Determining which Aircratf are the Lowest Risk for the Company to start a new Business endeavor

Please fill out:

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- Scheduled project review date/time: Teusday, 29^{th} April. 11.59pm
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- Blog post URL:

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

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Introduction

The analysis aims to assess safety and operational risks across different aircraft models to help the company choose low-risk airplanes for its new aviation business.

Business Understanding

The organization has embarked on industry expansion to achieve business diversification. The company wishes to acquire and manage aircraft for both commercial and private flight services yet remains unaware of aviation-related risks. The goal of this analysis includes finding the aircraft with the lowest potential risks to help your company launch its new aviation business.

Primarily it is tasked with the responsibility of presenting essential findings that will guide the new aviation division head in determining which aircraft will be most beneficial for acquisition.

Libraries

Importing Libraries

```
# Importing Required Libraries for this project

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

Loading Data Sets

```
# Load the Aviation Dataset
# The data is stored in the df_Aviation variable

df_Aviation = pd.read_csv('data/Aviation_Data.csv', low_memory=False)
```

Understanding the Data

Understanding the Culumn and categorizing them twith respect to the required Analysis

The Aviation Dataset enatails several features that can be attributed to aircraft accidents and those that are safety related. For instance;

Information about Events

- Event.ID
- Unvestigation.Type
- Accident.Number
- Event.Date
- Location, Country,Lattitude, Longitude
- Airport.Code, Airport.Name
- FAR.Description

Injury and Damage Information

- Injury.Severity
- AirCraft.Damage
- TOtal.Fatal.Injuries, Total.Serious.Injuries, Total.Minor.Injuries, Total.Uninjured

Aircraft and Flight Information

- Aircraft.Category
- Registration.Number
- Make, Model
- Amateur.Built
- Number.of.Engines, ENgine.Type
- Schedule, Purpose.of.Flight

Flight COndition and Weather

- Weather.Condition
- Broad.phase.of.flight

Relevant Columns for Risk Analysis

- Aircraft.Damage - This will determin how severe the accidents were which closely relates to the level risk associated with the specific aircrafts
- Total.Fatal.Injuries, TOtal.Serious.Injuries, Total.Minor.Injuries - Provides into how safe an aircraft can be
- Aircraft.Category - helps in identifying whether the aircraft is commercial or private which inturn helps in identifying the threshold of the risk We can also check the Purpose.of.flight Column
- Make, Model - Helps in analysziing Trends with rerspect to safety and performance among different aricrafts
- Engine.Type - Helps to know if certain Engines have safety records
- Weather.Condition - WIll be used to check if adverse weather conditions plays a role in causing accidents with respect to aircraft
- Broad.phase.of.flight - will be used to identify if specific phases of a flight like landing or takeoff would be a potential risk for specific aircrafts

Data Types

```
#check datatypes per column and the number of none null columns
df_Aviation.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
```

Summary Statistics

```
# Summary statistics like count, mean mode and median and std
deviation for float and interger columns
df_Aviation.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
```

Examine the first 5 rows of the dataframe

```
# Set display option to show all columns
pd.set_option('display.max_columns', None)
df_Aviation.head(5)

         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 Injury.Severity Aircraft.damage Aircraft.Category  \
0          NaN        Fatal(2)       Destroyed               NaN
1          NaN        Fatal(4)       Destroyed               NaN
2          NaN        Fatal(3)       Destroyed               NaN
3          NaN        Fatal(2)       Destroyed               NaN
4          NaN        Fatal(1)       Destroyed               NaN

  Registration.Number      Make     Model Amateur.Built
Number.of.Engines  \
0              NC6404   Stinson     108-3            No
1.0
1              N5069P     Piper  PA24-180            No
1.0
2              N5142R    Cessna      172M            No
1.0
```

```
3               N1168J  Rockwell       112            No
1.0
4                N15NY    Cessna       501            No
NaN

     Engine.Type FAR.Description Schedule Purpose.of.flight
Air.carrier  \
0  Reciprocating             NaN      NaN          Personal
NaN
1  Reciprocating             NaN      NaN          Personal
NaN
2  Reciprocating             NaN      NaN          Personal
NaN
3  Reciprocating             NaN      NaN          Personal
NaN
4            NaN             NaN      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


   Total.Uninjured Weather.Condition Broad.phase.of.flight
Report.Status  \
0              0.0               UNK                Cruise  Probable
Cause
1              0.0               UNK               Unknown  Probable
Cause
2              NaN               IMC                Cruise  Probable
Cause
3              0.0               IMC                Cruise  Probable
Cause
4              0.0               VMC              Approach  Probable
Cause

  Publication.Date
0              NaN
1       19-09-1996
2       26-02-2007
3       12-09-2000
4       16-04-1980
```

```
#f_Aviation[df_Aviation['Model' , 'Make'] == Nan]
df_Aviation.sort_values(by = 'Make', ascending=False)
# df_Aviation[['Make', 'Model']]
df_Aviation['Make'].isna().sum()
```

```
np.int64(1522)
```

Column Names

```
#Check column names
print(df_Aviation.columns)

print()

#Check dataframe shape

df_Aviation.shape
```

```
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')
```

```
(90348, 31)
```

Data Cleaning

Filter the data to the columns that are required for this analysis then drop null values

```
# Filter Required Columns
df_Aviation_Risk_Analysis_Data =
df_Aviation[['Aircraft.damage','Make', 'Model', 'Engine.Type',
'Purpose.of.flight', 'Total.Fatal.Injuries', 'Total.Serious.Injuries',
'Total.Minor.Injuries', 'Weather.Condition', 'Broad.phase.of.flight']]

#Check percentage og Missing Values per Column
print(df_Aviation_Risk_Analysis_Data.isnull().mean()*100)
```

```
print()

#Print Shape od the new dataframe
print(df_Aviation_Risk_Analysis_Data.shape)
```

```
Aircraft.damage            5.150086
Make                       1.684597
Model                      1.716695
Engine.Type                9.468942
Purpose.of.flight          8.468367
Total.Fatal.Injuries      14.233851
Total.Serious.Injuries    15.461327
Total.Minor.Injuries      14.822686
Weather.Condition          6.586753
Broad.phase.of.flight     31.681941
dtype: float64

(90348, 10)
```

Since the data requires an analysis of the low cost air crafts to purchase. Make and Model will be higly used

```
#check the number of missing values in Make and Model

#missing values in Make column
print(f'The number of missing values in the Make Column are:',
df_Aviation_Risk_Analysis_Data['Make'].isna().sum())

#Missing values in Model COlumn
print(f'The number of missing values in the Model Column are:',
df_Aviation_Risk_Analysis_Data['Model'].isna().sum())
```

```
The number of missing values in the Make Column are: 1522
The number of missing values in the Model Column are: 1551
```

1. Clean Make and Model Column

```
#Drop null values in the make and Model Columns
df_Aviation_Risk_Analysis_Data =
df_Aviation_Risk_Analysis_Data.dropna(subset=['Model','Make'], axis=0)

#Check culumns with null values in the new dataframe
df_Aviation_Risk_Analysis_Data.isna().sum()
```

```
Aircraft.damage            3172
Make                          0
Model                         0
Engine.Type                7025
Purpose.of.flight          6138
Total.Fatal.Injuries      11386
```

```
Total.Serious.Injuries    12490
Total.Minor.Injuries      11914
Weather.Condition          4439
Broad.phase.of.flight     27094
dtype: int64
```

```
df_Aviation_Risk_Analysis_Data.count()
```

```
Aircraft.damage           85605
Make                      88777
Model                     88777
Engine.Type               81752
Purpose.of.flight         82639
Total.Fatal.Injuries      77391
Total.Serious.Injuries    76287
Total.Minor.Injuries      76863
Weather.Condition         84338
Broad.phase.of.flight     61683
dtype: int64
```

2. CLean Aircraft.damage Column

```
#Check categorical Data in Aircraft.damage
df_Aviation_Risk_Analysis_Data['Aircraft.damage'].unique()
```

```
array(['Destroyed', 'Substantial', 'Minor', nan, 'Unknown'],
dtype=object)
```

- The Aircraft.damage column has a nan and Unkown Column.
- Impute the nan with Unkown

```
#Impute nan with Unkown
df_Aviation_Risk_Analysis_Data['Aircraft.damage'] =
df_Aviation_Risk_Analysis_Data['Aircraft.damage'].fillna("Unknown")

df_Aviation_Risk_Analysis_Data['Aircraft.damage'].unique()
```

```
array(['Destroyed', 'Substantial', 'Minor', 'Unknown'], dtype=object)
```

3. Clean Broad.phase.of.flight Column

```
#Check categorical Data in Broad.phase.of.flight
df_Aviation_Risk_Analysis_Data['Broad.phase.of.flight'].unique()
```

```
array(['Cruise', 'Unknown', 'Approach', 'Climb', 'Takeoff', 'Landing',
       'Taxi', 'Descent', 'Maneuvering', 'Standing', 'Go-around',
'Other',
       nan], dtype=object)
```

```
# Impute Impute Unknown, Other and nan with Unkown
df_Aviation_Risk_Analysis_Data['Broad.phase.of.flight']=df_Aviation_Ri
sk_Analysis_Data['Broad.phase.of.flight'].fillna('Unknown')
```

```
#Replace the values of Other to Unkown
df_Aviation_Risk_Analysis_Data['Broad.phase.of.flight']=df_Aviation_Ri
sk_Analysis_Data['Broad.phase.of.flight'].replace('Other', 'Unknown')
```

5. Clean Weather.Condition

```
#CHeck categorical data in Weather Condition
df_Aviation_Risk_Analysis_Data['Weather.Condition'].unique()

array(['UNK', 'IMC', 'VMC', nan, 'Unk'], dtype=object)

# Impute the nan and UnK with UNK meaning unkown
df_Aviation_Risk_Analysis_Data['Weather.Condition'] =
df_Aviation_Risk_Analysis_Data['Weather.Condition'].fillna('UNK')
df_Aviation_Risk_Analysis_Data['Weather.Condition'] =
df_Aviation_Risk_Analysis_Data['Weather.Condition'].replace('Unk',
'UNK')
```

6. Clean Engine.Type

```
df_Aviation_Risk_Analysis_Data['Engine.Type'].unique()

array(['Reciprocating', nan, 'Turbo Fan', 'Turbo Shaft', 'Unknown',
       'Turbo Prop', 'Turbo Jet', 'Electric', 'Hybrid Rocket',
       'Geared Turbofan', 'LR', 'NONE', 'UNK'], dtype=object)

#Impute nan with Unkown
df_Aviation_Risk_Analysis_Data['Engine.Type'] =
df_Aviation_Risk_Analysis_Data['Engine.Type'].fillna('Unknown')

# Replace NONE and UNK with Unkown
df_Aviation_Risk_Analysis_Data['Engine.Type'] =
df_Aviation_Risk_Analysis_Data['Engine.Type'].replace('NONE',
'Unknown')
df_Aviation_Risk_Analysis_Data['Engine.Type'] =
df_Aviation_Risk_Analysis_Data['Engine.Type'].replace('UNK',
'Unknown')
```

7. Clean Purpose.of.flight

```
#CHeck unique values Purpose.of.flight
df_Aviation_Risk_Analysis_Data['Purpose.of.flight'].unique()

array(['Personal', nan, 'Business', 'Instructional', 'Unknown',
'Ferry',
       'Executive/corporate', 'Aerial Observation', 'Aerial
Application',
       'Public Aircraft', 'Skydiving', 'Other Work Use',
'Positioning',
       'Flight Test', 'Air Race/show', 'Air Drop',
```

```
       'Public Aircraft - Federal', 'Glider Tow',
       'Public Aircraft - Local', 'External Load',
       'Public Aircraft - State', 'Banner Tow', 'Firefighting',
       'Air Race show', 'PUBS', 'ASHO', 'PUBL'], dtype=object)

#Impute nan with Unkown
df_Aviation_Risk_Analysis_Data['Purpose.of.flight'] =
df_Aviation_Risk_Analysis_Data['Purpose.of.flight'].fillna('Unknown')
```

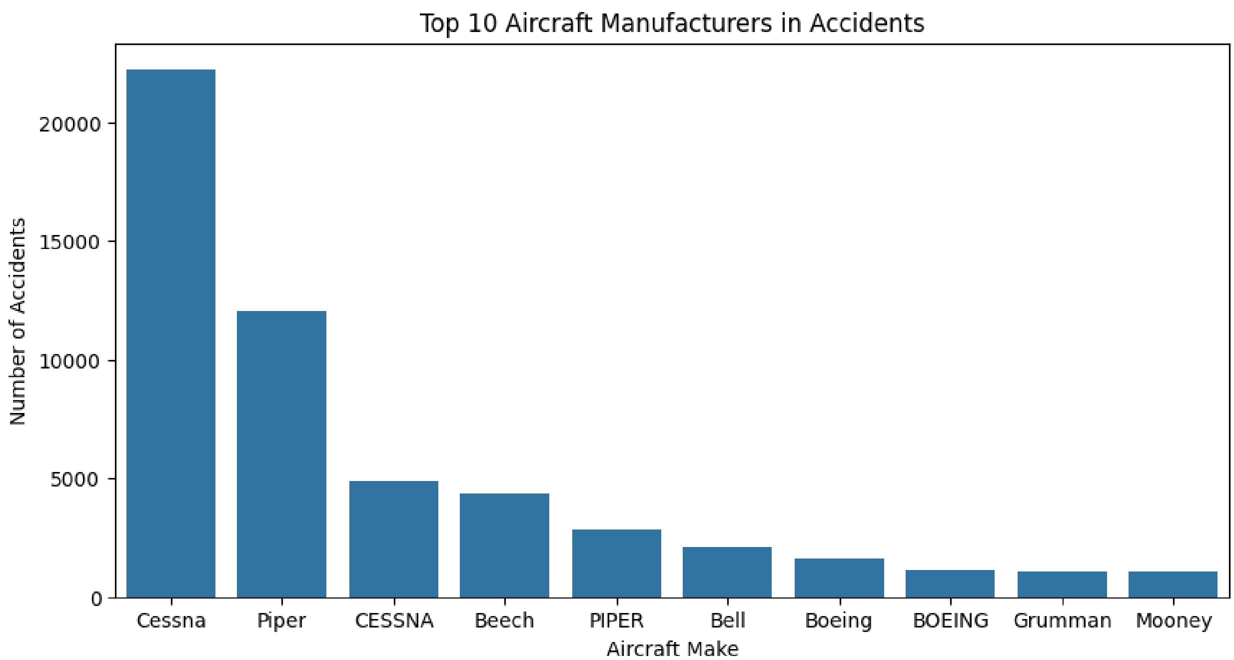
8. Clean Total.Fatal.Injuries, Total.Serious.Injuries, Total.Minor.Injuries

```
#Impute the Columns with Mode

#Total.Fatal.Injuries
tfi = df_Aviation_Risk_Analysis_Data['Total.Fatal.Injuries'].mode()[0]
df_Aviation_Risk_Analysis_Data['Total.Fatal.Injuries'] =
df_Aviation_Risk_Analysis_Data['Total.Fatal.Injuries'].fillna(tfi)

#Total.Serious.Injuries
tsi = df_Aviation_Risk_Analysis_Data['Total.Serious.Injuries'].mode()
[0]
df_Aviation_Risk_Analysis_Data['Total.Serious.Injuries'] =
df_Aviation_Risk_Analysis_Data['Total.Serious.Injuries'].fillna(tsi)

#Total.Minor.Injuries
tmi = df_Aviation_Risk_Analysis_Data['Total.Minor.Injuries'].mode()[0]
df_Aviation_Risk_Analysis_Data['Total.Minor.Injuries'] =
df_Aviation_Risk_Analysis_Data['Total.Minor.Injuries'].fillna(tmi)

df_Aviation_Risk_Analysis_Data.info()

<class 'pandas.core.frame.DataFrame'>
Index: 88777 entries, 0 to 90347
Data columns (total 10 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Aircraft.damage         88777 non-null  object 
 1   Make                    88777 non-null  object 
 2   Model                   88777 non-null  object 
 3   Engine.Type             88777 non-null  object 
 4   Purpose.of.flight       88777 non-null  object 
 5   Total.Fatal.Injuries    88777 non-null  float64
 6   Total.Serious.Injuries  88777 non-null  float64
 7   Total.Minor.Injuries    88777 non-null  float64
 8   Weather.Condition       88777 non-null  object 
 9   Broad.phase.of.flight   88777 non-null  object 
dtypes: float64(3), object(7)
memory usage: 7.5+ MB
```

Analysis

1. The Most Common Aircraft Makes that are prone to accidents

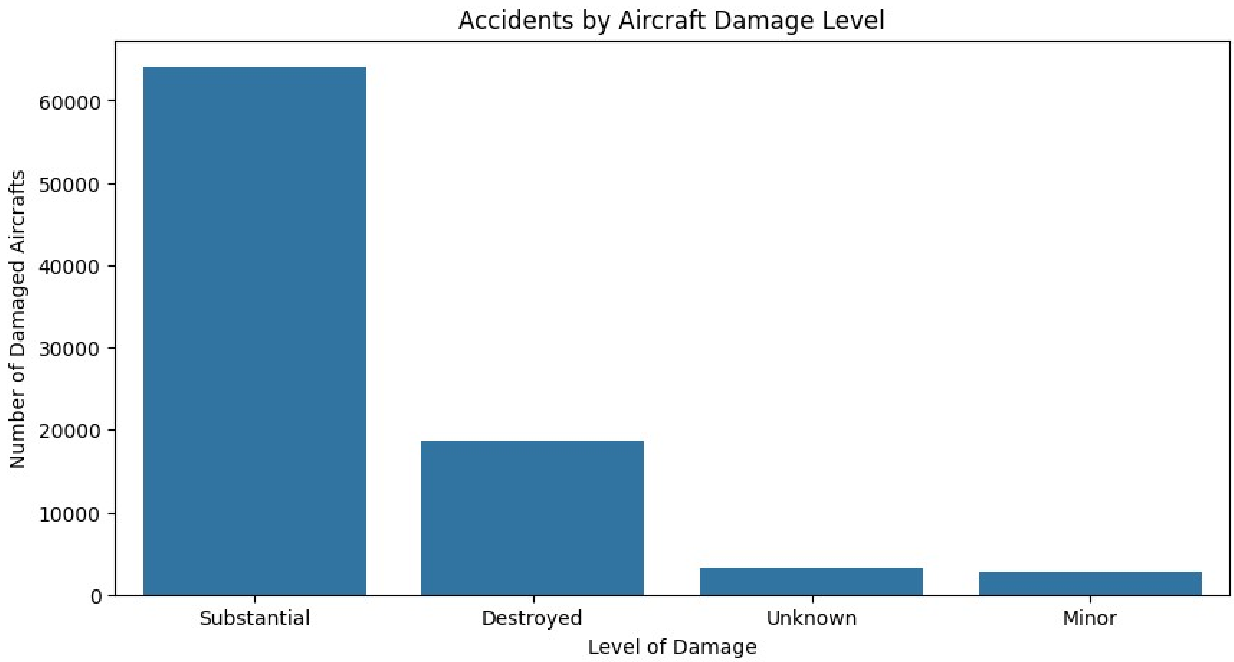
```
#top_makes_models =
df_Aviation_Risk_Analysis_Data['Make'].value_counts().head(10)

plt.figure(figsize=(10,5))
sns.barplot(x=top_makes_models.index, y=top_makes_models.values)
plt.title("Top 10 Aircraft Manufacturers in Accidents")
plt.ylabel("Number of Accidents")
plt.xlabel("Aircraft Make")
plt.show()
```



- The graph shows that Cessna, Piper, and Beech recorded over 2000 accidents, therefore they are the most common aircrafts.

2. Level of Damage of an Aircraft after an accident

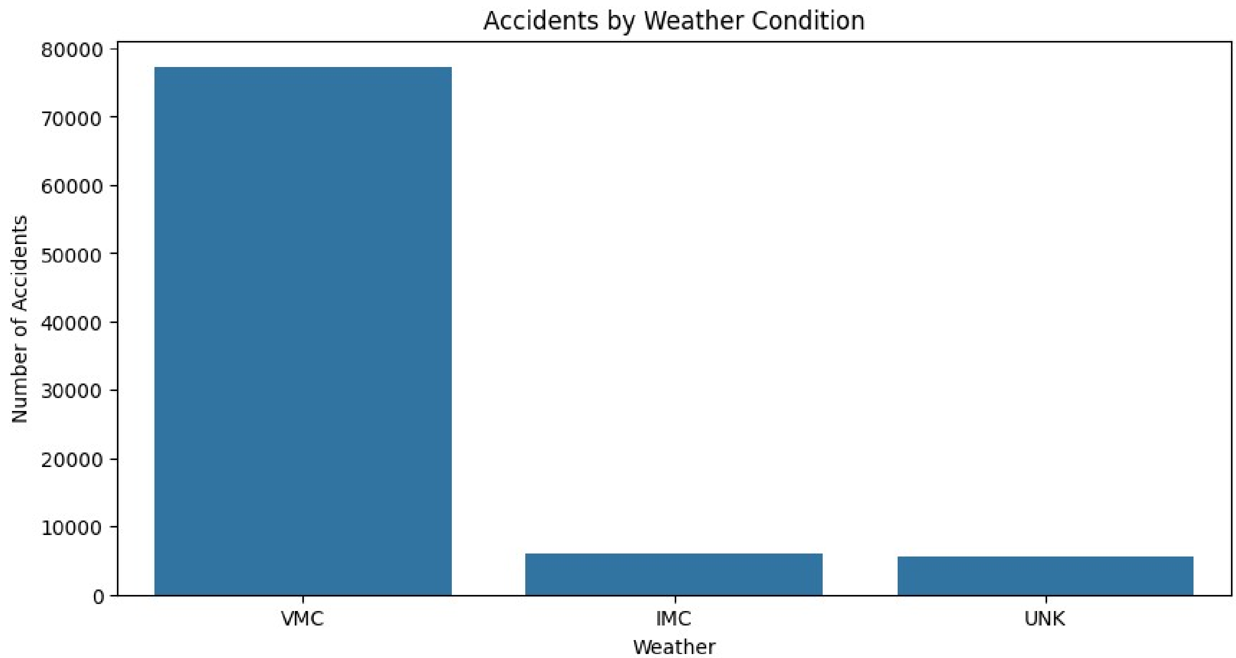
```
plt.figure(figsize=(10,5))
sns.countplot(data=df_Aviation_Risk_Analysis_Data,
x='Aircraft.damage',
order=df_Aviation_Risk_Analysis_Data['Aircraft.damage'].value_counts()
.index)
plt.title("Accidents by Aircraft Damage Level")
plt.ylabel("Number of Damaged Aircrafts")
plt.xlabel("Level of Damage")
plt.show()
```



- majority of the aircrafts ended in substantial damages. On the other hand not all were totaly damaged while very few had minor damages.

3. Impact of Weather on Accidents

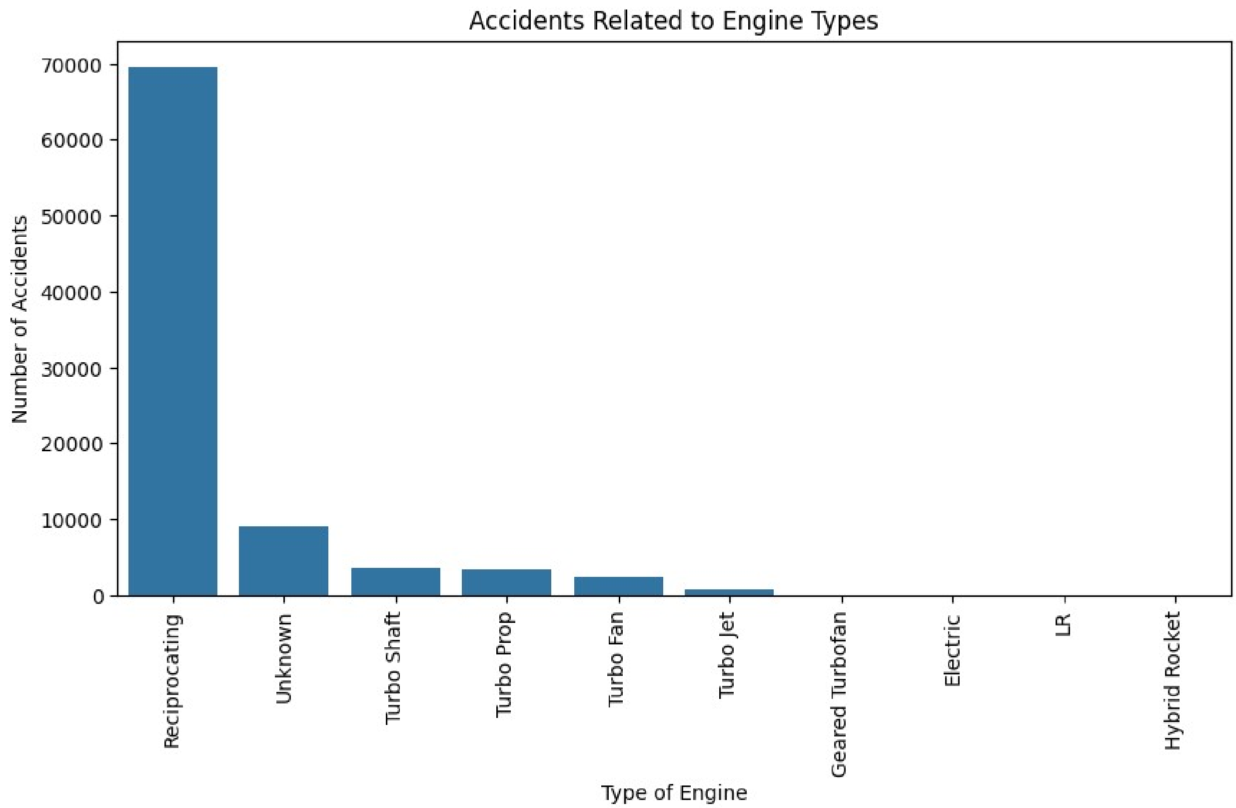
```
weather_condition_accidents_counts =
df_Aviation_Risk_Analysis_Data['Weather.Condition'].value_counts().to_
frame()

plt.figure(figsize=(10,5))
sns.barplot(data=weather_condition_accidents_counts ,x='Weather.Condit
ion', y=weather_condition_accidents_counts.columns[0])
plt.title('Accidents by Weather Condition')
plt.xlabel('Weather')
plt.ylabel('Number of Accidents')
plt.show()
```



- Many accidents are experienced during VMC

4. Accidents by Engine Types

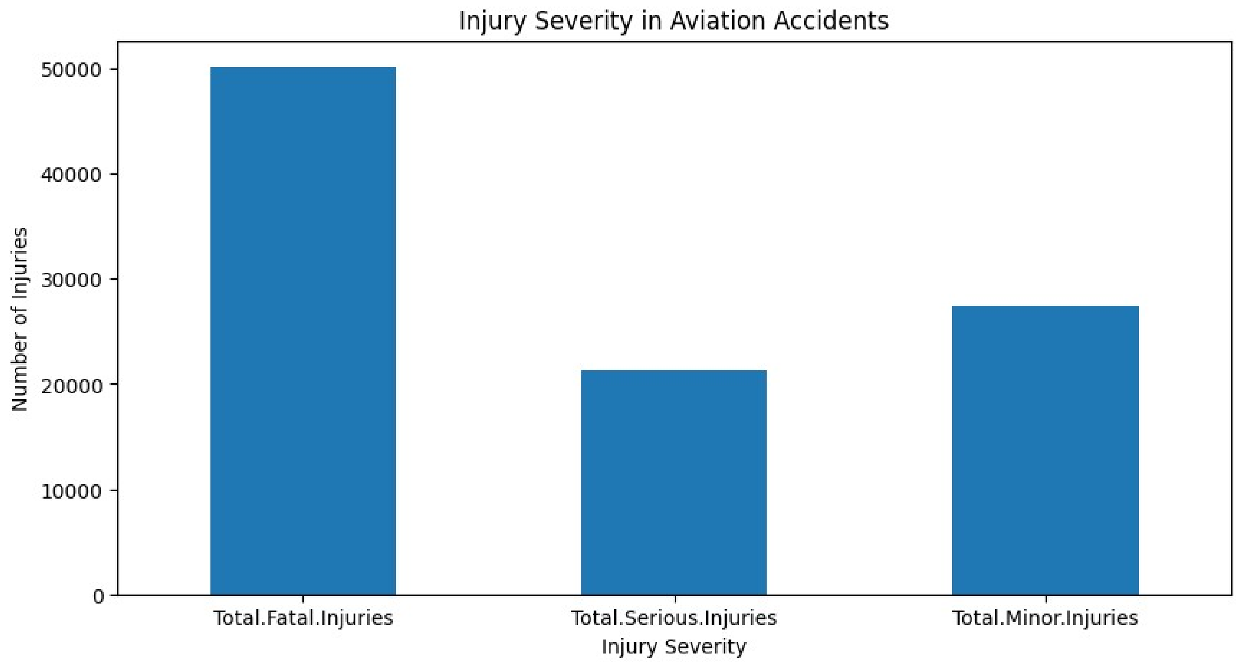
```
engine_counts =
df_Aviation_Risk_Analysis_Data['Engine.Type'].value_counts().to_frame(
)
plt.figure(figsize = (10,5))
sns.barplot(data=engine_counts, x='Engine.Type',
y=engine_counts.columns[0])
plt.title('Accidents Related to Engine Types')
plt.ylabel('Number of Accidents')
plt.xlabel('Type of Engine')
plt.xticks(rotation=90)
plt.show()
```



- Reciprocating Engines caused the most number of accidents, on the other hand, Turbo Shafts, Turbo Prop, Turbo Fan and Turbo Jet registered minimal accidents.
- Small piston planes use use reciprocating engine while Turbofan and Turbo Jet Engines are used in business jets.

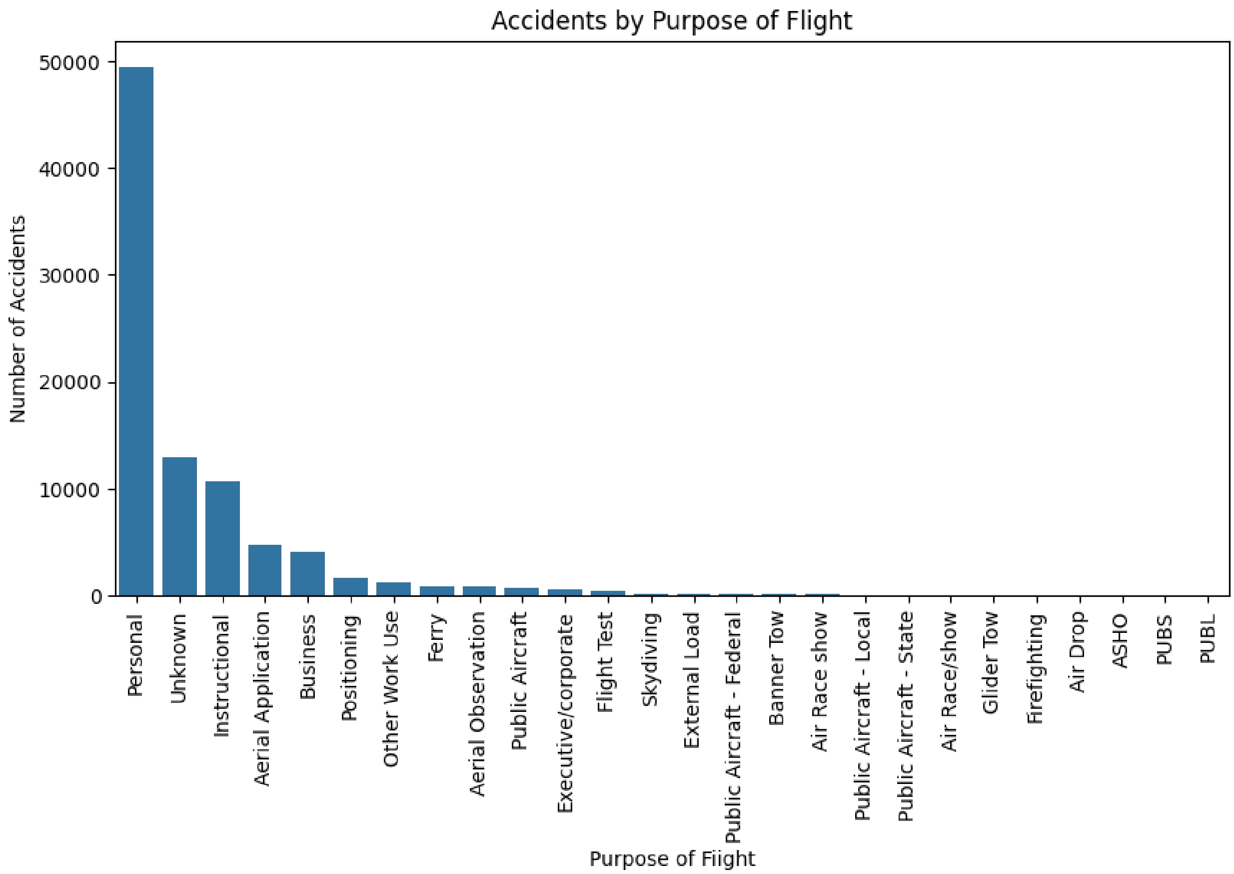
5. Analysis by Injury Severity

```
# Injury distribution
injury_severity =
df_Aviation_Risk_Analysis_Data[['Total.Fatal.Injuries',
'Total.Serious.Injuries', 'Total.Minor.Injuries',]].sum()

injury_severity.plot(kind='bar', figsize=(10,5))
plt.title('Injury Severity in Aviation Accidents')
plt.ylabel('Number of Injuries')
plt.xlabel('Injury Severity')
plt.xticks(rotation=0)
plt.show()
```



6. Analysis by Pupose of Flight

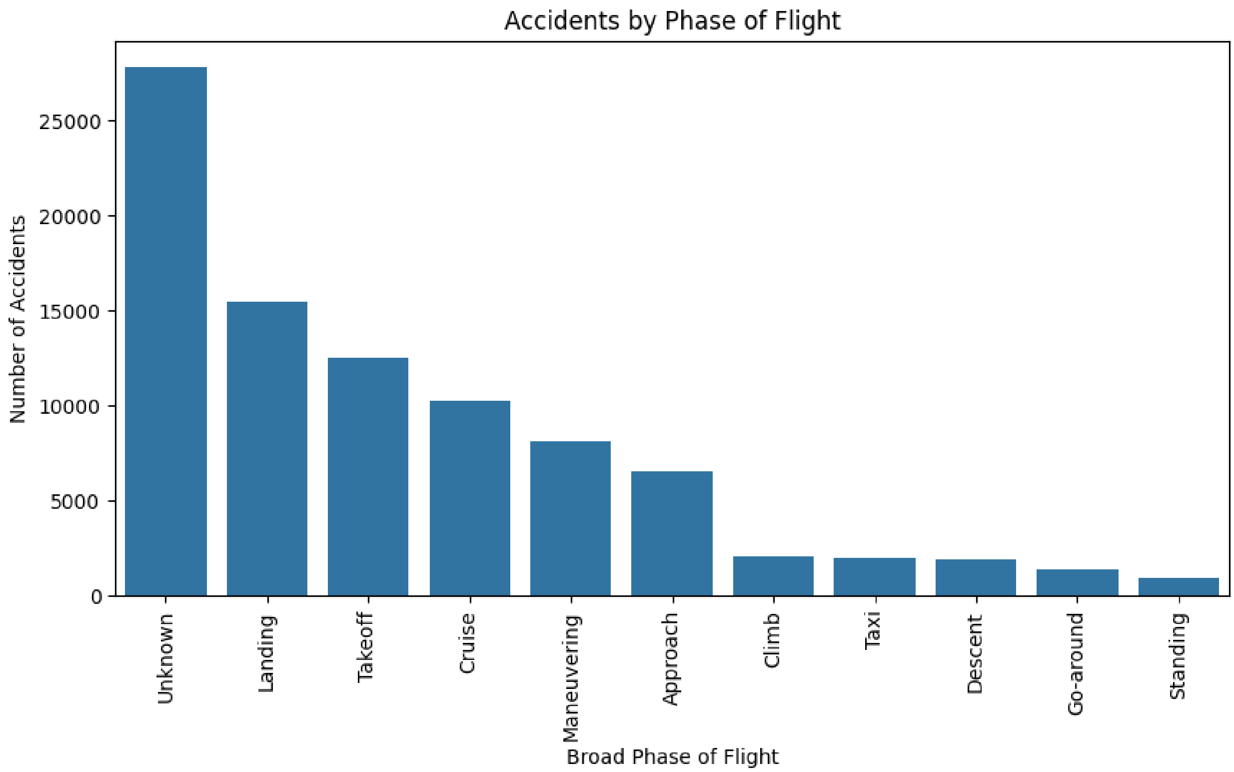
```
purpose_of_flight_counts =
df_Aviation_Risk_Analysis_Data['Purpose.of.flight'].value_counts().to_
frame()

plt.figure(figsize=(10,5))
sns.barplot(data=purpose_of_flight_counts, x='Purpose.of.flight',
y=purpose_of_flight_counts.columns[0])
plt.title('Accidents by Purpose of Flight')
plt.ylabel('Number of Accidents')
plt.xlabel('Purpose of Fiight')
plt.xticks(rotation=90)
plt.show()
```



- More accidents are experienced when the purpose is to fly the aircraft personally. This could be associated to the fact that private pilots are not professional and tend to fly cassually and carelessly

7. Analysis by Phase of FLight

```
phase_of_flights_counts =
df_Aviation_Risk_Analysis_Data['Broad.phase.of.flight'].value_counts()
.to_frame()

plt.figure(figsize=(10,5))
sns.barplot(data=phase_of_flights_counts, x='Broad.phase.of.flight',
y=phase_of_flights_counts.columns[0],)
plt.title('Accidents by Phase of Flight')
plt.ylabel('Number of Accidents')
plt.xlabel('Broad Phase of Flight')
plt.xticks(rotation=90)
plt.show()
```




```
#Export dataframe to csv for visualization using Tableau
df_Aviation_Risk_Analysis_Data.to_csv('data/cleaned_aviation_data.csv'
, index=False)
```

Recommendations

- Turbofan Engines which are mostly used for commercial aircrafts caused fewer accidents compared to reciprocating which are primarily piston based and commonly used for small jets. Therefore the organization should consider Purchasing Turbo Engines. On the other hand Engines like Electric and LR and Hybrid Rocket recorded low accidents. They caould also be considered
- It is important to know that many accidents in the aviation sector occur during landing and takeoff. This means that the organization should consider training their pilots frequetly not only on safety procedures but also profeciency and keenness.
- More accidents are experienced when the purpose is to fly the aircraft personally. This could be associated to the fact that private pilots are not professional and tend to fly cassually and carelessly. The organization should enact rules that will allow private customers to be flown by a professional pilot provoded by the organization.