1.0 BUSINESS PROBLEM

Our company is expanding into new industries by purchasing and operating aircraft for both commercial and private enterprises. To ensure a successful entry into this market, it is crucial to identify aircraft with the lowest potential risk of accidents.

1.1 PROBLEM STATEMENT

The primary challenge in selecting an aircraft is evaluating its historical safety performance to minimize the risk of accidents.

1.2 METRICS OF SUCCESS

To gauge the success of this analysis and assist the head of the new aviation division in making informed decisions about aircraft purchases, the following metrics will be used:

1. **Clarity and Actionability of Recommendations:**
   - **Objective:** Provide clear and actionable recommendations for aircraft selection.
   - **Measure:** Evaluate how well the recommendations align with the company's risk tolerance and operational requirements.
2. **Industry Standards Compliance:**
   - **Objective:** Ensure that the recommendations are consistent with industry safety standards and best practices.
   - **Measure:** Review recommendations against established safety ratings and industry benchmarks.

In [153…

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

In [154…

```
#Reading the data
Aviation_data=pd.read_csv('archive/AviationData.csv',encoding='cp1252',low_memory=False
#print(Aviation_data.head())
Us_state_codes=pd.read_csv('archive/USState_Codes.csv',encoding='cp1252',low_memory=Fal
```

In [155…

```
Aviation_data.info()
'''
The dataset has:
82,474 rows (entries)
31 columns, including:
6 float variables
26 object data types
'''
```

```
<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            50249 non-null  object 
 9   Airport.Name            52790 non-null  object 
 10  Injury.Severity         87889 non-null  object 
 11  Aircraft.damage         85695 non-null  object 
 12  Aircraft.Category       32287 non-null  object 
 13  Registration.Number     87572 non-null  object 
 14  Make                    88826 non-null  object 
 15  Model                   88797 non-null  object 
 16  Amateur.Built           88787 non-null  object 
 17  Number.of.Engines       82805 non-null  float64
 18  Engine.Type             81812 non-null  object 
 19  FAR.Description         32023 non-null  object 
 20  Schedule                12582 non-null  object 
 21  Purpose.of.flight       82697 non-null  object 
 22  Air.carrier             16648 non-null  object 
 23  Total.Fatal.Injuries    77488 non-null  float64
 24  Total.Serious.Injuries  76379 non-null  float64
 25  Total.Minor.Injuries    76956 non-null  float64
 26  Total.Uninjured         82977 non-null  float64
 27  Weather.Condition       84397 non-null  object 
 28  Broad.phase.of.flight   61724 non-null  object 
 29  Report.Status           82508 non-null  object 
 30  Publication.Date        75118 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

Out[155…

```
'\nThe dataset has:\n82,474 rows (entries)\n31 columns, including:\n6 float variables\n2
6 object data types\n'
```

2.0 DATA MANIPULATION

In [156…

```
#check for missing values composition
missing_values=Aviation_data.isnull().sum()
#missing_values_percentage=missing_values[2]
sorted_values=missing_values.sort_values(ascending=False)
total_rows = Aviation_data.shape[0]
missing_values_percentage=(missing_values/total_rows)*100
missing_values_percentage=missing_values_percentage.sort_values(ascending=False).round(

# We will drop all columns with missing values composition of 30% and above.
#The columns Schedule Air.carrier, FAR.Description, Aircraft.Category, Longitude,
# Latitude, Airport.Code, Airport.Name and Broad.phase.of.flight will be dropped
above_threshold=missing_values_percentage>30.0
#print(missing_values_percentage)
print("\nColumns with missing values above 30% threshold:")
print(missing_values_percentage)
#print(sorted_values)
'''
columns having missing values above 30% threshold:
Schedule                86.0
Air.carrier             81.0
```

```
FAR.Description         64.0
Aircraft.Category       64.0
Longitude               61.0
Latitude                61.0
Airport.Code            43.0
Airport.Name            41.0
Broad.phase.of.flight   31.0
'''
```

```
Columns with missing values above 30% threshold:
Schedule                  86.0
Air.carrier               81.0
FAR.Description           64.0
Aircraft.Category         64.0
Longitude                 61.0
Latitude                  61.0
Airport.Code              43.0
Airport.Name              41.0
Broad.phase.of.flight     31.0
Publication.Date          15.0
Total.Serious.Injuries    14.0
Total.Minor.Injuries      13.0
Total.Fatal.Injuries      13.0
Engine.Type                8.0
Report.Status              7.0
Purpose.of.flight          7.0
Number.of.Engines          7.0
Total.Uninjured            7.0
Weather.Condition          5.0
Aircraft.damage            4.0
Registration.Number        1.0
Injury.Severity            1.0
Country                    0.0
Amateur.Built              0.0
Model                      0.0
Make                       0.0
Location                   0.0
Event.Date                 0.0
Accident.Number            0.0
Investigation.Type         0.0
Event.Id                   0.0
dtype: float64
```

Out[156…

```
'\ncolumns having missing values above 30% threshold:\nSchedule                  86.0\nAir.carrier               81.0\nFAR.Description           64.0\nAircraft.Category         64.0\nLongitude                 61.0\nLatitude                  61.0\nAirport.Code              43.0\nAirport.Name              41.0\nBroad.phase.of.flight     31.0\n'
```

In [157…

```
# drop the columns with over 30% of missing values
columns_to_drop=missing_values_percentage[above_threshold]
columns_to_drop=columns_to_drop.index

for col in columns_to_drop:
    Aviation_data.drop(columns=col,inplace=True)
print(Aviation_data.shape) # indicates that the new dataframe contains 88,889 rows and
```

```
(88889, 22)
```

In [158…

```
#drop other irrelevant columns that i may not need in my analysis
Aviation_data=Aviation_data.drop(columns=['Publication.Date'])
Aviation_data=Aviation_data.drop(columns=['Registration.Number'])
Aviation_data.columns # Returns the resultant columns in our dataframe
```

Out[158…

```
Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Date',
       'Location', 'Country', 'Injury.Severity', 'Aircraft.damage', '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',
       'Report.Status'],
      dtype='object')
```

In [159…

```
#convert columns make/model cells to contain upper case Strings
Aviation_data['Make']=Aviation_data['Make'].str.upper()
Aviation_data['Make']=Aviation_data['Make'].str.strip()
Aviation_data['Model']=Aviation_data['Model'].str.upper()

#print(sorted_by_index_and_values.iloc[1:100]) '''
```

In [160…

```
print(Aviation_data.describe(include=object).T) #show a summary of all variables in our

'''
Investigation Type and Amateur.Built, have two unique categories. Aircraft.damage and We
Event.Id,Accident.Number have huge number of uniques entries.
'''
```

```
                    count unique              top   freq
Event.Id            88889  87951   20001212X19172      3
Investigation.Type  88889      2         Accident  85015
Accident.Number     88889  88863       WPR22LA143      2
Event.Date          88889  14782       2000-07-08     25
Location            88837  27758    ANCHORAGE, AK    434
Country             88663    219    United States  82248
Injury.Severity     87889    109        Non-Fatal  67357
Aircraft.damage     85695      4      Substantial  64148
Make                88826   7587           CESSNA  27149
Model               88797  11646              152   2367
Amateur.Built       88787      2               No  80312
Engine.Type         81812     13    Reciprocating  69530
Purpose.of.flight   82697     26         Personal  49448
Weather.Condition   84397      4              VMC  77303
Report.Status       82508  17075   Probable Cause  61754
```

Out[160…

```
'\nInvestigation Type and Amateur.Built, have two unique categories. Aircraft.damage and
Weather.Condition have 4 unique categories.\nEvent.Id,Accident.Number have huge number o
f uniques entries.\n'
```

In [161…

```
# calculate the mean values for numerical data type variables in our dataset
mean_values=Aviation_data.mean().round(0)
mean_values
```

Out[161…

```
Number.of.Engines         1.0
Total.Fatal.Injuries      1.0
Total.Serious.Injuries    0.0
Total.Minor.Injuries      0.0
Total.Uninjured           5.0
dtype: float64
```

In [162…

```
# we will replace all missing values in all columns with numerical data types using the
numerical_colums=mean_values.index
for i in numerical_colums:
    Aviation_data.fillna(mean_values,inplace=True)
print(Aviation_data.isna().sum())
```

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

```
Event.Date                0
Location                 52
Country                 226
Injury.Severity        1000
Aircraft.damage        3194
Make                     63
Model                    92
Amateur.Built           102
Number.of.Engines         0
Engine.Type            7077
Purpose.of.flight      6192
Total.Fatal.Injuries      0
Total.Serious.Injuries    0
Total.Minor.Injuries      0
Total.Uninjured           0
Weather.Condition      4492
Report.Status          6381
dtype: int64
```

In [163…

```
#Summarize numerical variables
Aviation_data.describe().T
```

Out[163…

	count	mean	std	min	25%	50%	75%	max
Number.of.Engines	88889.0	1.136552	0.432545	0.0	1.0	1.0	1.0	8.0
Total.Fatal.Injuries	88889.0	0.693022	5.123423	0.0	0.0	0.0	1.0	349.0
Total.Serious.Injuries	88889.0	0.240491	1.434614	0.0	0.0	0.0	0.0	161.0
Total.Minor.Injuries	88889.0	0.309127	2.083715	0.0	0.0	0.0	0.0	380.0
Total.Uninjured	88889.0	5.303795	26.969508	0.0	0.0	1.0	2.0	699.0

- Number of Engines: Most aircraft have a single engine, with a small number having up to 8 engines.
- Total Fatal Injuries: Most incidents result in no fatalities, but there is significant variability, with a few incidents having very high fatality counts.
- Total Serious Injuries: Serious injuries are rare and mostly zero, though some incidents report up to 161 serious injuries.
- Total Minor Injuries: Minor injuries are generally low, with occasional incidents reporting up to 380 minor injuries.
- Total Uninjured: The average number of uninjured individuals per incident is high, but there is a wide range, with some incidents involving up to 699 uninjured people.

In [164…

```
#summarize all variables including categorical variables
categorical_variables=Aviation_data.describe(include=object).T.index
for i in categorical_variables:
    mode_value = Aviation_data[i].mode()[0]  # Get the first mode for the column
    Aviation_data[i].fillna(mode_value, inplace=True)  # Fill missing values with mode
# Print the number of missing values in each column
print(Aviation_data.isna().sum())
'''
The dataset has no missing values at this level
'''
```

```
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
Amateur.Built             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
Report.Status             0
dtype: int64
```

Out[164…
```
'\nThe dataset has no missing values at this level\n'
```

In [165…
```
#format Event.Date column and add an extra column called year.
#Extract year from Event.Date and create a new column called year
Aviation_data['Event.Date'] = pd.to_datetime(Aviation_data['Event.Date'], format='%Y-%m
# Extract just the year part
Aviation_data['Year']=Aviation_data['Event.Date'].dt.strftime('%Y')
#print(Aviation_data['Year'].value_counts())
```

In [166…
```
# we will analyze the number of aircrafts per country
Aviation_data['Country'].value_counts()
'''
Most aircraft accidents operate in the United States as shown below:
United States                        82474
Brazil                                 374
Canada                                 359
Mexico                                 358
United Kingdom                         344
'''
#we will then pick to analyze our data for United states since most of the airctafts ar
Aviation_data=Aviation_data[Aviation_data['Country']=='United States']
```

In [167…
```
#Accidents vs incidents
Aviation_data['Investigation.Type'].value_counts()
'''
Accidents form majority of the Investigation Types conducted as compared to Incident ty
'''
```

Out[167…
```
'\nAccidents form majority of the Investigation Types conducted as compared to Incident
type\n'
```

In [168…
```
# our second dataset called 'Us_state codes' needs to be cleaned and merged with our fi
# Extract the state or location code from the 'Location' column
# Split the 'Location' string by commas
# Select the second part (index 1) of the split string which should be the state code
# Remove any leading or trailing whitespace from the extracted string
Aviation_data['Location_code']=Aviation_data['Location'].str.split(',').str[1].str.stri

# Remove any leading or trailing whitespace from the 'Abbreviation' column in the Us_st
Us_state_codes['Abbreviation']=Us_state_codes['Abbreviation'].str.strip()
```

In [169…

```
#Merge the two data frame on Location code
Clean_aviation_data=pd.merge(Aviation_data,Us_state_codes,how='left',left_on='Location_
Missing_data=Clean_aviation_data.isna().sum()
for col in Clean_aviation_data.columns:
    if Missing_data[col]>0:
          col_mode=Clean_aviation_data[col].mode()[0]
          Clean_aviation_data[col].fillna(col_mode,inplace=True)
print(Clean_aviation_data.isna().sum())
```

```
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
Amateur.Built             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
Report.Status             0
Year                      0
Location_code             0
US_State                  0
Abbreviation              0
dtype: int64
```

In [170…

```
#Replace all engine types indicated as 'None','NONE' to Unknown as a valid category
Clean_aviation_data['Engine.Type'] = Clean_aviation_data['Engine.Type'].replace(['NONE'
```

In [171…

```
Clean_aviation_data_merged=Clean_aviation_data.copy() # Making a copy of our clean_avia
Clean_aviation_data_merged.to_csv("C:\\Users\\rkeoye\\Documents\\AUDIT_2024\\DATA_SCIEN
Clean_aviation_data_merged.head()
```

Out[171…

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

5 rows × 24 columns

3.0 DATA ANALYIS AND VISUALIZATION

In [172…

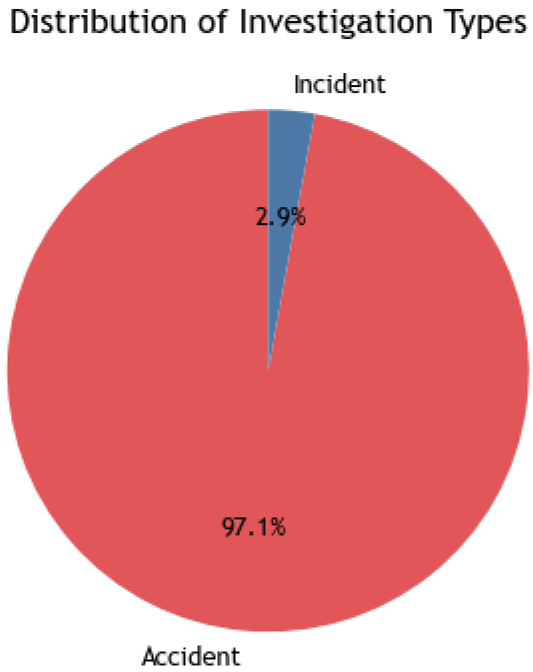
```
#Accidents vs incidents
Clean_aviation_data_merged['Investigation.Type'].value_counts()
# Count the occurrences of each Investigation Type
'''
Accidents form a huge junk of the type of aircraft investigations i.e.,
80112 as compared to Incident type of investigation i.e.,2362
'''
```

Out[172…

```
'\nAccidents form a huge junk of the type of aircraft investigations i.e., \n80112 as co
mpared to Incident type of investigation i.e.,2362\n'
```

In [173…

```
#Graphical representation of type of investigations in a pie chart
investigation_type_counts = Clean_aviation_data_merged['Investigation.Type'].value_coun
# Create the pie chart
font_properties = {'fontname': 'Trebuchet MS', 'fontsize': 13}
plt.figure(figsize=(6, 6),facecolor='white')
plt.pie(investigation_type_counts,
        labels=investigation_type_counts.index, autopct='%1.1f%%',
        startangle=90, colors=['#e15759', '#4e79a7'],
        textprops=font_properties)

# Equal aspect ratio ensures that pie is drawn as a circle
#plt.axis('equal')

# Title for the chart
plt.title('Distribution of Investigation Types',fontname='Trebuchet Ms',fontsize=17)

# Show the pie chart
plt.show()
'''
Accidents comprise 97% of all Investigations done whereas Incidences comprise 3%.
'''
```



Out[173…
```
'\nAccidents comprise 97% of all Investigations done whereas Incidences comprise 3%.\n'
```

In [174…
```
#To categorise accidents per make and model
#Aircraft_make analysis for number of accidents since accidents form 97% of the Inestig
Aircraft_accidents=Clean_aviation_data[Clean_aviation_data['Investigation.Type']=='Acci
Aircraft_Accidents_Makewise=Clean_aviation_data.groupby('Make').size().sort_values(asce
Aircraft_Accidents_Modelwise=Clean_aviation_data.groupby('Model').size().sort_values(as
#Top 10 Airctaft makes and models with high number of accidents
print(f'Top Airctaft Makes with many accidents:\n{Aircraft_Accidents_Makewise.head(10)}
print(f'Top Airctaft Models with many accidents:\n{Aircraft_Accidents_Modelwise.head(10

'''
Aircraft Makes:
CESSNA and PIPER are the most frequently involved in accidents.
BOEING and BELL, while having fewer accidents compared to CESSNA and PIPER, still have

Aircraft Models:
152 and 172 are the most frequently involved models in accidents, reflecting their high
PA-28-140 and 150 also show notable accident rates, which could be linked to their oper

'''
```

```
Top Airctaft Makes with many accidents:
Make
CESSNA      25917
PIPER       14193
BEECH        5067
BELL         2352
BOEING       1494
MOONEY       1294
GRUMMAN      1145
BELLANCA     1040
ROBINSON      924
HUGHES        879
dtype: int64
Top Airctaft Models with many accidents:
Model
152          2362
```

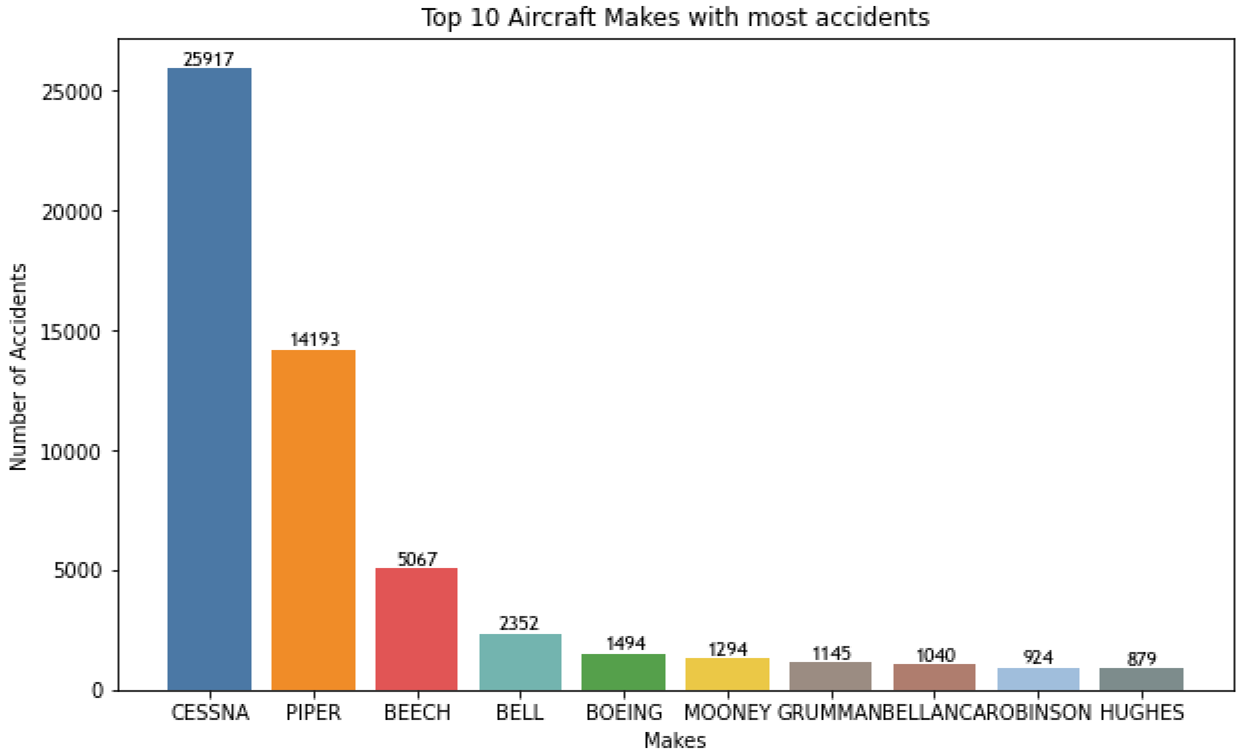
```
172          1639
172N         1139
PA-28-140     911
150           791
172M          776
172P          681
180           617
182           589
150M          579
dtype: int64
```

Out[174…

```
'\nAircraft Makes:\nCESSNA and PIPER are the most frequently involved in accidents.\nBOE
ING and BELL, while having fewer accidents compared to CESSNA and PIPER, still have sign
ificant numbers. \n\nAircraft Models:\n152 and 172 are the most frequently involved mode
ls in accidents, reflecting their high usage.\nPA-28-140 and 150 also show notable accid
ent rates, which could be linked to their operational contexts or frequency of use.\n\n'
```

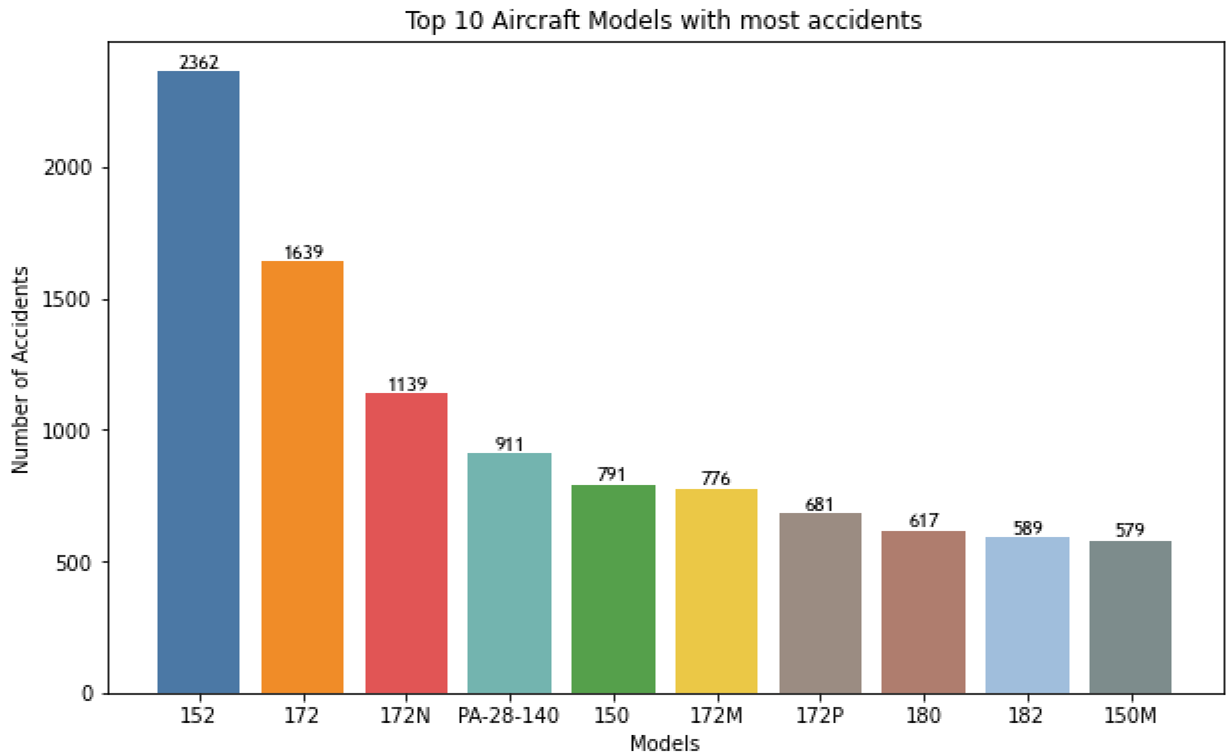
In [175…

```
top_aircraft_count_figure, ax = plt.subplots(figsize=(10, 6))
bar_chart_title = 'Top 10 Aircraft Makes with most accidents'
bar_chart_count_label = 'Number of Accidents'
bar_chart_series_label = 'Makes'
x = Aircraft_Accidents_Makewise.head(10).index
#print (x)
heights = Aircraft_Accidents_Makewise.head(10).values

#ax.bar(x, heights)
# Add data labels on top of the bars
bars=ax.bar(x, heights,color=['#4e79a7', '#f28e2b', '#e15759', '#76b7b2', '#59a14f', '#
          '#9b8d82', '#b07d72', '#a2c2e0', '#7f8c8d'])
for bar in bars:
    height = bar.get_height()
    ax.text(
        bar.get_x() + bar.get_width() / 2,  # X-coordinate: center of the bar
        height,  # Y-coordinate: top of the bar
        f'{height}',  # Text: height of the bar
        ha='center',  # Horizontal alignment: center
        va='bottom',
        fontname='Trebuchet Ms'  # Vertical alignment: just above the bar
    )
# title
ax.set_title(bar_chart_title)
# x-axis label
ax.set_xlabel(bar_chart_series_label)
# y-axis label
ax.set_ylabel(bar_chart_count_label)
# Display the chart
plt.show()
```



In [176…

```
top_aircraft_count_figure, ax = plt.subplots(figsize=(10, 6))
bar_chart_title = 'Top 10 Aircraft Models with most accidents'
bar_chart_count_label = 'Number of Accidents'
bar_chart_series_label = 'Models'
x = Aircraft_Accidents_Modelwise.head(10).index
#print (x)
heights = Aircraft_Accidents_Modelwise.head(10).values

#ax.bar(x, heights)
# Add data labels on top of the bars
bars=ax.bar(x, heights,color=['#4e79a7', '#f28e2b', '#e15759', '#76b7b2', '#59a14f', '#
          '#9b8d82', '#b07d72', '#a2c2e0', '#7f8c8d'])
for bar in bars:
    height = bar.get_height()
    ax.text(
        bar.get_x() + bar.get_width() / 2,  # X-coordinate: center of the bar
        height,  # Y-coordinate: top of the bar
        f'{height}',  # Text: height of the bar
        ha='center',  # Horizontal alignment: center
        va='bottom',
        fontname='Trebuchet Ms'  # Vertical alignment: just above the bar
    )
# title
ax.set_title(bar_chart_title)
# x-axis label
ax.set_xlabel(bar_chart_series_label)
# y-axis label
ax.set_ylabel(bar_chart_count_label)
# Display the chart
plt.show()
```



In [177...

```
#Weather Condition Analysis for Aircraft Accidents
Weather_cond_accidents=Aircraft_accidents.groupby('Weather.Condition').size().sort_valu
print(Weather_cond_accidents)
'''
VMC weather conditions exhibit huge accidents  as compared to IMC and other weather conc
'''
```

```
Weather.Condition
VMC    74090
IMC     5402
UNK      523
Unk       97
dtype: int64
```

Out[177...

```
'\nVMC weather conditions exhibit huge accidents  as compared to IMC and other weather c
ondition categories.\n'
```

In [178...

```
Clean_aviation_data_merged.columns
```

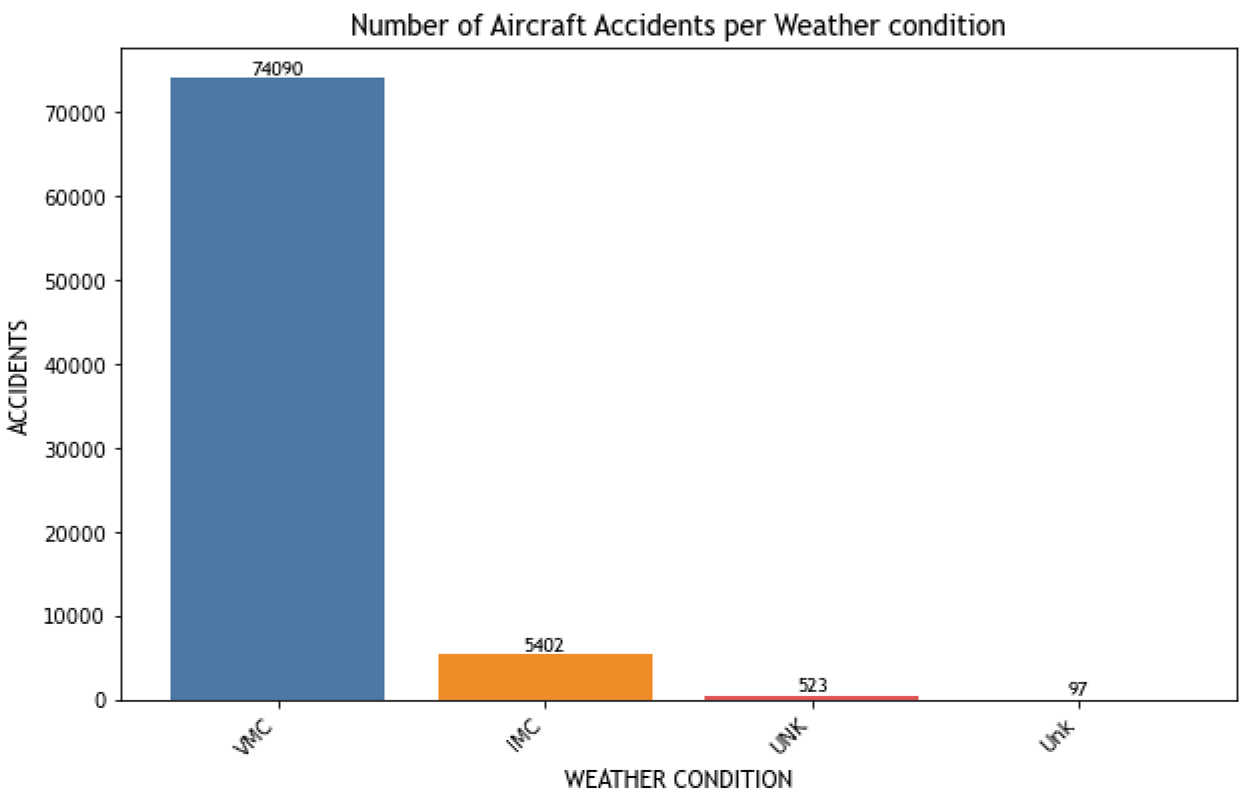
Out[178...

```
Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Date',
       'Location', 'Country', 'Injury.Severity', 'Aircraft.damage', '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',
       'Report.Status', 'Year', 'Location_code', 'US_State', 'Abbreviation'],
      dtype='object')
```

In [179...

```
# Create the bar chart
Weather_cond_figure, ax = plt.subplots(figsize=(10, 6))
x=Weather_cond_accidents.index
heights=Weather_cond_accidents.values

bar_chart_title ='Number of Aircraft Accidents per Weather condition'
bar_chart_count_label = 'ACCIDENTS'
bar_chart_series_label = 'WEATHER CONDITION'

bars=ax.bar(x, heights,color = ['#4e79a7', '#f28e2b', '#e15759', '#76b7b2'])
```

```
for bar in bars:
    height = bar.get_height()
    ax.text(
        bar.get_x() + bar.get_width() / 2,  # X-coordinate: center of the bar
        height,  # Y-coordinate: top of the bar
        f'{height}',  # Text: height of the bar
        ha='center',  # Horizontal alignment: center
        va='bottom',
        fontname='Trebuchet MS'  # Vertical alignment: just above the bar
    )

# Rotate x-axis labels
plt.xticks(rotation=45, ha='right')

# title
ax.set_title(bar_chart_title, fontname='Trebuchet MS',fontsize=14)
# x-axis label
ax.set_xlabel(bar_chart_series_label, fontname='Trebuchet MS',fontsize=12)
# y-axis label
ax.set_ylabel(bar_chart_count_label, fontname='Trebuchet MS', fontsize=12)
# Display the chart
plt.show()
```



In [180…

```
#Location with the highest number of Airctaft Accidents
Accidents_location=Aircraft_accidents.groupby('Location').size().sort_values(ascending=
print(Accidents_location.head(10))
'''
ANCHORAGE, AK experinec majority number of accidents  as compared to  ALBUQUERQUE, NM a
'''
```

```
Location
ANCHORAGE, AK      417
ALBUQUERQUE, NM    192
HOUSTON, TX        174
FAIRBANKS, AK      169
```

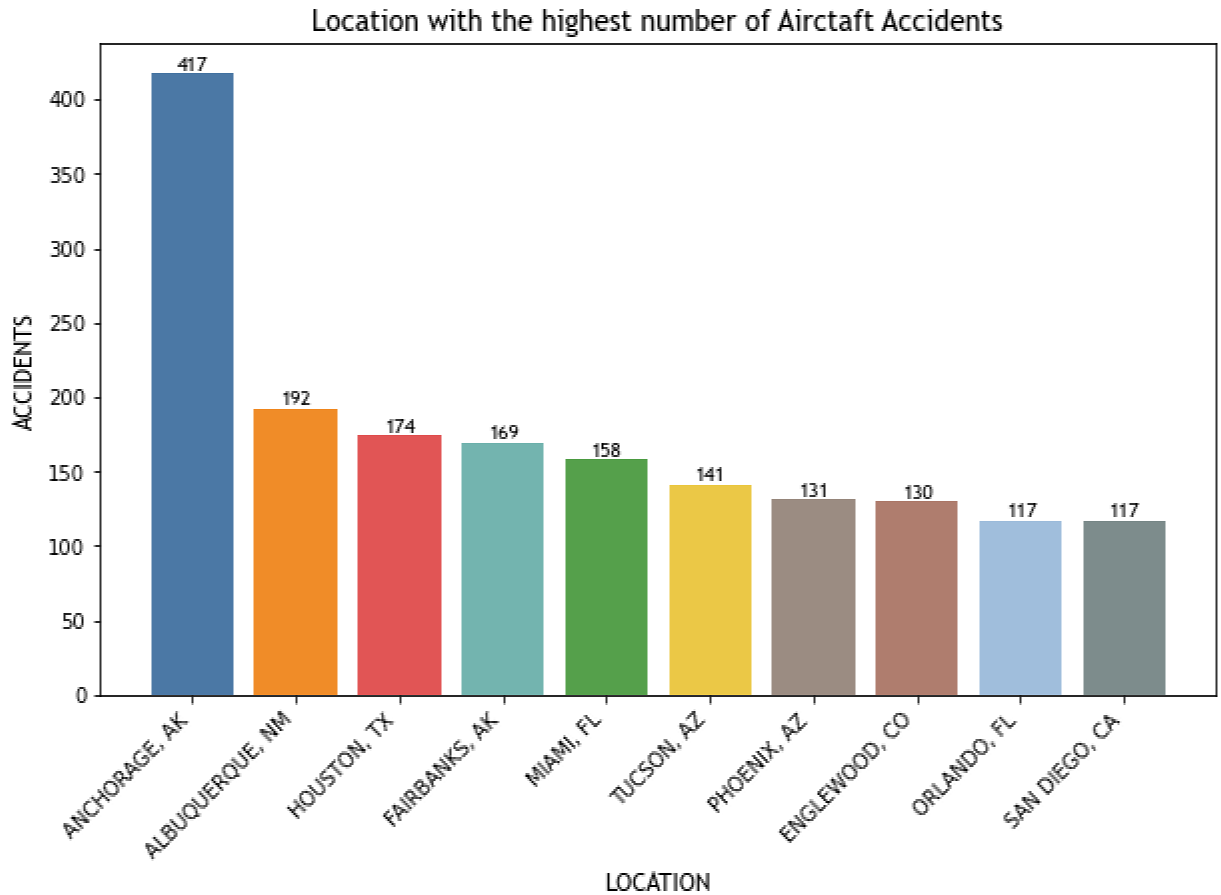
```
MIAMI, FL          158
TUCSON, AZ         141
PHOENIX, AZ        131
ENGLEWOOD, CO      130
ORLANDO, FL        117
SAN DIEGO, CA      117
dtype: int64
```

Out[180…

```
'\nANCHORAGE, AK experinec majority number of accidents  as compared to  ALBUQUERQUE, NM
and other regions.\n'
```

In [181…

```
# Create the bar chart
model_count_figure, ax = plt.subplots(figsize=(10, 6))
x=Accidents_location.index
heights=Accidents_location.values

#bar_chart_locations = ['England', 'Germany', 'Spain', 'France', 'Argentina']

bar_chart_title ='Location with the highest number of Airctaft Accidents'
bar_chart_count_label = 'ACCIDENTS'
bar_chart_series_label = 'LOCATION'

bars=ax.bar(x, heights,color=['#4e79a7', '#f28e2b', '#e15759', '#76b7b2', '#59a14f', '#
          '#9b8d82', '#b07d72', '#a2c2e0', '#7f8c8d'])
for bar in bars:
    height = bar.get_height()
    ax.text(
        bar.get_x() + bar.get_width() / 2,  # X-coordinate: center of the bar
        height,  # Y-coordinate: top of the bar
        f'{height}',  # Text: height of the bar
        ha='center',  # Horizontal alignment: center
        va='bottom',
        fontname='Trebuchet MS'  # Vertical alignment: just above the bar
    )

# Rotate x-axis labels
plt.xticks(rotation=45, ha='right')

# title
ax.set_title(bar_chart_title, fontname='Trebuchet MS',fontsize=14)
# x-axis label
ax.set_xlabel(bar_chart_series_label, fontname='Trebuchet MS',fontsize=12)
# y-axis label
ax.set_ylabel(bar_chart_count_label, fontname='Trebuchet MS', fontsize=12)
# Display the chart
plt.show()
```



In [182…

```
#Purpose of flight analysis
Accidents_by_purpose_of_flight=Clean_aviation_data_merged['Purpose.of.flight'].value_co
#Top 10 flight purpose by Accidents
top_10_purpose_by_accidents=Accidents_by_purpose_of_flight.head(10)
print(top_10_purpose_by_accidents)
'''
Aircrafts used for Personal reasons experienced a huge number of accidents i.e. 51,035 a
used for business purpose which experienced 3,856 accidents
'''
```

```
Personal              51035
Instructional         10440
Unknown                5839
Aerial Application     4627
Business               3856
Positioning            1584
Other Work Use         1197
Ferry                   733
Aerial Observation      714
Public Aircraft         687
Name: Purpose.of.flight, dtype: int64
```

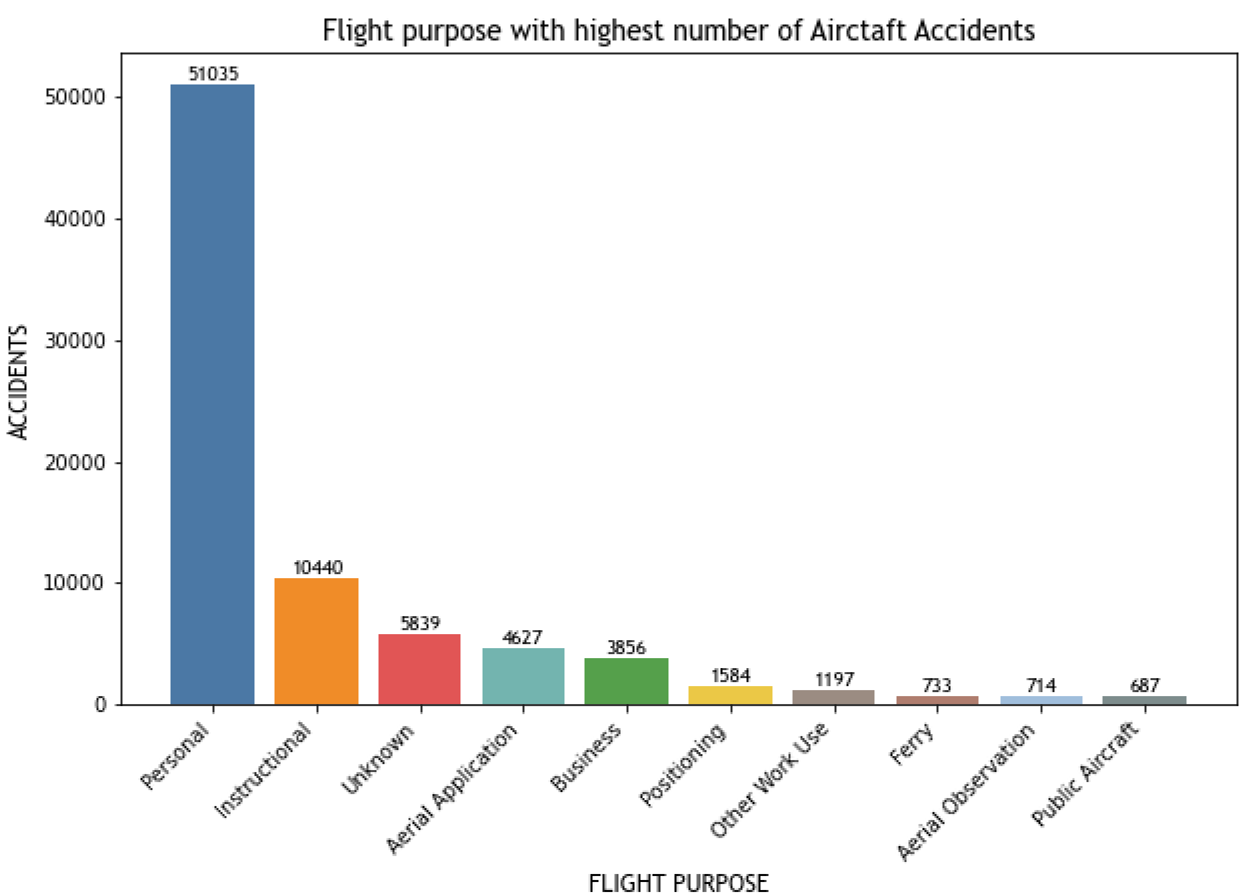
Out[182…

```
'\nAircrafts used for Personal reasons experienced a huge number of accidents i.e. 51,03
5 as compared to those\nused for business purpose which experienced 3,856 accidents\n'
```

In [183…

```
flight_purpose_count_figure, ax = plt.subplots(figsize=(10, 6),)
Flight_purpose=Clean_aviation_data_merged
x=top_10_purpose_by_accidents.index
heights=top_10_purpose_by_accidents.values
bar_chart_title ='Flight purpose with highest number of Airctaft Accidents'
bar_chart_count_label = 'ACCIDENTS'
bar_chart_series_label = 'FLIGHT PURPOSE'
```

```
bars=ax.bar(x, heights,color=['#4e79a7', '#f28e2b', '#e15759', '#76b7b2', '#59a14f', '#
          '#9b8d82', '#b07d72', '#a2c2e0', '#7f8c8d'])
for bar in bars:
    height = bar.get_height()
    ax.text(
        bar.get_x() + bar.get_width() / 2,  # X-coordinate: center of the bar
        height,  # Y-coordinate: top of the bar
        f'{height}',  # Text: height of the bar
        ha='center',  # Horizontal alignment: center
        va='bottom',
        fontname='Trebuchet MS'  # Vertical alignment: just above the bar
    )

# Rotate x-axis labels
plt.xticks(rotation=45, ha='right')

# title
ax.set_title(bar_chart_title, fontname='Trebuchet MS',fontsize=14)
# x-axis label
ax.set_xlabel(bar_chart_series_label, fontname='Trebuchet MS',fontsize=12)
# y-axis label
ax.set_ylabel(bar_chart_count_label, fontname='Trebuchet MS', fontsize=12)
# Display the chart
plt.show()
```



In [184…

```
# Analyzing engine types
Engine_types = Clean_aviation_data_merged['Engine.Type'].value_counts()
print(Engine_types)

'''
```

```
Analysis of Engine Types:

Reciprocating engines dominate the dataset, accounting for the vast majority of cases w
This suggests that reciprocating engines are the most commonly used type of engine in t
Other engine types such as Turbo Shaft, Turbo Prop, and Turbo Fan appear significantly
Here is the breakdown of the engine types:
1. **Reciprocating**: 71,646
2. **Turbo Shaft**: 3,416
3. **Turbo Prop**: 3,217
4. **Turbo Fan**: 2,101
5. **Unknown**: 1,390
6. **Turbo Jet**: 669

The dominance of reciprocating engines could imply that smaller, general aviation aircr
'''
```

```
Reciprocating    71646
Turbo Shaft       3416
Turbo Prop        3217
Turbo Fan         2101
Unknown           1411
Turbo Jet          669
Electric            10
LR                   2
Hybrid Rocket        1
UNK                  1
Name: Engine.Type, dtype: int64
```

Out[184…

```
'\nAnalysis of Engine Types:\n\nReciprocating engines dominate the dataset, accounting f
or the vast majority of cases with 71,646 entries. \nThis suggests that reciprocating en
gines are the most commonly used type of engine in the analyzed aircraft accidents.\nOth
er engine types such as Turbo Shaft, Turbo Prop, and Turbo Fan appear significantly less
frequently in the data.\nHere is the breakdown of the engine types:\n1. **Reciprocating*
*: 71,646\n2. **Turbo Shaft**: 3,416\n3. **Turbo Prop**: 3,217\n4. **Turbo Fan**: 2,101
\n5. **Unknown**: 1,390\n6. **Turbo Jet**: 669\n\nThe dominance of reciprocating engines
could imply that smaller, general aviation aircraft (which commonly use these engines) a
re more prone to accidents, or simply more prevalent in the dataset.\n'
```

In [185…

```
#analysis of number of accidents by engine type.
accidents_only=Clean_aviation_data_merged[Clean_aviation_data_merged['Investigation.Typ
#count the number of accidents by engine type
accidents_by_engine_type=accidents_only['Engine.Type'].value_counts()
print(accidents_by_engine_type.reset_index())

'''
Reciprocating engines are involved in the overwhelming majority of accidents, with 70,9
while other engine types such as Turbo Shaft and
Turbo Prop contribute to a much smaller number of accidents.
'''
```

```
           index  Engine.Type
0  Reciprocating        70920
1    Turbo Shaft         3309
2     Turbo Prop         2816
3        Unknown         1380
4      Turbo Fan         1237
5      Turbo Jet          437
6       Electric            9
7             LR            2
8            UNK            1
9  Hybrid Rocket            1
```

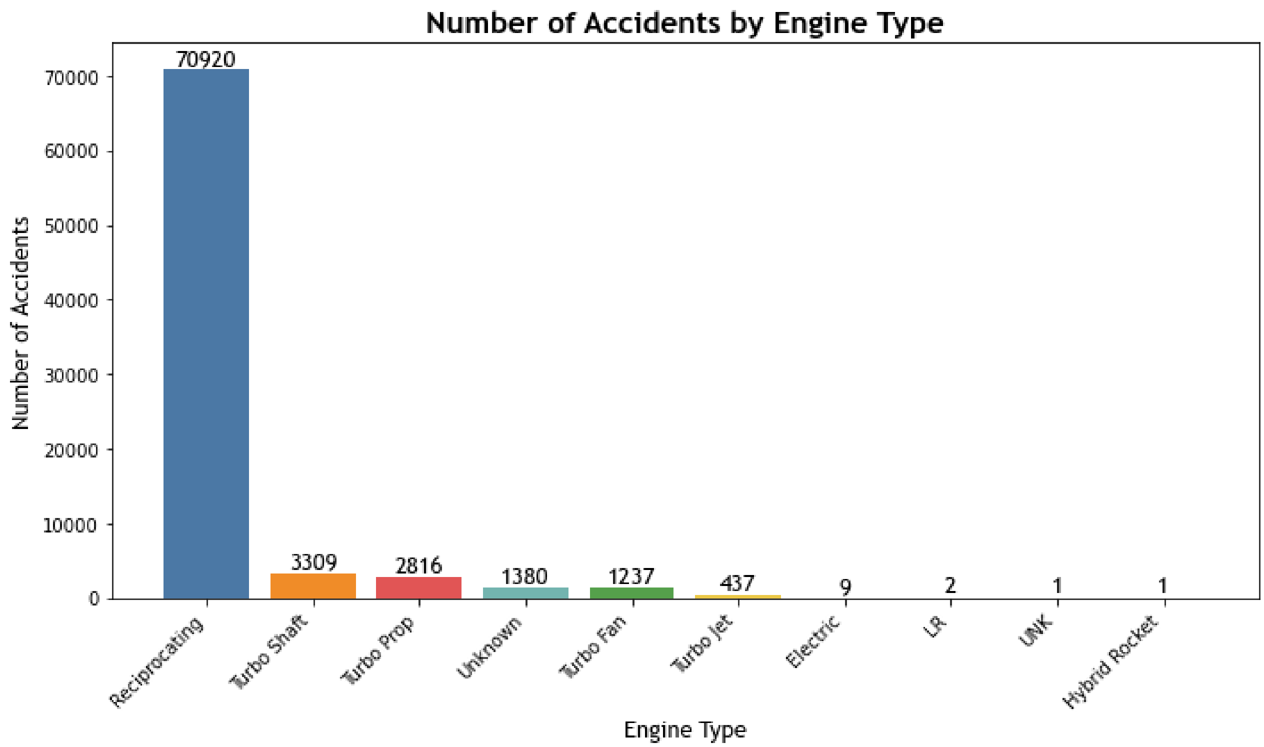
Out[185…

```
'\nReciprocating engines are involved in the overwhelming majority of accidents, with 7
0,920 incidents,\nwhile other engine types such as Turbo Shaft and \nTurbo Prop contribu
```

```
te to a much smaller number of accidents.\n'
```

In [186…

```
# Plotting the data
fig, ax = plt.subplots(figsize=(10, 6))  # Set the figure size
x=accidents_by_engine_type.index
heights=accidents_by_engine_type.values
bars = ax.bar(x,heights,color=['#4e79a7', '#f28e2b', '#e15759', '#76b7b2', '#59a14f', '

# Rotating x-axis labels for better readability
ax.set_xticks(x)  # Set x-ticks to match the x values
ax.set_xticklabels(x, rotation=45, ha='right')

# Adding value labels on the bars
for bar in bars:
    height = bar.get_height()
    ax.text(bar.get_x() + bar.get_width() / 2, height,
            f'{int(height)}', ha='center', va='bottom', fontsize=13, fontname='Trebuche

# Adding title and labels
ax.set_title('Number of Accidents by Engine Type', fontname='Trebuchet Ms',fontsize=17,
ax.set_xlabel('Engine Type', fontsize=13,fontname='Trebuchet Ms')
ax.set_ylabel('Number of Accidents', fontsize=13,fontname='Trebuchet Ms')
# Show the plot
plt.tight_layout()
plt.show()
```



In [187…

```
#count of accident over the years
# Filter the data for accidents only
accidents_only = Clean_aviation_data_merged[Clean_aviation_data_merged['Investigation.T


# Create the pivot table to count accidents per year
Accidents_trend = pd.pivot_table(
    accidents_only,
    index='Year',
    values='Investigation.Type',  # Counts the number of rows, which corresponds to acc
```

```
    aggfunc=np.size
).reset_index()
print(Accidents_trend)
'''
Year 1982 experinced the highest number of accidents
The number of accidents post year 1983 is on a downward trend
Recent 10 years have experineced generally less number of accidents compared to previou
'''
```

```
    Year  Investigation.Type
0   1948                   1
1   1962                   1
2   1974                   1
3   1977                   1
4   1979                   2
5   1981                   1
6   1982                3455
7   1983                3409
8   1984                3306
9   1985                2983
10  1986                2769
11  1987                2680
12  1988                2547
13  1989                2421
14  1990                2416
15  1991                2361
16  1992                2243
17  1993                2180
18  1994                2144
19  1995                2163
20  1996                2055
21  1997                1977
22  1998                2038
23  1999                2040
24  2000                1990
25  2001                1860
26  2002                1834
27  2003                1892
28  2004                1738
29  2005                1804
30  2006                1613
31  2007                1763
32  2008                1642
33  2009                1549
34  2010                1496
35  2011                1551
36  2012                1533
37  2013                1282
38  2014                1281
39  2015                1289
40  2016                1317
41  2017                1311
42  2018                1336
43  2019                1296
44  2020                1131
45  2021                1173
46  2022                1237
```

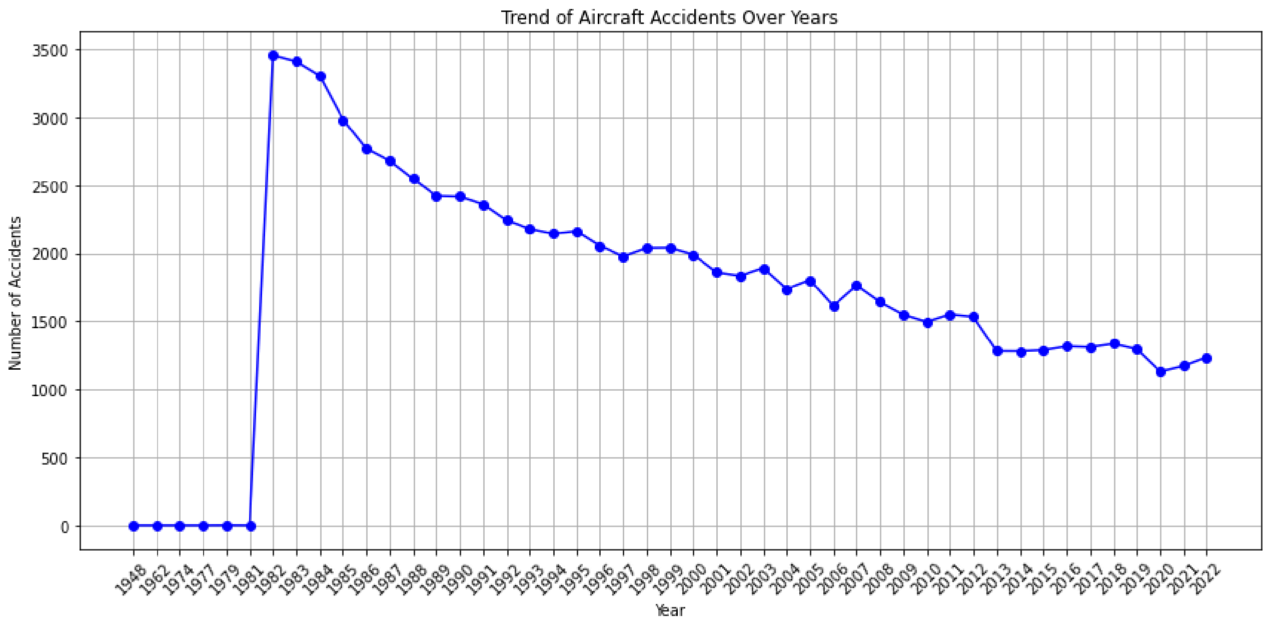
Out[187…

```
'\nYear 1982 experinced the highest number of accidents\nThe number of accidents post ye
ar 1983 is on a downward trend\nRecent 10 years have experineced generally less number o
f accidents compared to previous periods\n'
```

In [188…

```
#representation of the above in a trend line graph
# Plotting the trend line graph
plt.figure(figsize=(12, 6))
```

```
plt.plot(Accidents_trend['Year'], Accidents_trend['Investigation.Type'], marker='o', li
plt.title('Trend of Aircraft Accidents Over Years')
plt.xlabel('Year')
plt.ylabel('Number of Accidents')
plt.grid(True)
plt.xticks(rotation=45)  # Rotate x-axis labels if needed for better readability
plt.tight_layout()
plt.show()
```



In [189…

```
#count of injuries over the years
count_of_injuries=pd.pivot_table(Clean_aviation_data_merged,index='Year',values=['Total
                                                                                  'Total

count_of_injuries
```

Out[189…

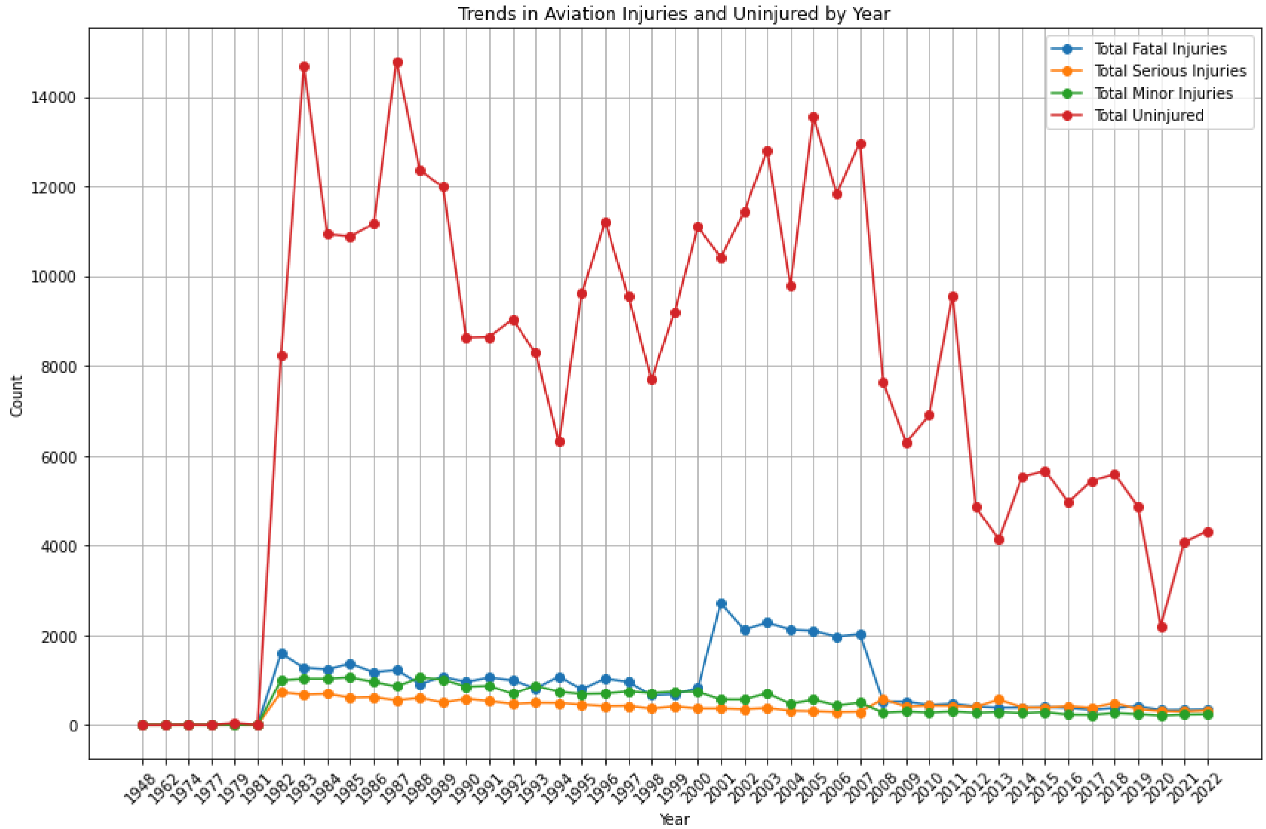
	Total.Fatal.Injuries	Total.Minor.Injuries	Total.Serious.Injuries	Total.Uninjured
Year				
1948	2.0	0.0	0.0	0.0
1962	4.0	0.0	0.0	0.0
1974	3.0	0.0	0.0	5.0
1977	2.0	0.0	0.0	0.0
1979	2.0	1.0	2.0	44.0
1981	4.0	0.0	0.0	0.0
1982	1586.0	994.0	723.0	8227.0
1983	1274.0	1029.0	672.0	14665.0
1984	1237.0	1029.0	689.0	10935.0
1985	1363.0	1058.0	605.0	10883.0
1986	1172.0	957.0	616.0	11169.0
1987	1223.0	856.0	544.0	14788.0
1988	912.0	1053.0	601.0	12358.0

	Total.Fatal.Injuries	Total.Minor.Injuries	Total.Serious.Injuries	Total.Uninjured
Year				
1989	1071.0	1013.0	498.0	11994.0
1990	957.0	850.0	579.0	8633.0
1991	1055.0	869.0	530.0	8646.0
1992	994.0	689.0	466.0	9038.0
1993	815.0	872.0	490.0	8289.0
1994	1076.0	737.0	486.0	6306.0
1995	795.0	685.0	452.0	9629.0
1996	1034.0	695.0	416.0	11218.0
1997	959.0	745.0	422.0	9562.0
1998	659.0	709.0	362.0	7700.0
1999	679.0	739.0	412.0	9192.0
2000	821.0	735.0	364.0	11097.0
2001	2705.0	564.0	364.0	10424.0
2002	2121.0	562.0	347.0	11435.0
2003	2277.0	702.0	375.0	12794.0
2004	2124.0	466.0	315.0	9790.0
2005	2097.0	560.0	304.0	13545.0
2006	1967.0	429.0	284.0	11830.0
2007	2026.0	493.0	291.0	12975.0
2008	519.0	272.0	572.0	7657.0
2009	515.0	296.0	405.0	6296.0
2010	443.0	272.0	426.0	6910.0
2011	470.0	298.0	420.0	9565.0
2012	407.0	269.0	395.0	4862.0
2013	383.0	287.0	560.0	4132.0
2014	385.0	262.0	390.0	5528.0
2015	397.0	285.0	383.0	5668.0
2016	378.0	227.0	416.0	4956.0
2017	333.0	222.0	377.0	5437.0
2018	377.0	266.0	487.0	5595.0
2019	412.0	239.0	350.0	4871.0
2020	330.0	207.0	305.0	2207.0
2021	336.0	228.0	297.0	4068.0

	Total.Fatal.Injuries	Total.Minor.Injuries	Total.Serious.Injuries	Total.Uninjured
Year				
2022	343.0	236.0	322.0	4320.0

In [190…

```
# Plotting
plt.figure(figsize=(12, 8))

# Plot for Total Fatal Injuries
plt.plot(count_of_injuries.index, count_of_injuries['Total.Fatal.Injuries'], label='Tot

# Plot for Total Serious Injuries
plt.plot(count_of_injuries.index, count_of_injuries['Total.Serious.Injuries'], label='T

# Plot for Total Minor Injuries
plt.plot(count_of_injuries.index, count_of_injuries['Total.Minor.Injuries'], label='Tot

# Plot for Total Uninjured
plt.plot(count_of_injuries.index, count_of_injuries['Total.Uninjured'], label='Total Un

# Adding labels and title
plt.xlabel('Year')
plt.ylabel('Count')
plt.title('Trends in Aviation Injuries and Uninjured by Year')
plt.legend()
plt.grid(True)
plt.xticks(rotation=45)  # Rotate year labels for better readability

# Show the plot
plt.tight_layout()
plt.show()
''''
The number of Total uninjured has significantly fallen over the years and is on a donwa
The number of Total fatal injuries has significantly fallen over the years and is on a 
The number of Total minor injuries has significantly fallen over the years and is on a 
 The number of Total serious injuries has significantly fallen over the years and is on
'''
```



Out[190…

```
"'\nThe number of Total uninjured has significantly fallen over the years and is on a do
nward trend over the last 10 years\nThe number of Total fatal injuries has significantly
fallen over the years and is on a donwatd trend over the last 10 years\nThe number of To
tal minor injuries has significantly fallen over the years and is on a donwatd trend ove
r the last 10 years\n The number of Total serious injuries has significantly fallen over
the years and is on a donwatd trend over the last 10 years\n"
```

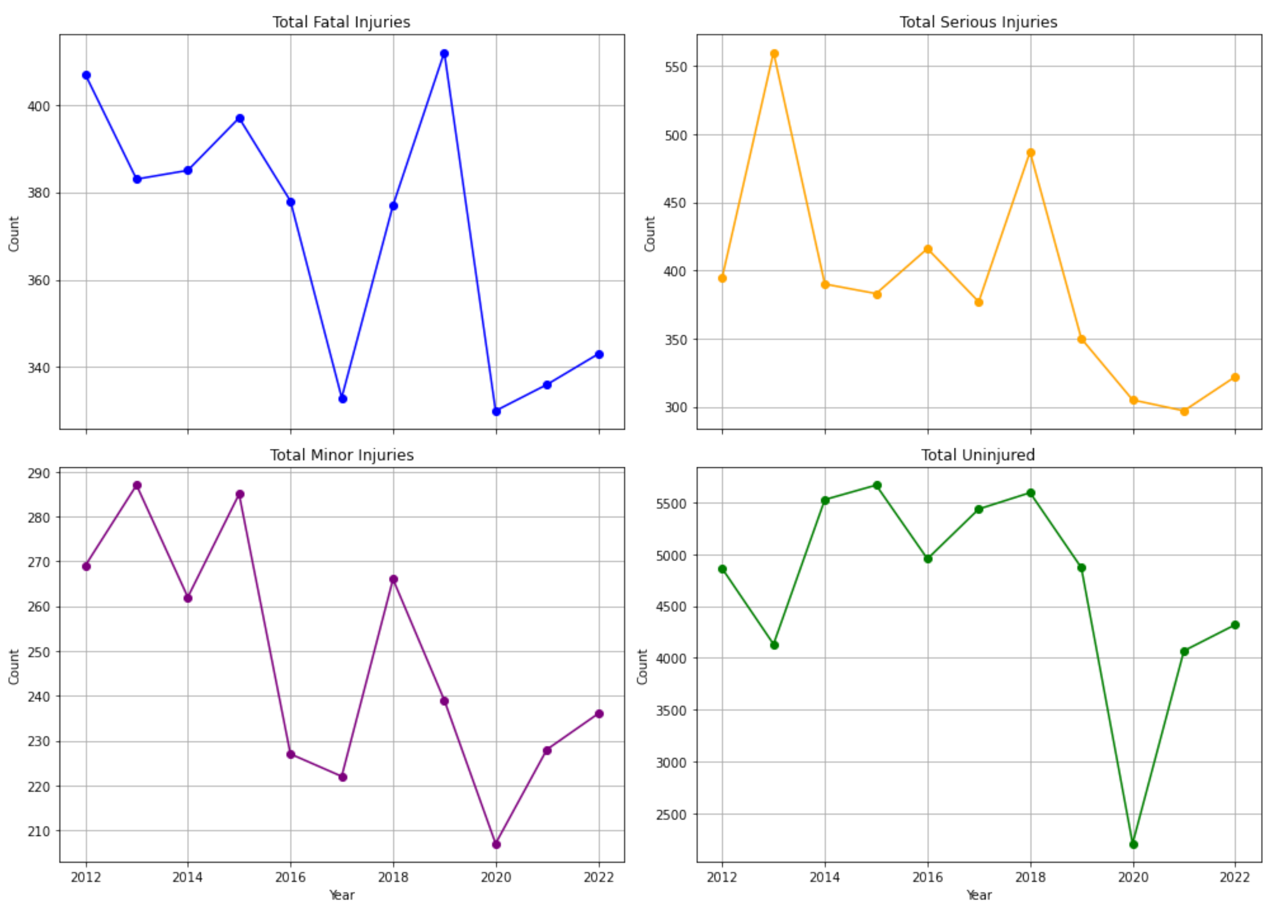
In [191…

```python
# Convert the 'Year' column to integers
Clean_aviation_data_merged['Year'] = pd.to_numeric(Clean_aviation_data_merged['Year'],

# Find the most recent year in the dataset
latest_year = Clean_aviation_data_merged['Year'].max()

# Calculate the start year for the last 10 years
start_year = int(latest_year) - 10

# Filter data for the last 10 years
filtered_data = Clean_aviation_data_merged[Clean_aviation_data_merged['Year'] >= start_

# Create the pivot table for the filtered data
count_of_injuries_last_10_yrs= pd.pivot_table(filtered_data,
                                  index='Year',
                                  values=['Total.Fatal.Injuries', 'Total.Serious.Injur
                                          'Total.Minor.Injuries', 'Total.Uninjured'],
                                  aggfunc=np.sum)
```

In [192…

```python
# Recent Trend analysis of Type of injuries over the last 10 years
# Set up the figure and axes for a 2x2 grid of subplots
fig, axes = plt.subplots(2, 2, figsize=(14, 10), sharex=True)

# Plot for Total Fatal Injuries for the last 10 years
axes[0, 0].plot(count_of_injuries_last_10_yrs.index, count_of_injuries_last_10_yrs['Tot
axes[0, 0].set_title('Total Fatal Injuries')
```

```
axes[0, 0].set_ylabel('Count')
axes[0, 0].grid(True)

# Plot for Total Serious Injuries
axes[0, 1].plot(count_of_injuries_last_10_yrs.index, count_of_injuries_last_10_yrs['Tot
axes[0, 1].set_title('Total Serious Injuries')
axes[0, 1].set_ylabel('Count')
axes[0, 1].grid(True)

# Plot for Total Minor Injuries
axes[1, 0].plot(count_of_injuries_last_10_yrs.index, count_of_injuries_last_10_yrs['Tot
axes[1, 0].set_title('Total Minor Injuries')
axes[1, 0].set_ylabel('Count')
axes[1, 0].set_xlabel('Year')
axes[1, 0].grid(True)

# Plot for Total Uninjured
axes[1, 1].plot(count_of_injuries_last_10_yrs.index, count_of_injuries_last_10_yrs['Tot
axes[1, 1].set_title('Total Uninjured')
axes[1, 1].set_ylabel('Count')
axes[1, 1].set_xlabel('Year')
axes[1, 1].grid(True)

# Adjust layout
plt.tight_layout()

# Show the plot
plt.show()
```



In [193…

```
# Analysis of number of accidents by number of engines Number.of.Engines,  Engine.Type
Accidents_by_engines=pd.pivot_table(Clean_aviation_data_merged,index='Number.of.Engines
```

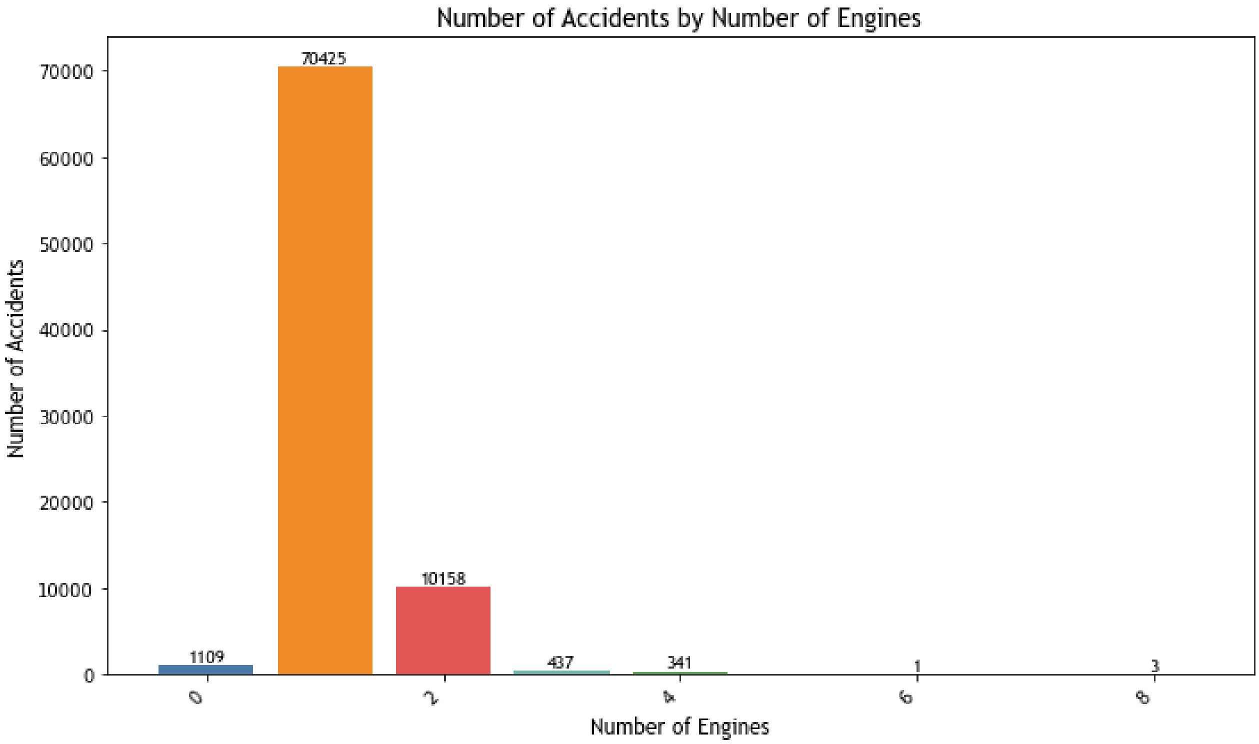
```
Accidents_by_engines
'''
Aircrafts with 1 engine experinced huge number of accidents i.e., 70,425 as compared wi
'''
```

Out[193…

```
'\nAircrafts with 1 engine experinced huge number of accidents i.e., 70,425 as compared with those with 2 engine i.e., 10,158 accidents.\n'
```

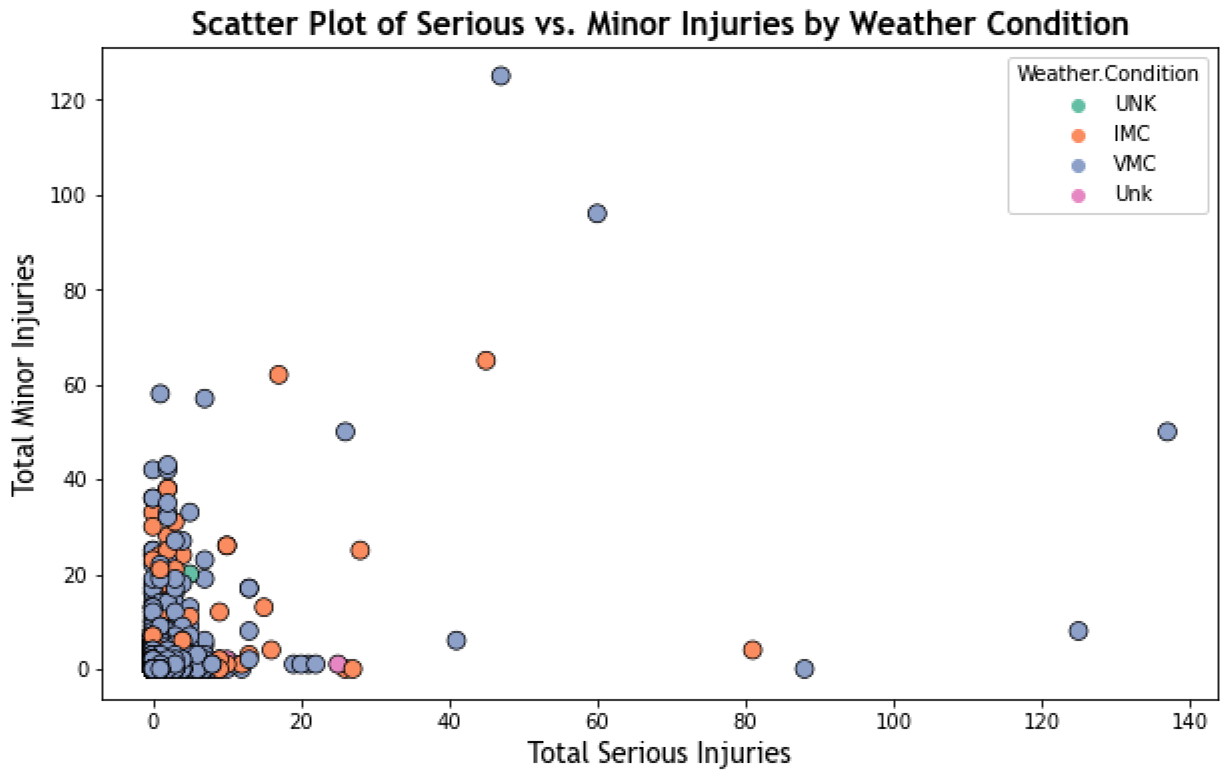
In [194…

```
# Define the data for plotting
x = Accidents_by_engines['Number.of.Engines']
heights = Accidents_by_engines['Investigation.Type']

# Create the figure and axis for the plot
fig, ax = plt.subplots(figsize=(10, 6))

# Create the bar chart
bars = ax.bar(x, heights, color=['#4e79a7', '#f28e2b', '#e15759', '#76b7b2', '#59a14f',
          '#9b8d82', '#b07d72', '#a2c2e0', '#7f8c8d'])

# Add labels to the bars
for bar in bars:
    height = bar.get_height()
    ax.text(
        bar.get_x() + bar.get_width() / 2,  # X-coordinate: center of the bar
        height,  # Y-coordinate: top of the bar
        f'{height}',  # Text: height of the bar
        ha='center',  # Horizontal alignment: center
        va='bottom',  # Vertical alignment: just above the bar
        fontname='Trebuchet MS'
    )

# Rotate x-axis labels
plt.xticks(rotation=45, ha='right')

# Set the title and labels
bar_chart_title = 'Number of Accidents by Number of Engines'
bar_chart_count_label = 'Number of Accidents'
bar_chart_series_label = 'Number of Engines'

ax.set_title(bar_chart_title, fontname='Trebuchet MS', fontsize=14)
ax.set_xlabel(bar_chart_series_label, fontname='Trebuchet MS', fontsize=12)
ax.set_ylabel(bar_chart_count_label, fontname='Trebuchet MS', fontsize=12)

# Display the chart
plt.tight_layout()
plt.show()
```



In [195…

```
#Scatter Plot of Serious vs. Minor Injuries by Weather Condition'
plt.figure(figsize=(10, 6))  # Adjust the figure size for better visualization
sns.scatterplot(x=Clean_aviation_data_merged['Total.Serious.Injuries'],
                y=Clean_aviation_data_merged['Total.Minor.Injuries'],
                hue=Clean_aviation_data_merged['Weather.Condition'],
                palette='Set2',  # A softer color palette for better distinction
                s=80,  # Increase marker size
                edgecolor='black')  # Add edge color for better marker visibility

# Adding labels and title
plt.title('Scatter Plot of Serious vs. Minor Injuries by Weather Condition', fontsize=1
plt.xlabel('Total Serious Injuries', fontsize=14, fontname='Trebuchet Ms')
plt.ylabel('Total Minor Injuries', fontsize=14,fontname='Trebuchet Ms')

# Show plot
plt.show()

'''
Most accidents seem to result in fewer than 20 serious injuries and fewer than 40 minor
The data is highly concentrated in this lower range, indicating that many accidents inv

Accidents under VMC (green) and IMC (orange) are scattered throughout, but both types o
range of outcomes. However, VMC accidents appear more frequently, which may imply more 

A few outliers can be observed where accidents involve more than 40 serious or minor in
'''
```

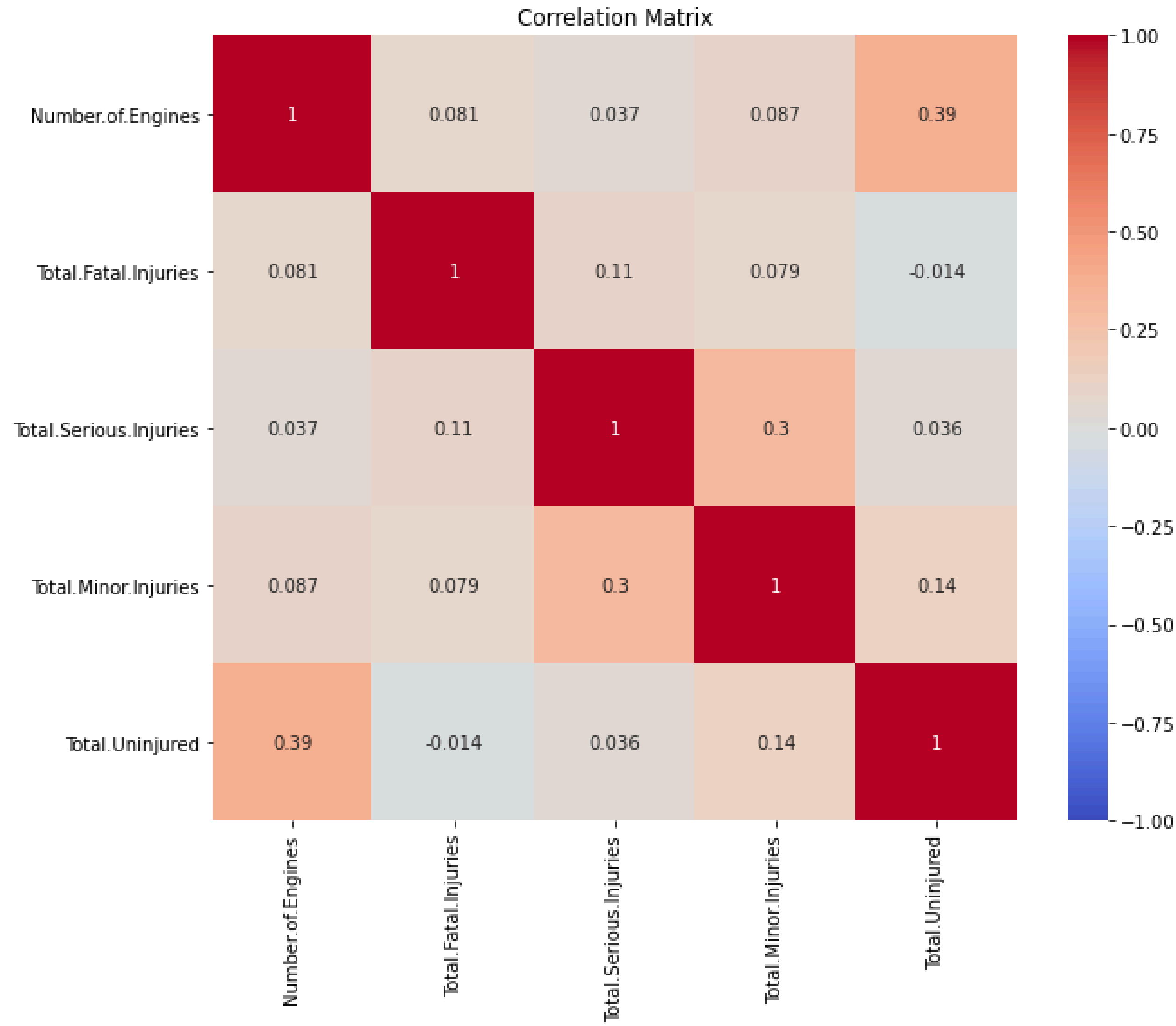


Out[195…

```
'\nMost accidents seem to result in fewer than 20 serious injuries and fewer than 40 min
or injuries. \nThe data is highly concentrated in this lower range, indicating that many
accidents involve a relatively small number of injuries.\n\nAccidents under VMC (green)
and IMC (orange) are scattered throughout, but both types of weather conditions have a w
ide \nrange of outcomes. However, VMC accidents appear more frequently, which may imply
more accidents happen under clear weather (or visually navigable conditions).\n\nA few o
utliers can be observed where accidents involve more than 40 serious or minor injuries.
These could represent catastrophic accidents with higher injury counts.\n'
```

In [196…

```
#Correlation matrix for numerical values
numerical_data = Clean_aviation_data_merged.select_dtypes(include='number').drop(column
# Generate the correlation matrix
correlation_matrix = numerical_data.corr()
# Create a heatmap of the correlation matrix
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Correlation Matrix')
plt.show()

'''
Positive Correlations:
Number of Engines and Total Uninjured (0.39): Indicates that as the number of engines i
positive correlation with the number of uninjured individuals. Aircraft with more engin
Total Serious Injuries and Total Minor Injuries (0.30): This shows a moderate correlati
Weak Correlations:
Most other variables, such as Total Fatal Injuries with other injury categories, have w
'''
```

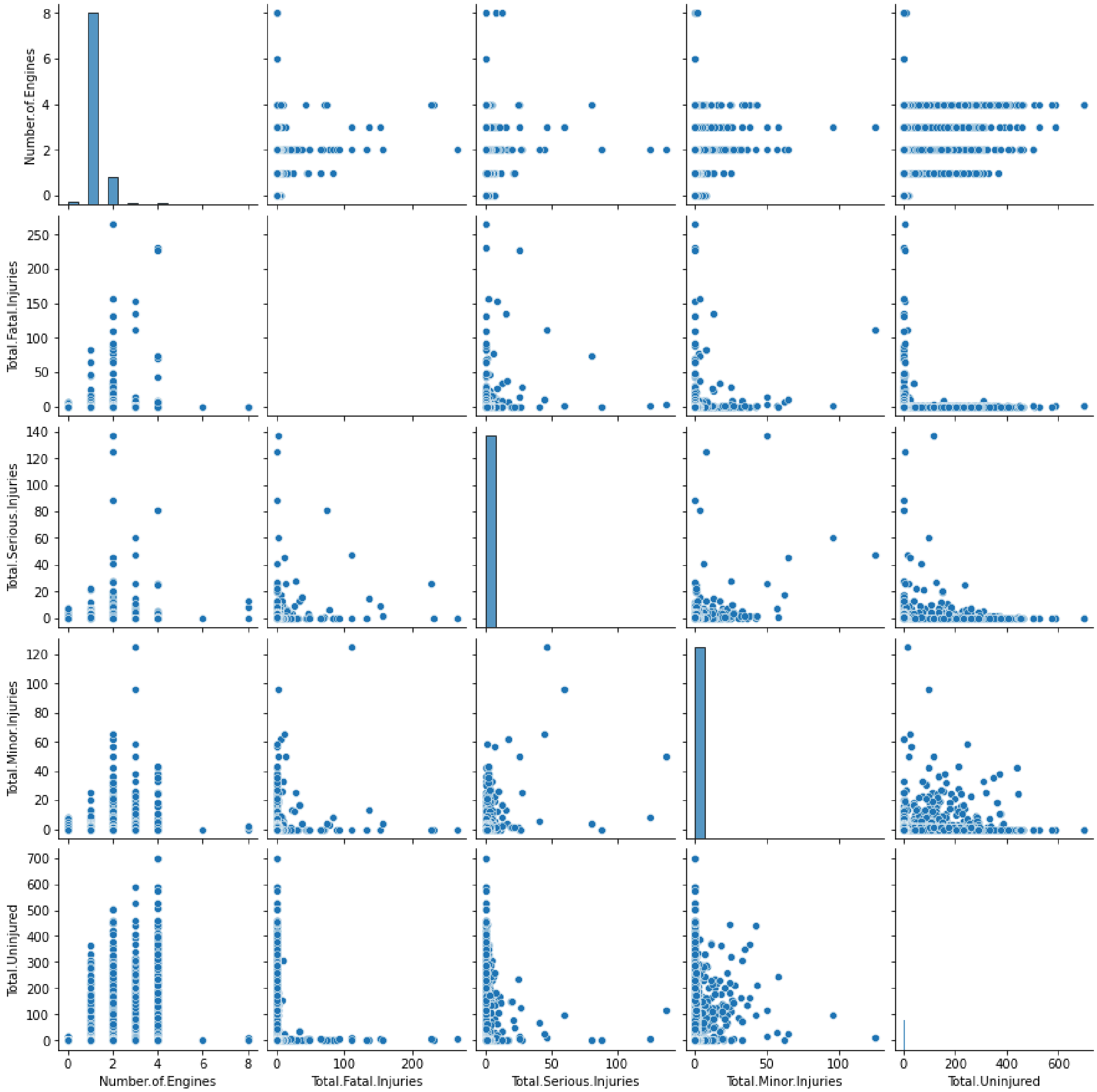


Out[196…

```
'\nPositive Correlations:\nNumber of Engines and Total Uninjured (0.39): Indicates that
as the number of engines increases, there is a moderate \npositive correlation with the
number of uninjured individuals. Aircraft with more engines may provide better safety in
accidents, leading to more survivors.\nTotal Serious Injuries and Total Minor Injuries
(0.30): This shows a moderate correlation, meaning that accidents with a higher number o
f serious injuries tend to also involve more minor injuries.\nWeak Correlations:\nMost o
ther variables, such as Total Fatal Injuries with other injury categories, have weak pos
itive correlations (close to 0). This suggests that while there is some relationship, i
t’s very weak or no relationship.\n'
```

In [197…

```python
# Represnettaion of the above findings in a graph
# scatter plots to show the relationships
numerical_data = Clean_aviation_data_merged.select_dtypes(include='number').drop(column

# Create scatter plots for each pair of numerical variables
sns.pairplot(numerical_data)

# Display the plot
plt.show()
```



4.0 CONCLUSION

Based on our analysis, we conclude as follows:

- **Number of engines:** Aircrafts with 1 engine are involved in the vast majority of accidents. Aircraft with 2 engines show a significantly lower number of accident investigations compared to single-engine aircraft, likely because dual-engine setups provide redundancy in case of engine failure, lowering the risk.
- **Weather conditions:** The vast majority of accidents occur under VMC, likely because these conditions are far more common than IMC (Instrument Meteorological Conditions).
- **Location:** Anchorage, Alaska, has the highest number of recorded aircraft accidents. Other locations such as Albuquerque,Houston,Miami experinec relatively low number of accidents as compared to Ancholarge AK.

- **Flight purpose:** The overwhelming majority of accidents are associated with personal flights. This may be due to the higher volume of personal flights compared to other categories.Business flights, which are typically more organized and may involve more professional pilots, have fewer accidents compared to personal flights. This suggests that these flights are generally safer due to more stringent operational and maintenance practices.
- **Trend aalysis for number of accidents across the years:** Year 1982 recorded the highest number of accidents. After the initial spike, the number of accidents seems to generally decrease over time. This could indicate improvements in safety or changes in reporting standards. Recent Years(i.e. past 10 years): The number of accidents in recent years (2012-2022) appears to be lower compared to earlier years, suggesting a positive trend in reducing accidents.
- **Aircraft Makes and Models:** CESSNA and PIPER are the most frequently involved in accidents, which could be due to their high number of flights or other factors. BOEING and BELL, while having fewer accidents compared to CESSNA and PIPER, still have significant numbers, likely due to their widespread use in commercial aviation.

152 and 172 are the most frequently involved models in accidents, reflecting their high usage and possibly their operational profiles. PA-28-140 and 150 also show notable accident rates, which could be linked to their operational contexts or frequency of use.

- **Injury types:** Fatal injuries have generally decreased, while the number of minor and serious injuries shows varying patterns. The number of uninjured individuals also fluctuates, which may reflect changes in the number of accidents or improvements in safety measures. Notably, the total number of injuries and uninjured individuals has shown a decreasing trend in recent years, suggesting overall improvements in aviation safety.
- **correlation analysis:** Number of Engines shows a moderate positive correlation with the number of uninjured individuals, suggesting that aircraft with more engines tend to have a higher number of uninjured passengers. Other correlations involving the number of engines are weak. Total Fatal Injuries has weak positive correlations with serious and minor injuries, indicating some association but not a strong one. Total Serious Injuries has a moderate positive correlation with minor injuries, suggesting that more serious injuries are somewhat associated with more minor injuries. Overall, the relationships among these variables are generally weak, with a notable moderate correlation between serious and minor injuries.

5.0 Rcommendations

1. **Number of Engines:** Opt for aircraft with at least 2 engines. Dual-engine aircraft generally have lower accident rates due to redundancy in case of engine failure.
2. **Weather Considerations:** While accidents are more frequent under VMC (Visual Meteorological Conditions), ensure the aircraft is equipped to handle a range of weather conditions, including IMC (Instrument Meteorological Conditions), for added safety.
3. **Location:** Consider operational history and risk factors of specific regions. Aircraft based in or frequently flying to high-accident locations like Anchorage, Alaska, may face higher risks. The business can consider other routes other thanAnchorage, Alaska.

4. **Flight Purpose:** Prioritize aircraft used primarily for business or professional purposes over those used for personal flights, as business flights typically have lower accident rates due to stricter operational standards.
5. **Avoid High-Accident Makes:** The top makes with the highest number of accidents are: CESSNA: 27,212 accidents PIPER: 14,870 accidents BEECH: 5,372 accidents If safety is a primary concern, you might consider aircraft from makes with fewer accidents. Makes with fewer accidents such as MOONEY (1,334) or ROBINSON (1,230) might offer better safety profiles.

Avoid High-Accident Models: The top models with the highest number of accidents are: 152: 2,459 accidents 172: 1,756 accidents 172N: 1,164 accidents Models with fewer accidents such as 150M (585) might be better choices for enhanced safety.

1. **Trend Analysis:** Choose newer aircraft models or those with recent safety updates, as the trend indicates decreasing accident rates over time and improvements in aviation safety.