       27-12-2022
90346             NaN              NaN
90347             NaN       30-12-2022

[88958 rows x 31 columns]
```

[41]:
```
data.columns
```

[41]:
```
Index(['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'],
      dtype='object')
```

[ ]:
```
#Removing white spaces in the dataframe
data = data.apply(lambda x: x.str.strip() if x.dtype == "object" else x)
data = data.apply(lambda x: x.str.replace(" ", "") if x.dtype == "object" else␣
↪x)
```

[43]:
```
df = data.drop(["Event.Date","Location", "Country", "Latitude", "Longitude",␣
↪"Airport.Code",
       "Airport.Name","Report.Status","Publication.Date","Broad.phase.of.
↪flight","Air.carrier","Schedule",
       "FAR.Description","Registration.Number"], axis = 1)
```

[44]:
```
df.columns
```

[44]:
```
Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Injury.Severity',
       'Aircraft.damage', 'Aircraft.Category', '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'],
      dtype='object')
```

[45]:
```
missing_values = df.isna().sum()
missing_values.sort_values(ascending=False)
```

[45]:
```
Aircraft.Category         56671
Total.Serious.Injuries    12579
Total.Minor.Injuries      12002
Total.Fatal.Injuries      11470
Engine.Type                7165
Purpose.of.flight          6261
Number.of.Engines          6153
Total.Uninjured            5981
Weather.Condition          4561
Aircraft.damage            3263
Injury.Severity            1069
Amateur.Built               171
Model                       161
Make                        132
Accident.Number              69
Event.Id                     69
Investigation.Type            0
dtype: int64
```

[46]:
```
df
```

[46]:
```
             Event.Id Investigation.Type Accident.Number Injury.Severity  \
0      20001218X45444           Accident      SEA87LA080        Fatal(2)
1      20001218X45447           Accident      LAX94LA336        Fatal(4)
2      20061025X01555           Accident      NYC07LA005        Fatal(3)
3      20001218X45448           Accident      LAX96LA321        Fatal(2)
4      20041105X01764           Accident      CHI79FA064        Fatal(1)
…                 …                  …               …               …
90343  20221227106491           Accident      ERA23LA093           Minor
90344  20221227106494           Accident      ERA23LA095             NaN
90345  20221227106497           Accident      WPR23LA075       Non-Fatal
90346  20221227106498           Accident      WPR23LA076             NaN
90347  20221230106513           Accident      ERA23LA097           Minor

      Aircraft.damage Aircraft.Category                    Make      Model  \
0           Destroyed               NaN                 Stinson      108-3
1           Destroyed               NaN                   Piper   PA24-180
2           Destroyed               NaN                  Cessna       172M
3           Destroyed               NaN                Rockwell        112
```

```
4          Destroyed             NaN                      Cessna        501
…                …               …                       …         …
90343            NaN             NaN                       PIPER  PA-28-151
90344            NaN             NaN                    BELLANCA       7ECA
90345    Substantial        Airplane  AMERICANCHAMPIONAIRCRAFT      8GCBC
90346            NaN             NaN                      CESSNA       210N
90347            NaN             NaN                       PIPER  PA-24-260

      Amateur.Built  Number.of.Engines    Engine.Type Purpose.of.flight  \
0                No                1.0  Reciprocating          Personal
1                No                1.0  Reciprocating          Personal
2                No                1.0  Reciprocating          Personal
3                No                1.0  Reciprocating          Personal
4                No                NaN            NaN          Personal
…               …                 …             …                 …
90343            No                NaN            NaN          Personal
90344            No                NaN            NaN               NaN
90345            No                1.0            NaN          Personal
90346            No                NaN            NaN          Personal
90347            No                NaN            NaN          Personal

       Total.Fatal.Injuries  Total.Serious.Injuries  Total.Minor.Injuries  \
0                       2.0                     0.0                   0.0
1                       4.0                     0.0                   0.0
2                       3.0                     NaN                   NaN
3                       2.0                     0.0                   0.0
4                       1.0                     2.0                   NaN
…                      …                       …                     …
90343                   0.0                     1.0                   0.0
90344                   0.0                     0.0                   0.0
90345                   0.0                     0.0                   0.0
90346                   0.0                     0.0                   0.0
90347                   0.0                     1.0                   0.0

       Total.Uninjured Weather.Condition
0                  0.0               UNK
1                  0.0               UNK
2                  NaN               IMC
3                  0.0               IMC
4                  0.0               VMC
…                 …                …
90343              0.0               NaN
90344              0.0               NaN
90345              1.0               VMC
90346              0.0               NaN
90347              1.0               NaN
```

```
[88958 rows x 17 columns]
```

[47]:
```python
df.describe()
```

[47]:
```
       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
```

[48]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 88958 entries, 0 to 90347
Data columns (total 17 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                88889 non-null  object
 1   Investigation.Type      88958 non-null  object
 2   Accident.Number         88889 non-null  object
 3   Injury.Severity         87889 non-null  object
 4   Aircraft.damage         85695 non-null  object
 5   Aircraft.Category       32287 non-null  object
 6   Make                    88826 non-null  object
 7   Model                   88797 non-null  object
 8   Amateur.Built           88787 non-null  object
 9   Number.of.Engines       82805 non-null  float64
 10  Engine.Type             81793 non-null  object
 11  Purpose.of.flight       82697 non-null  object
 12  Total.Fatal.Injuries    77488 non-null  float64
 13  Total.Serious.Injuries  76379 non-null  float64
 14  Total.Minor.Injuries    76956 non-null  float64
 15  Total.Uninjured         82977 non-null  float64
 16  Weather.Condition       84397 non-null  object
```

```
dtypes: float64(5), object(12)
memory usage: 12.2+ MB
```

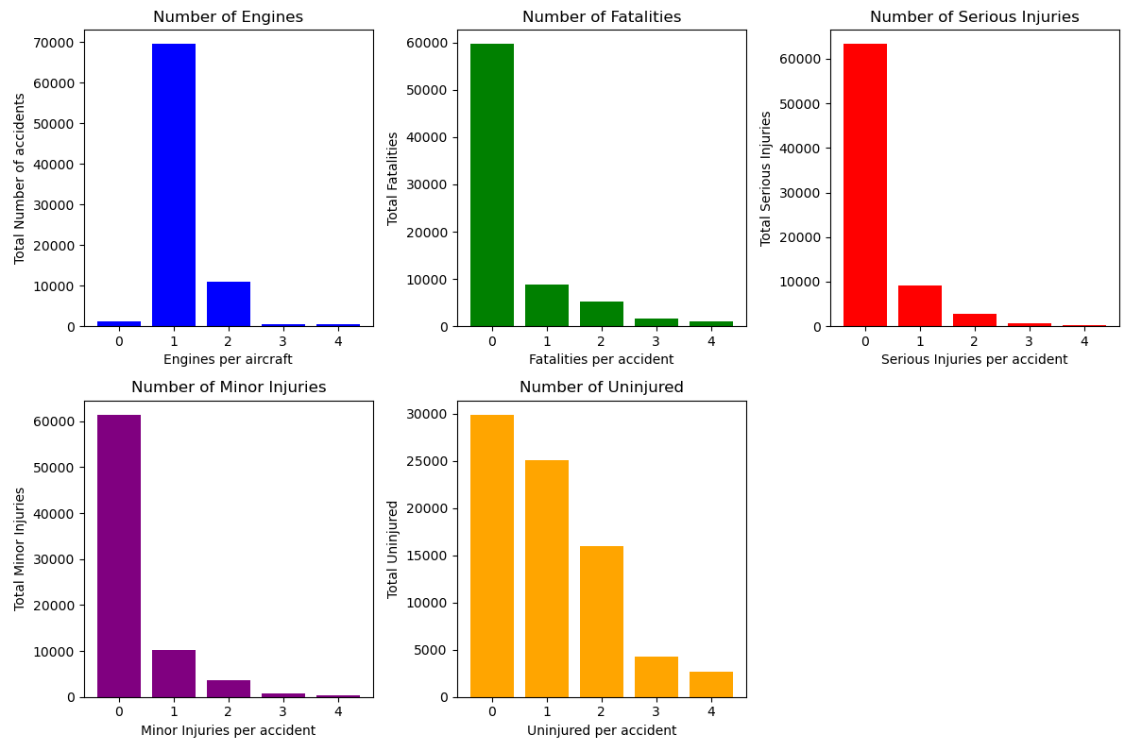
5.2 Step Two: Data Analysing and Visualization

5.2.1 1. Aggregate and analyze the data to identify low-risk aircraft

5.2.2 2. Create visualizations to support findings.

[49]:
```python
plt.figure(figsize=(12, 8))

# No of Engines
plt.subplot(2, 3, 1)
plt.bar(df["Number.of.Engines"].value_counts().index[0:5], df["Number.of.
 ↪Engines"].value_counts().values[0:5], color="blue")
plt.title("Number of Engines")
plt.xlabel("Engines per aircraft")
plt.ylabel("Total Number of accidents")

# Fatalities
plt.subplot(2, 3, 2)
plt.bar(df["Total.Fatal.Injuries"].value_counts().index[0:5], df["Total.Fatal.
 ↪Injuries"].value_counts().values[0:5], color="green")
plt.title("Number of Fatalities")
plt.xlabel("Fatalities per accident")
plt.ylabel("Total Fatalities")

# Serious
plt.subplot(2, 3, 3)
plt.bar(df["Total.Serious.Injuries"].value_counts().index[0:5], df["Total.
 ↪Serious.Injuries"].value_counts().values[0:5], color="red")
plt.title("Number of Serious Injuries")
plt.xlabel("Serious Injuries per accident")
plt.ylabel("Total Serious Injuries")

# Minor
plt.subplot(2, 3, 4)
plt.bar(df["Total.Minor.Injuries"].value_counts().index[0:5], df["Total.Minor.
 ↪Injuries"].value_counts().values[0:5], color="purple")
plt.title("Number of Minor Injuries")
plt.xlabel("Minor Injuries per accident")
plt.ylabel("Total Minor Injuries")

# Uninjured
plt.subplot(2, 3, 5)
plt.bar(df["Total.Uninjured"].value_counts().index[0:5], df["Total.Uninjured"].
 ↪value_counts().values[0:5], color="orange")
plt.title("Number of Uninjured")
```

```
plt.xlabel("Uninjured per accident")
plt.ylabel("Total Uninjured")

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



From the graph above its clearly that all the data have a positive skewed, so we will replace the null values with medium.We will do all this in all the columns but Total Injured.

[50]:
```
#Replacing null values with median

cols = ["Number.of.Engines", "Total.Serious.Injuries", "Total.Minor.Injuries",␣
↪"Total.Uninjured"]
for col in cols:
    df[col].fillna(df[col].median(), inplace=True)
```

```
/tmp/ipykernel_9880/956387134.py:5: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
```

```
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df[col].fillna(df[col].median(), inplace=True)
```

[51]:
```python
#verify there are no nulls
df.isna().sum().sort_values(ascending=True)
```

[51]:
```
Investigation.Type            0
Total.Minor.Injuries          0
Total.Serious.Injuries        0
Number.of.Engines             0
Total.Uninjured               0
Event.Id                     69
Accident.Number              69
Make                        132
Model                       161
Amateur.Built               171
Injury.Severity            1069
Aircraft.damage            3263
Weather.Condition          4561
Purpose.of.flight          6261
Engine.Type                7165
Total.Fatal.Injuries      11470
Aircraft.Category         56671
dtype: int64
```

[52]:
```python
# Replacing NAN values with unkown for the following columns
df["Purpose.of.flight"].fillna(value = "Unknown", inplace=True)
df["Engine.Type"].fillna(value = "Unknown", inplace=True)
df["Engine.Type"] = df["Engine.Type"].map(lambda x: "Unkown" if x == "UNK" or x␣
 ↪== "None" or x == "NONE" else x)
df["Aircraft.damage"].fillna(value = "Unknown", inplace=True)

# Replacing NAN values with UNK for unkown weather information and␣
 ↪standardizing text strings
df["Weather.Condition"].fillna(value = "UNK", inplace=True)
df["Weather.Condition"] = df["Weather.Condition"].map(lambda x: "UNK" if x ==␣
 ↪"Unk" else x)
```

```
/tmp/ipykernel_9880/3048449977.py:2: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.
```

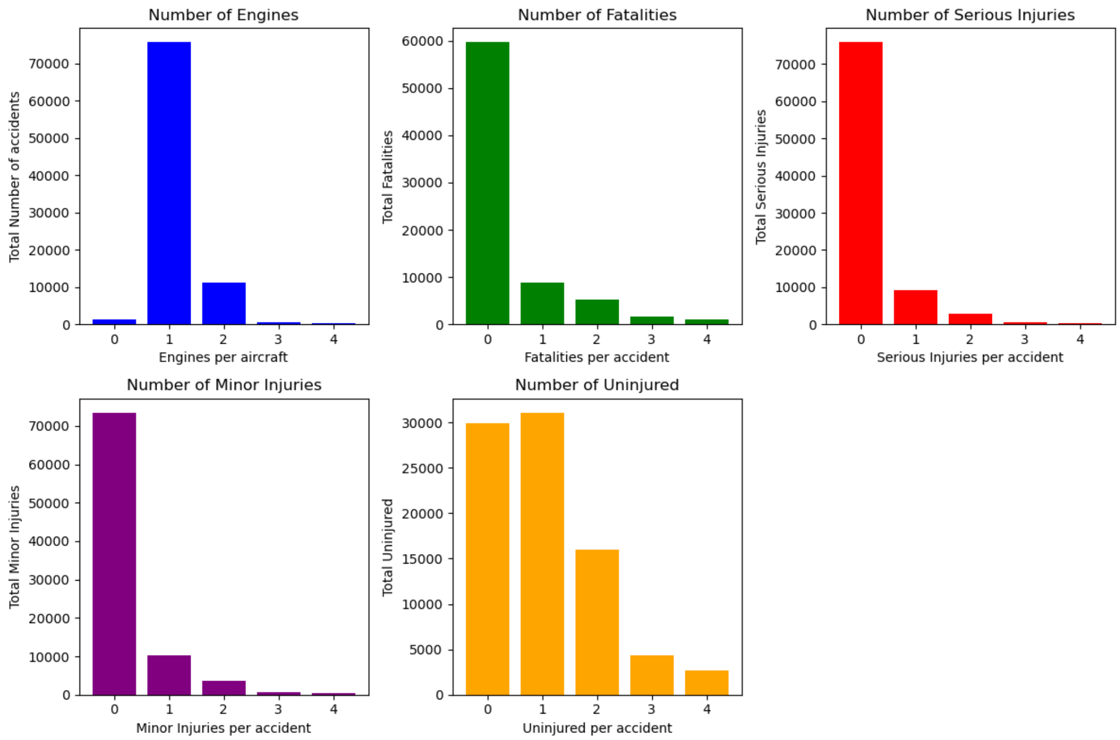
```
For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df["Purpose.of.flight"].fillna(value = "Unknown", inplace=True)
/tmp/ipykernel_9880/3048449977.py:3: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df["Engine.Type"].fillna(value = "Unknown", inplace=True)
/tmp/ipykernel_9880/3048449977.py:5: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df["Aircraft.damage"].fillna(value = "Unknown", inplace=True)
/tmp/ipykernel_9880/3048449977.py:8: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df["Weather.Condition"].fillna(value = "UNK", inplace=True)
```

[53]:
```
df.isnull().sum().sort_values()
```

[53]:
```
Weather.Condition            0
Investigation.Type           0
Total.Minor.Injuries         0
Total.Serious.Injuries       0
Aircraft.damage              0
Purpose.of.flight            0
Engine.Type                  0
Number.of.Engines            0
Total.Uninjured              0
Event.Id                    69
Accident.Number             69
Make                       132
Model                      161
Amateur.Built              171
Injury.Severity           1069
Total.Fatal.Injuries     11470
Aircraft.Category        56671
dtype: int64
```

[54]:
```
plt.figure(figsize=(12, 8))

# No of Engines
plt.subplot(2, 3, 1)
plt.bar(df["Number.of.Engines"].value_counts().index[0:5], df["Number.of.
↪Engines"].value_counts().values[0:5], color="blue")
plt.title("Number of Engines")
plt.xlabel("Engines per aircraft")
plt.ylabel("Total Number of accidents")

# Fatalities
plt.subplot(2, 3, 2)
plt.bar(df["Total.Fatal.Injuries"].value_counts().index[0:5], df["Total.Fatal.
↪Injuries"].value_counts().values[0:5], color="green")
plt.title("Number of Fatalities")
plt.xlabel("Fatalities per accident")
plt.ylabel("Total Fatalities")

# Serious
plt.subplot(2, 3, 3)
plt.bar(df["Total.Serious.Injuries"].value_counts().index[0:5], df["Total.
↪Serious.Injuries"].value_counts().values[0:5], color="red")
plt.title("Number of Serious Injuries")
plt.xlabel("Serious Injuries per accident")
plt.ylabel("Total Serious Injuries")

# Minor
plt.subplot(2, 3, 4)
```

```
plt.bar(df["Total.Minor.Injuries"].value_counts().index[0:5], df["Total.Minor.
↪Injuries"].value_counts().values[0:5], color="purple")
plt.title("Number of Minor Injuries")
plt.xlabel("Minor Injuries per accident")
plt.ylabel("Total Minor Injuries")

# Uninjured
plt.subplot(2, 3, 5)
plt.bar(df["Total.Uninjured"].value_counts().index[0:5], df["Total.Uninjured"].
↪value_counts().values[0:5], color="orange")
plt.title("Number of Uninjured")
plt.xlabel("Uninjured per accident")
plt.ylabel("Total Uninjured")

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

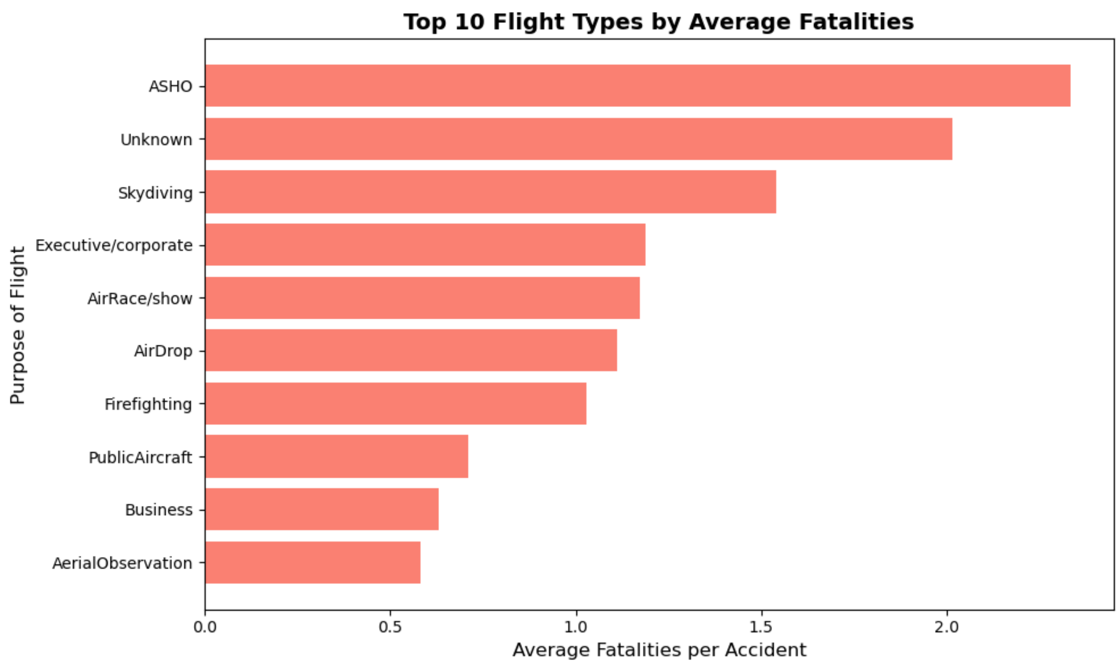


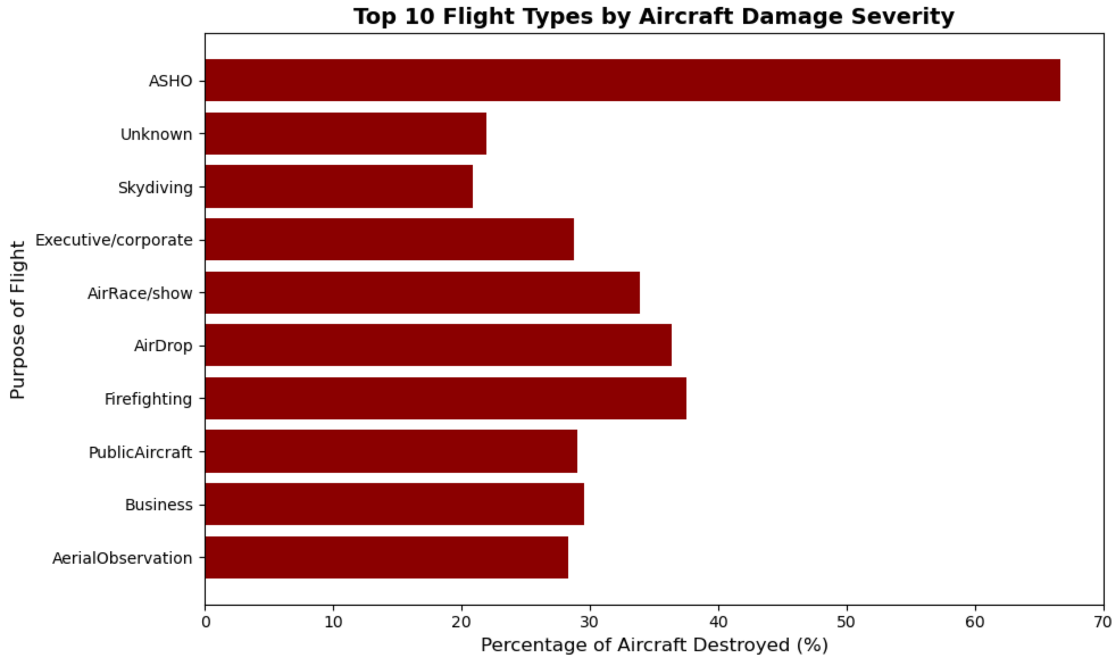
6 Aggregate and analyze the data to identify low-risk aircraft.

6.0.1 Goal 1: Which flight types have the highest average fatalities and aircraft damage?

[55]:
```
# Fatalities Analysis
flight_stats = df.groupby("Purpose.of.flight").agg(
    total_accidents=("Total.Fatal.Injuries", "count"),
    total_fatalities=("Total.Fatal.Injuries", "sum")
).reset_index()

# Calculate average fatalities per accident
flight_stats["avg_fatalities_per_accident"] = (
    flight_stats["total_fatalities"] / flight_stats["total_accidents"]
)

#Damage Analysis
# Calculate proportion of destroyed aircraft for each flight type
damage_counts = df.groupby(["Purpose.of.flight", "Aircraft.damage"]).size().
 ↪unstack(fill_value=0)
damage_counts["total"] = damage_counts.sum(axis=1)
damage_counts["percent_destroyed"] = (damage_counts["Destroyed"] /␣
 ↪damage_counts["total"]) * 100

# Merge fatalities and damage stats
merged_stats = flight_stats.merge(
    damage_counts[["percent_destroyed"]], on="Purpose.of.flight", how="left"
).fillna(0)

# Sort by average fatalities
top10 = merged_stats.sort_values("avg_fatalities_per_accident",␣
 ↪ascending=False).head(10)

# --- Visualization 1: Average Fatalities per Accident ---
plt.figure(figsize=(10,6))
plt.barh(top10["Purpose.of.flight"], top10["avg_fatalities_per_accident"],␣
 ↪color="salmon")
plt.xlabel("Average Fatalities per Accident", fontsize=12)
plt.ylabel("Purpose of Flight", fontsize=12)
plt.title("Top 10 Flight Types by Average Fatalities", fontsize=14,␣
 ↪weight="bold")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()

# --- Visualization 2: % Aircraft Destroyed by Flight Type ---
plt.figure(figsize=(10,6))
```

```
plt.barh(top10["Purpose.of.flight"], top10["percent_destroyed"],␣
 ↪color="darkred")
plt.xlabel("Percentage of Aircraft Destroyed (%)", fontsize=12)
plt.ylabel("Purpose of Flight", fontsize=12)
plt.title("Top 10 Flight Types by Aircraft Damage Severity", fontsize=14,␣
 ↪weight="bold")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()

# Display merged table
display(top10[["Purpose.of.flight", "avg_fatalities_per_accident",␣
 ↪"percent_destroyed"]])
```





	Purpose.of.flight	avg_fatalities_per_accident	percent_destroyed
0	ASHO	2.333333	66.666667
25	Unknown	2.015381	21.916864
24	Skydiving	1.539474	20.879121
8	Executive/corporate	1.188867	28.752260
4	AirRace/show	1.172414	33.898305
3	AirDrop	1.111111	36.363636
11	Firefighting	1.027778	37.500000
20	PublicAircraft	0.709790	29.027778
7	Business	0.629730	29.517173
2	AerialObservation	0.581461	28.337531

6.1 Insights form the graphs

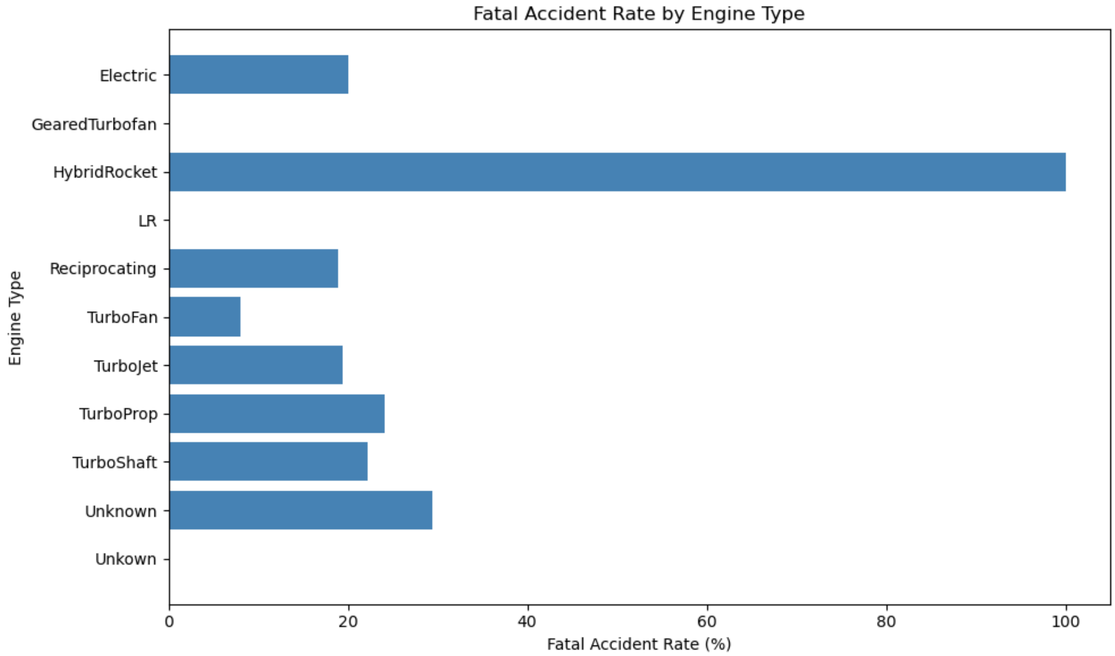
1. Skydiving ,Airdrop and Air rate have the highest fatality rates and aircraft destruction percentages. This means that they have a higher operational risk.
2. Business and Executive/Corporate flights show moderate fatality averages and slightly lower destruction rates.Suggesting stronger safety oversight and maintenance.

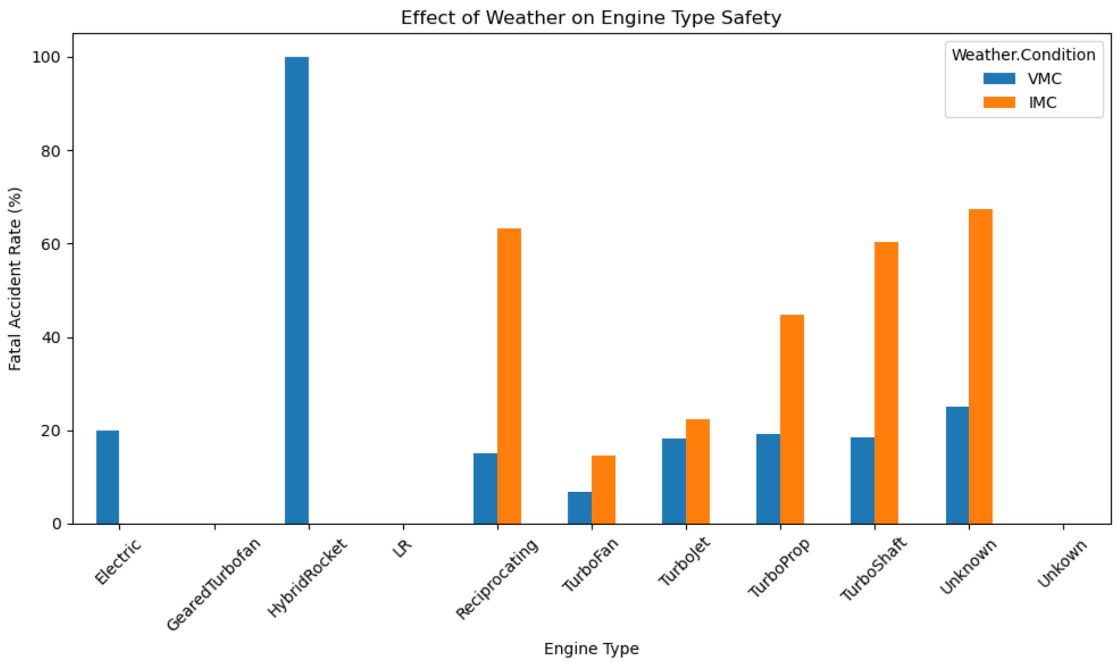
6.2 Goal 2: What effect do engine types have on safety, and how is this affected by weather conditions?

IMC (Instrument Meteorological Conditions) and VMC (Visual Meteorological Conditions) are aviation terms describing weather that affects flight. VMC is when weather is good enough for pilots to fly by visual reference, meeting specific minimums for visibility and cloud clearance. IMC is when weather conditions are poorer, falling below the VMC minimums and requiring pilots to navigate solely by their instruments.

[56]:

```
# Define a column indicating whether an accident was fatal
df["Fatal"] = df["Total.Fatal.Injuries"].apply(lambda x: 1 if x > 0 else 0)

# Engine Type Safety Summary
engine_stats = df.groupby("Engine.Type").agg(
    total_accidents=("Fatal", "count"),
    fatal_accidents=("Fatal", "sum")
).reset_index()

# Fatality rate per engine type
engine_stats["fatality_rate_%"] = (engine_stats["fatal_accidents"] /␣
↪engine_stats["total_accidents"]) * 100

# Effect of Weather on Engine Type
engine_weather = df.groupby(["Engine.Type", "Weather.Condition"]).agg(
    total_accidents=("Fatal", "count"),
    fatal_accidents=("Fatal", "sum")
).reset_index()

engine_weather["fatality_rate_%"] = (engine_weather["fatal_accidents"] /␣
↪engine_weather["total_accidents"]) * 100

#Visualization: Fatality Rate by Engine Type
plt.figure(figsize=(10,6))
plt.barh(engine_stats["Engine.Type"], engine_stats["fatality_rate_%"],␣
↪color="steelblue")
plt.xlabel("Fatal Accident Rate (%)")
plt.ylabel("Engine Type")
plt.title("Fatal Accident Rate by Engine Type")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()

#Visualization: Weather vs Engine Type
pivot_weather = engine_weather.pivot(index="Engine.Type", columns="Weather.
↪Condition", values="fatality_rate_%").fillna(0)

pivot_weather[["VMC","IMC"]].plot(kind="bar", figsize=(10,6))
plt.xlabel("Engine Type")
plt.ylabel("Fatal Accident Rate (%)")
plt.title("Effect of Weather on Engine Type Safety")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# Display summary table
display(engine_weather.sort_values("fatality_rate_%", ascending=False).head(10))
```



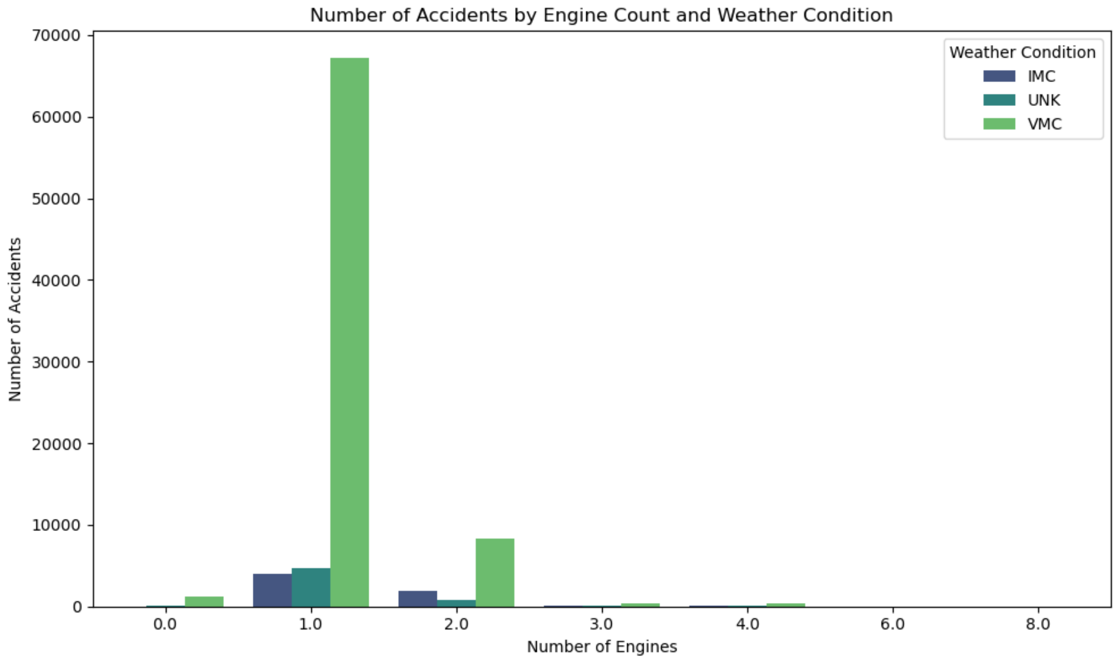


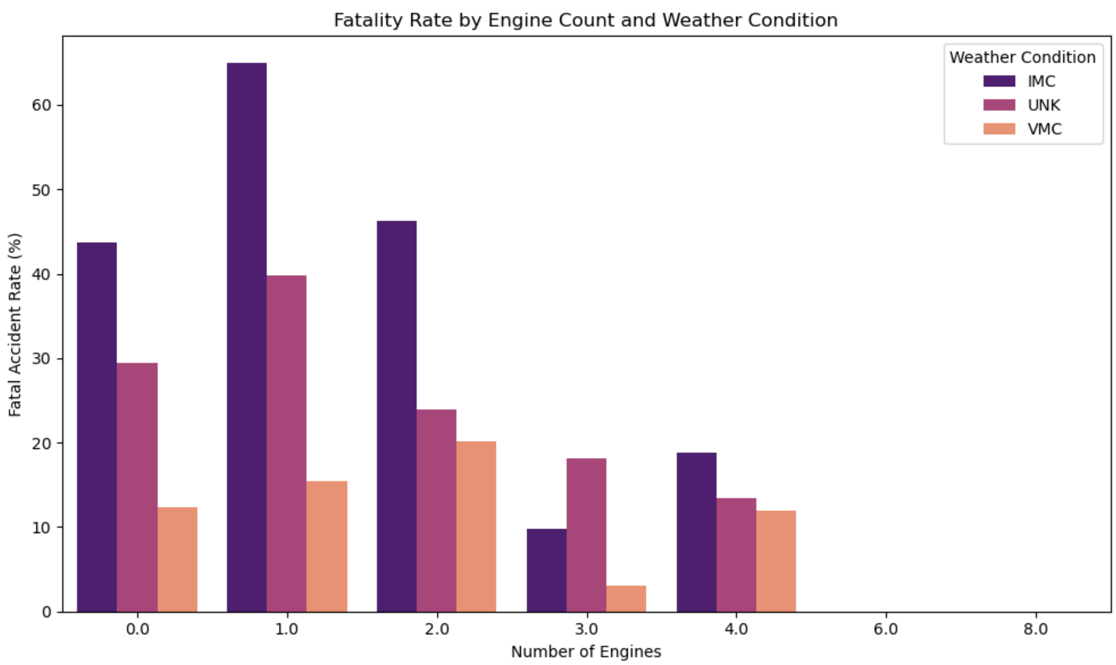

```
     Engine.Type Weather.Condition  total_accidents  fatal_accidents  \
3   HybridRocket               VMC                1                1
20       Unknown               IMC              352              237
6   Reciprocating              UNK             1023              678
```

```
5   Reciprocating                IMC           4393              2773
17     TurboShaft                IMC            234               141
18     TurboShaft                UNK            126                60
14      TurboProp                IMC            523               234
15      TurboProp                UNK            133                58
21        Unknown                UNK           4001              1264
12       TurboJet                UNK             28                 8

    fatality_rate_%
3        100.000000
20        67.329545
6         66.275660
5         63.123150
17        60.256410
18        47.619048
14        44.741874
15        43.609023
21        31.592102
12        28.571429
```

[57]:
```python
eng_weather_accidents = df.groupby(["Number.of.Engines", "Weather.Condition"]).
 ↪agg(
    total_accidents=("Fatal", "count"),
    fatal_accidents=("Fatal", "sum")
).reset_index()

eng_weather_accidents["fatality_rate_%"] =␣
 ↪(eng_weather_accidents["fatal_accidents"] /␣
 ↪eng_weather_accidents["total_accidents"]) * 100

# Visualization: Total accidents by number of engines and weather
plt.figure(figsize=(10,6))
sns.barplot(data=eng_weather_accidents, x="Number.of.Engines",␣
 ↪y="total_accidents", hue="Weather.Condition", palette="viridis")
plt.title("Number of Accidents by Engine Count and Weather Condition")
plt.xlabel("Number of Engines")
plt.ylabel("Number of Accidents")
plt.legend(title="Weather Condition")
plt.tight_layout()
plt.show()

# Visualization: Fatality rate by number of engines and weather
plt.figure(figsize=(10,6))
sns.barplot(data=eng_weather_accidents, x="Number.of.Engines",␣
 ↪y="fatality_rate_%", hue="Weather.Condition", palette="magma")
plt.title("Fatality Rate by Engine Count and Weather Condition")
plt.xlabel("Number of Engines")
```

```
plt.ylabel("Fatal Accident Rate (%)")
plt.legend(title="Weather Condition")
plt.tight_layout()
plt.show()
```





The analysis reveals that reciprocating-engine aircraft experience the highest fatal accident rates, especially under Instrument Meteorological Conditions (IMC).

Turbofan,turbojet and turboprop engines tend to have lower fatality rates, likely due to more advanced systems and better-equipped aircraft. Poor weather (IMC) amplifies risk across all engine types, but its effect is most severe for reciprocating aircraft and turboshaft aircraft, highlighting their vulnerability to adverse weather and limited instrument capability.

Aircraft with more engines and advanced engine types (turboprops, jets) are significantly safer, particularly in adverse weather. For business or corporate operations, prioritizing twin-engine turboprop or jet aircraft minimizes operational risk.

In conlusion, weather conditions shows a positive correlation with fatalities and weather.Confirming that poor visibility and adverse weather significantly increase risk.

6.3 Goal 3: What Aircraft models have the lowest risk for commercial ventures?

To answer this question we We will focus on flights where the purpose is Commercial,Air Taxi, Business and Executive/Corporate, since those represent business/commercial operations.Also we will only use airplanes used for commercial purposes.We will focus only on top 10 safest airplane makes and top 10 most risk airplane.

To ensure in the series, there are no duplicates , lets convert all the data in the series to uppercase

[61]:
```
df['Make'] = df['Make'].str.upper()
```

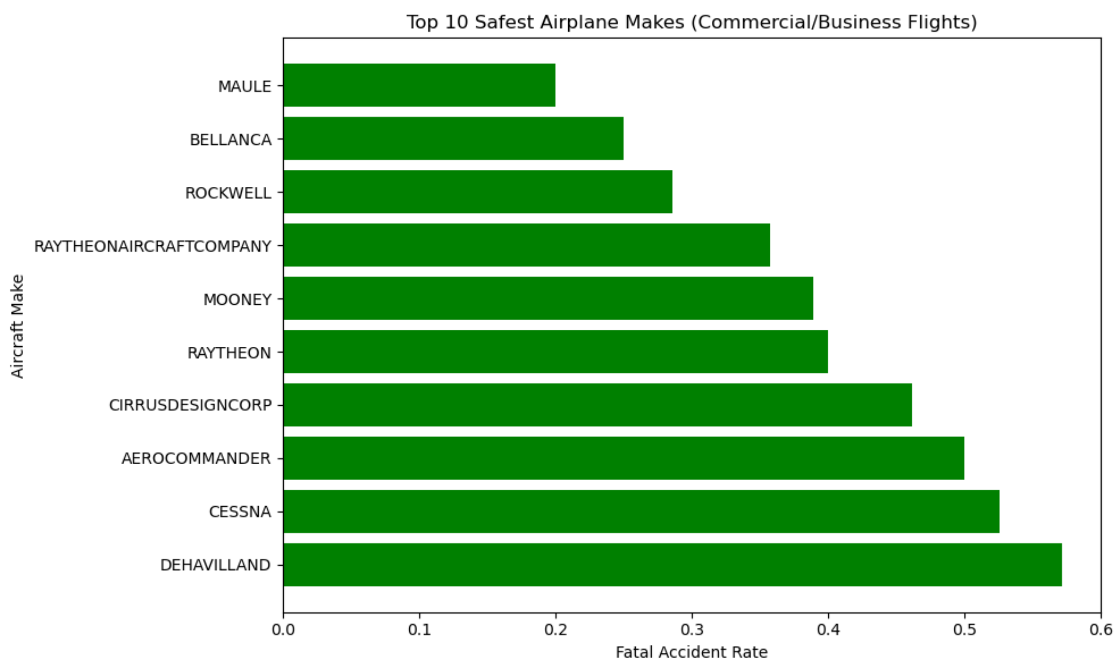
[62]:
```
# Filter for only airplane-type aircraft
airplane_df = df[df["Aircraft.Category"].str.contains("Airplane", case=False,␣
↪na=False)]

# Focus on commercial/business-related flights only
commercial_flights = airplane_df[
    airplane_df["Purpose.of.flight"].str.
↪contains("Business|Executive|Corporate|Commercial", case=False, na=False)
]

# Group by Make
make_stats = commercial_flights.groupby("Make").agg(
    total_accidents=("Total.Fatal.Injuries", "count"),
    total_fatalities=("Total.Fatal.Injuries", "sum")
).reset_index()

# Calculate fatal accident rate
make_stats["fatal_accident_rate"] = make_stats["total_fatalities"] /␣
↪make_stats["total_accidents"]

# Drop makes with very few accidents (less than 5) to reduce bias
make_stats = make_stats[make_stats["total_accidents"] >= 5]

# Get top 10 safest and riskiest
```

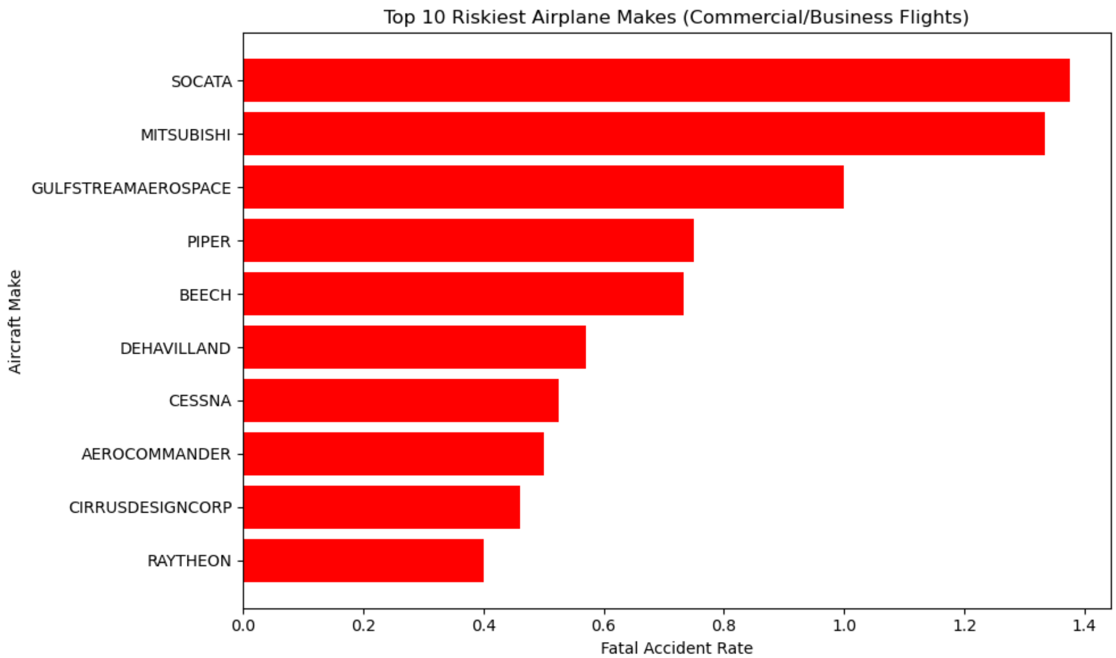
```
safest_makes = make_stats.sort_values("fatal_accident_rate", ascending=True).
  ↪head(10)
riskiest_makes = make_stats.sort_values("fatal_accident_rate", ascending=False).
  ↪head(10)
```

Lets create visual to see our findings

[63]:

```
# Plot safest
plt.figure(figsize=(10,6))
plt.barh(safest_makes["Make"], safest_makes["fatal_accident_rate"],␣
  ↪color="green")
plt.xlabel("Fatal Accident Rate")
plt.ylabel("Aircraft Make")
plt.title("Top 10 Safest Airplane Makes (Commercial/Business Flights)")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()

# Plot riskiest
plt.figure(figsize=(10,6))
plt.barh(riskiest_makes["Make"], riskiest_makes["fatal_accident_rate"],␣
  ↪color="red")
plt.xlabel("Fatal Accident Rate")
plt.ylabel("Aircraft Make")
plt.title("Top 10 Riskiest Airplane Makes (Commercial/Business Flights)")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```





From the chart, Bellanca, and Rockwell aircraft exhibit the lowest fatal accident rates, indicating a strong safety record in commercial operations. Manufacturers such as Raytheon Aircraft Company and Mooney also maintain relatively low fatality rates, suggesting dependable safety outcomes.SOCATA and Mitsubishi pose the greatest operational risk for commercial ventures,

6.3.1 Conclusion and Recommendation

1. Based on the data, skydiving, firefighting, and executive flights show the highest risk of fatalities and aerial application activities demonstrate the least risk.
2. The data suggests that a single-engine setup might be more conducive to surviving adverse weather conditions. The larger volume of data for single-engine aircraft likely contributes to its higher accuracy.I believe the dataset lacked enough data for multiple engine planes.
3. Begin operations with Executive/Corporate or Small Business Charter aircraft, where accident frequency and fatality rates are lower.
4. For commercial ventures prioritizing safety, aircraft from Maule, Bellanca, and Rockwell represent the lowest risk choices in this dataset. Overall, consistent maintenance practices, pilot training, and operational oversight remain the key determinants of aviation safety, regardless of manufacturer.
5. Choosing aircraft with low fatality and damage rates helps reduce financial risk and improve profitability in commercial aviation.
6. Invest in pilot training programs, aircraft maintenance, and weather monitoring systems to make the airplane extra safe.