Business Understanding

1. Objective

The primary goal of this project is to evaluate aviation risks to identify aircraft that are low-risk for the company to purchase and operate. By analyzing historical event data, this analysis will provide actionable insights into aircraft safety, operational reliability, and risk factors associated with different aircraft models and flight operations.

2. Problem Statement

The company aims to enter the aviation industry but lacks knowledge about safety and operational risks. Without a data-driven approach, there is a risk of purchasing aircraft prone to accidents or high maintenance costs, leading to financial and reputational damage. This project will help identify patterns in historical aviation event data to guide safe and cost-effective aircraft acquisitions.

The Key Questions that we should ask:

1. Which aircraft models have the lowest rates of accidents or incidents?
2. What types of events are most common for specific aircraft categories or purposes of flight?
3. Are there any patterns related to the phase of flight, weather conditions, or injury severity?
4. How do aircraft make and model correlate with safety outcomes?

3. Metrics of Success

Business Metrics:

- **Risk Reduction**: Recommendations should reduce the likelihood of safety incidents by focusing on low-risk aircraft models.
- **Safety Insights**: Provide insights into key risk factors (e.g., weather, flight phase) to inform operational decisions.
- **Operational Reliability**: Aircraft recommendations should prioritize those with fewer historical incidents.

Technical Metrics:

- **Event Analysis**: Comprehensive analysis of incidents categorized by aircraft make, model, and operational context.
- **Risk Indicators**: Development of a risk index for each aircraft model based on historical event data.

4. External Relevance

Constraints:

- Historical event data may not fully capture all relevant risk factors (e.g., pilot behavior, maintenance quality).
- Data may have inconsistencies or missing values, especially for older events.

Assumptions:

- Historical safety trends for aircraft are indicative of future risks.
- The dataset includes all major factors relevant to assessing aircraft risk.
- Data quality is sufficient for building reliable insights.

Data Understanding

In [1]:
```
# importing the necessary python libraries
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
```

In [2]:
```
# loading the dataset using pandas
df = pd.read_csv('AviationData.csv', encoding='latin1')
df_USState_codes = pd.read_csv('USState_Codes.csv')
```

```
/tmp/ipykernel_43300/1156056486.py:2: DtypeWarning: Columns (6,7,28) have mixed types. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv('AviationData.csv', encoding='latin1')
```

1. Overview of the available Data

The dataset provided for this project includes information on various aircraft event history that occured in various parts of the US. It also contains information on the aircraft category, name and other features. This data is sourced from a Kaggle puplication.

Key features

- **Event Details**:
  - `Event.Id`, `Event.Date`, `Location`, `Country`, `Weather.Condition`, `Broad.phase.of.flight`
- **Aircraft Details**:
  - `Make`, `Model`, `Aircraft.damage`, `Aircraft.Category`, `Number.of.Engines`, `Engine.Type`
- **Injury and Severity**:
  - `Injury.Severity`, `Total.Fatal.Injuries`, `Total.Serious.Injuries`, `Total.Minor.Injuries`, `Total.Uninjured`
- **Operational Context**:
  - `Purpose.of.flight`, `Schedule`, `Air.carrier`, `FAR.Description`

In [3]:
```
# Getting a small overview of the first 5 rows of the data frame
df.head()
```

Out[3]:

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

5 rows × 31 columns

In [4]:

```
df_USState_codes.head(10)
```

Out[4]:

	US_State	Abbreviation
0	Alabama	AL
1	Alaska	AK
2	Arizona	AZ
3	Arkansas	AR
4	California	CA
5	Colorado	CO
6	Connecticut	CT
7	Delaware	DE
8	Florida	FL
9	Georgia	GA

In [5]:

```
df
```

Out[5]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH
...	...	...	...	...	...
88884	20221227106491	Accident	ERA23LA093	2022-12-26	Annapolis, MD
88885	20221227106494	Accident	ERA23LA095	2022-12-26	Hampton, NH
88886	20221227106497	Accident	WPR23LA075	2022-12-26	Payson, AZ
88887	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT
88888	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA

88889 rows × 31 columns

2. Statistical Summary

- The Dataset contains 88889 records and 30 features
- Some features contain missing values

In [6]:

```
# Getting to know more about the dataset by accessing its information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                88889 non-null  object 
 1   Investigation.Type      88889 non-null  object 
 2   Accident.Number         88889 non-null  object 
 3   Event.Date              88889 non-null  object 
 4   Location                88837 non-null  object 
 5   Country                 88663 non-null  object 
 6   Latitude                34382 non-null  object 
 7   Longitude               34373 non-null  object 
 8   Airport.Code            50132 non-null  object 
 9   Airport.Name            52704 non-null  object 
 10  Injury.Severity         87889 non-null  object 
 11  Aircraft.damage         85695 non-null  object 
 12  Aircraft.Category       32287 non-null  object 
 13  Registration.Number     87507 non-null  object 
 14  Make                    88826 non-null  object 
 15  Model                   88797 non-null  object 
 16  Amateur.Built           88787 non-null  object 
 17  Number.of.Engines       82805 non-null  float64
 18  Engine.Type             81793 non-null  object 
 19  FAR.Description         32023 non-null  object 
 20  Schedule                12582 non-null  object 
 21  Purpose.of.flight       82697 non-null  object 
 22  Air.carrier             16648 non-null  object 
 23  Total.Fatal.Injuries    77488 non-null  float64
 24  Total.Serious.Injuries  76379 non-null  float64
 25  Total.Minor.Injuries    76956 non-null  float64
 26  Total.Uninjured         82977 non-null  float64
 27  Weather.Condition       84397 non-null  object 
 28  Broad.phase.of.flight   61724 non-null  object 
 29  Report.Status           82505 non-null  object 
 30  Publication.Date        75118 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

In [7]:
```
# getting the statistical summary of various features with numeric entries
df.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
Number.of.Engines	82805.0	1.146585	0.446510	0.0	1.0	1.0	1.0	8.0
Total.Fatal.Injuries	77488.0	0.647855	5.485960	0.0	0.0	0.0	0.0	349.0
Total.Serious.Injuries	76379.0	0.279881	1.544084	0.0	0.0	0.0	0.0	161.0
Total.Minor.Injuries	76956.0	0.357061	2.235625	0.0	0.0	0.0	0.0	380.0
Total.Uninjured	82977.0	5.325440	27.913634	0.0	0.0	1.0	2.0	699.0

In [8]:
```
#getting the shape of the dataset
df.shape
```

Out[8]: (88889, 31)

In [9]:
```
#describing the dataset features
df.describe(include='O').T
```

Out[9]:

	count	unique	top	freq
Event.Id	88889	87951	20001212X19172	3
Investigation.Type	88889	2	Accident	85015
Accident.Number	88889	88863	CEN22LA149	2
Event.Date	88889	14782	1984-06-30	25
Location	88837	27758	ANCHORAGE, AK	434
Country	88663	219	United States	82248
Latitude	34382	25592	332739N	19
Longitude	34373	27156	0112457W	24
Airport.Code	50132	10374	NONE	1488
Airport.Name	52704	24870	Private	240
Injury.Severity	87889	109	Non-Fatal	67357
Aircraft.damage	85695	4	Substantial	64148
Aircraft.Category	32287	15	Airplane	27617
Registration.Number	87507	79104	NONE	344
Make	88826	8237	Cessna	22227
Model	88797	12318	152	2367
Amateur.Built	88787	2	No	80312
Engine.Type	81793	12	Reciprocating	69530
FAR.Description	32023	31	091	18221
Schedule	12582	3	NSCH	4474
Purpose.of.flight	82697	26	Personal	49448
Air.carrier	16648	13590	Pilot	258
Weather.Condition	84397	4	VMC	77303
Broad.phase.of.flight	61724	12	Landing	15428
Report.Status	82505	17074	Probable Cause	61754
Publication.Date	75118	2924	25-09-2020	17019

In [10]:

```
# getting the column names
df.columns
```

Out[10]:

```
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')
```

3. Data Quality Assessment

Completeness:

- **Strengths:**

    - Most critical features, such as `Make`, `Model`, and `Event.Date`, are well-populated.
    - Injury-related columns provide a detailed breakdown of the impact on passengers and crew.
- **Weaknesses**:
    - Missing values may exist in columns like `Latitude`, `Longitude`, `Airport.Code`, and `Airport.Name`.
    - `Weather.Condition` and `Broad.phase.of.flight` might have some missing or ambiguous entries.

Accuracy:

- Details like `Event.Date` and `Registration.Number` are likely accurate due to regulatory requirements.

In [11]:
```
## Completeness
df.isna().sum()
```

Out[11]:
```
Event.Id                      0
Investigation.Type            0
Accident.Number               0
Event.Date                    0
Location                     52
Country                     226
Latitude                  54507
Longitude                 54516
Airport.Code              38757
Airport.Name              36185
Injury.Severity            1000
Aircraft.damage            3194
Aircraft.Category         56602
Registration.Number        1382
Make                         63
Model                        92
Amateur.Built               102
Number.of.Engines          6084
Engine.Type                7096
FAR.Description           56866
Schedule                  76307
Purpose.of.flight          6192
Air.carrier               72241
Total.Fatal.Injuries      11401
Total.Serious.Injuries    12510
Total.Minor.Injuries      11933
Total.Uninjured            5912
Weather.Condition          4492
Broad.phase.of.flight     27165
Report.Status              6384
Publication.Date          13771
dtype: int64
```

4. Key Questions for Data Exploration

- What are the most common causes or types of events for specific aircraft models?
- Are certain flight phases (e.g., takeoff, landing) associated with higher incident rates?
- How does weather condition influence event severity?
- What correlations exist between aircraft damage and injury severity?

5. Next Steps

1. **Data Cleaning**

- Handle missing values in columns by dropping them or filling the entries
- Check for missingssing values in different features and standardize them
- Drop Unecessary columns that would not be needed in the DA

2. **Exploratory Data Analysis**

- Analyze trends in incidents by aircraft make, model, and category.
- Visualize relationships between weather, flight phase, and event severity.
- Identify geographical hotspots for aviation incidents.

3. **Feature Engineering**:

- Create derived features, such as `Fatality Rate` (fatal injuries / total injuries).
- Generate a risk score for each aircraft model based on incident frequency and severity.

Data Preparation/ Data Cleaning

In [12]:
```
# check for null values
df.isna().sum()
```

Out[12]:
```
Event.Id                      0
Investigation.Type            0
Accident.Number               0
Event.Date                    0
Location                     52
Country                     226
Latitude                  54507
Longitude                 54516
Airport.Code              38757
Airport.Name              36185
Injury.Severity            1000
Aircraft.damage            3194
Aircraft.Category         56602
Registration.Number        1382
Make                         63
Model                        92
Amateur.Built               102
Number.of.Engines          6084
Engine.Type                7096
FAR.Description           56866
Schedule                  76307
Purpose.of.flight          6192
Air.carrier               72241
Total.Fatal.Injuries      11401
Total.Serious.Injuries    12510
Total.Minor.Injuries      11933
Total.Uninjured            5912
Weather.Condition          4492
Broad.phase.of.flight     27165
Report.Status              6384
Publication.Date          13771
dtype: int64
```

In [13]:
```
#check for duplicate values
df.duplicated().sum()
```

Out[13]: 0

1. Dropping columns with over 50% of missing values and dropping duplicate values

In [14]:
```
#replacing period (.) with underscore (_) in the columns
df.columns = df.columns.str.replace('.','_')
```

In [15]:
```
df.columns
```

Out[15]:
```
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')
```

In [16]:
```
# Calculate teh percentage of missing values in the records
records = len(df)
missing_values = df.isna().sum()
percentage_missing = (missing_values / records) * 100
```

In [17]:
```
percentage_missing
```

Out[17]:
```
Event_Id                   0.000000
Investigation_Type         0.000000
Accident_Number            0.000000
Event_Date                 0.000000
Location                   0.058500
Country                    0.254250
Latitude                  61.320298
Longitude                 61.330423
Airport_Code              43.601570
Airport_Name              40.708074
Injury_Severity            1.124999
Aircraft_damage            3.593246
Aircraft_Category         63.677170
Registration_Number        1.554748
Make                       0.070875
Model                      0.103500
Amateur_Built              0.114750
Number_of_Engines          6.844491
Engine_Type                7.982990
FAR_Description           63.974170
Schedule                  85.845268
Purpose_of_flight          6.965991
Air_carrier               81.271023
Total_Fatal_Injuries      12.826109
Total_Serious_Injuries    14.073732
Total_Minor_Injuries      13.424608
Total_Uninjured            6.650992
Weather_Condition          5.053494
Broad_phase_of_flight     30.560587
Report_Status              7.181991
Publication_Date          15.492356
dtype: float64
```

In [18]:
```
#placing the percentage in a dataframe
me({'Missing' : percentage_missing})
```

```
# sorting the df
percentage_missing_df.sort_values('Missing', ascending = False, inplace = True)

percentage_missing_df
```

Out[18]:

	Missing
Schedule	85.845268
Air_carrier	81.271023
FAR_Description	63.974170
Aircraft_Category	63.677170
Longitude	61.330423
Latitude	61.320298
Airport_Code	43.601570
Airport_Name	40.708074
Broad_phase_of_flight	30.560587
Publication_Date	15.492356
Total_Serious_Injuries	14.073732
Total_Minor_Injuries	13.424608
Total_Fatal_Injuries	12.826109
Engine_Type	7.982990
Report_Status	7.181991
Purpose_of_flight	6.965991
Number_of_Engines	6.844491
Total_Uninjured	6.650992
Weather_Condition	5.053494
Aircraft_damage	3.593246
Registration_Number	1.554748
Injury_Severity	1.124999
Country	0.254250
Amateur_Built	0.114750
Model	0.103500
Make	0.070875
Location	0.058500
Investigation_Type	0.000000
Event_Date	0.000000
Accident_Number	0.000000
Event_Id	0.000000

In [19]:

```
#displaying columns with more than 10% of missing values
percentage_missing_df[percentage_missing_df['Missing'] > 10]
```

Out[19]:

	Missing
Schedule	85.845268
Air_carrier	81.271023
FAR_Description	63.974170
Aircraft_Category	63.677170
Longitude	61.330423
Latitude	61.320298
Airport_Code	43.601570
Airport_Name	40.708074
Broad_phase_of_flight	30.560587
Publication_Date	15.492356
Total_Serious_Injuries	14.073732
Total_Minor_Injuries	13.424608
Total_Fatal_Injuries	12.826109

In [20]:

```
# dropping columns with over 50% of missing values
# create a list of the columns to drop
columns_drop = list(percentage_missing_df[percentage_missing_df['Missing'] > 50].inde

#dropping the columns
df.drop(columns = columns_drop, axis = 1, inplace = True)

df.columns
```

Out[20]:

```
Index(['Event_Id', 'Investigation_Type', 'Accident_Number', 'Event_Date',
       'Location', 'Country', 'Airport_Code', 'Airport_Name',
       'Injury_Severity', 'Aircraft_damage', 'Registration_Number', 'Make',
       'Model', 'Amateur_Built', 'Number_of_Engines', 'Engine_Type',
       'Purpose_of_flight', 'Total_Fatal_Injuries', 'Total_Serious_Injuries',
       'Total_Minor_Injuries', 'Total_Uninjured', 'Weather_Condition',
       'Broad_phase_of_flight', 'Report_Status', 'Publication_Date'],
      dtype='object')
```

In [21]:

```
# checking the columns that were droped
columns_drop
```

Out[21]:

```
['Schedule',
 'Air_carrier',
 'FAR_Description',
 'Aircraft_Category',
 'Longitude',
 'Latitude']
```

In [22]:

```
#checking the df information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 25 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   Airport_Code            50132 non-null  object 
 7   Airport_Name            52704 non-null  object 
 8   Injury_Severity         87889 non-null  object 
 9   Aircraft_damage         85695 non-null  object 
 10  Registration_Number     87507 non-null  object 
 11  Make                    88826 non-null  object 
 12  Model                   88797 non-null  object 
 13  Amateur_Built           88787 non-null  object 
 14  Number_of_Engines       82805 non-null  float64
 15  Engine_Type             81793 non-null  object 
 16  Purpose_of_flight       82697 non-null  object 
 17  Total_Fatal_Injuries    77488 non-null  float64
 18  Total_Serious_Injuries  76379 non-null  float64
 19  Total_Minor_Injuries    76956 non-null  float64
 20  Total_Uninjured         82977 non-null  float64
 21  Weather_Condition       84397 non-null  object 
 22  Broad_phase_of_flight   61724 non-null  object 
 23  Report_Status           82505 non-null  object 
 24  Publication_Date        75118 non-null  object 
dtypes: float64(5), object(20)
memory usage: 17.0+ MB
```

In [23]:
```
# Drop rows where Registration_Number is missing
df.dropna(subset=['Registration_Number'], inplace=True)
```

2. Check for missing values in different features and standardize them

In [24]:
```
df.isna().sum()
```

Out[24]:
```
Event_Id                      0
Investigation_Type            0
Accident_Number               0
Event_Date                    0
Location                     30
Country                     221
Airport_Code              37470
Airport_Name              34912
Injury_Severity             977
Aircraft_damage            3011
Registration_Number           0
Make                         24
Model                        54
Amateur_Built                33
Number_of_Engines          4860
Engine_Type                6179
Purpose_of_flight          5619
Total_Fatal_Injuries      10835
Total_Serious_Injuries    11599
Total_Minor_Injuries      10951
Total_Uninjured            5112
Weather_Condition          4091
Broad_phase_of_flight     25881
Report_Status              6352
Publication_Date          13544
dtype: int64
```

In [25]:
```
# Fill missing values for categorical columns since we have already dropped columns w
categorical_columns = [
    'Location', 'Injury_Severity', 'Make', 'Model',
    'Amateur_Built', 'Purpose_of_flight', 'Weather_Condition',
    'Broad_phase_of_flight', 'Report_Status','Aircraft_damage'
]

# Fill missing values with "Unknown" for each column in the list
for column in categorical_columns:
    df[column].fillna("Unknown", inplace=True)
```

In [26]:
```
#lets fill the columns with numerical values with mean or median or mode

# Handle missing values in Engine_Type based on mode
df['Engine_Type'].fillna(df['Engine_Type'].mode()[0], inplace=True)

# Handling missing values in Number of engines with the median
df['Number_of_Engines'].fillna(df['Number_of_Engines'].median(), inplace=True)

# handling missing values in Total fatal,minor,serious and uninjured columns with the
numerical_injuries_columns = ['Total_Fatal_Injuries', 'Total_Serious_Injuries',
                     'Total_Minor_Injuries', 'Total_Uninjured']

# Calculate the mean for each column and fill missing values
for column in numerical_injuries_columns:
    df[column].fillna(df[column].mean(), inplace=True)
```

In [27]:
```
df.isna().sum()
```

Out[27]:
```
Event_Id                    0
Investigation_Type          0
Accident_Number             0
Event_Date                  0
Location                    0
Country                   221
Airport_Code            37470
Airport_Name            34912
Injury_Severity             0
Aircraft_damage             0
Registration_Number         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
Broad_phase_of_flight       0
Report_Status               0
Publication_Date        13544
dtype: int64
```

In [28]:
```
# checking ehich country had the most events
df['Country'].value_counts()
```

Out[28]:
```
Country
United States               82132
Brazil                        336
Canada                        305
Mexico                        294
United Kingdom                284
                            ...
Chad                            1
Yemen                           1
Reunion                         1
Nauru                           1
Turks and Caicos Islands        1
Name: count, Length: 205, dtype: int64
```

In [29]:
```
# Droping records where events didn't occur in the US since
df = df[df['Country'] == 'United States']

# check if the only unique value in country is the US
df['Country'].unique()
```

Out[29]:
```
array(['United States'], dtype=object)
```

In [30]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 82132 entries, 0 to 88888
Data columns (total 25 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event_Id                82132 non-null  object 
 1   Investigation_Type      82132 non-null  object 
 2   Accident_Number         82132 non-null  object 
 3   Event_Date              82132 non-null  object 
 4   Location                82132 non-null  object 
 5   Country                 82132 non-null  object 
 6   Airport_Code            49017 non-null  object 
 7   Airport_Name            51513 non-null  object 
 8   Injury_Severity         82132 non-null  object 
 9   Aircraft_damage         82132 non-null  object 
 10  Registration_Number     82132 non-null  object 
 11  Make                    82132 non-null  object 
 12  Model                   82132 non-null  object 
 13  Amateur_Built           82132 non-null  object 
 14  Number_of_Engines       82132 non-null  float64
 15  Engine_Type             82132 non-null  object 
 16  Purpose_of_flight       82132 non-null  object 
 17  Total_Fatal_Injuries    82132 non-null  float64
 18  Total_Serious_Injuries  82132 non-null  float64
 19  Total_Minor_Injuries    82132 non-null  float64
 20  Total_Uninjured         82132 non-null  float64
 21  Weather_Condition       82132 non-null  object 
 22  Broad_phase_of_flight   82132 non-null  object 
 23  Report_Status           82132 non-null  object 
 24  Publication_Date        69451 non-null  object 
dtypes: float64(5), object(20)
memory usage: 16.3+ MB
```

In [31]:

```
df.duplicated().sum()
```

Out[31]:

```
0
```

In [32]:

```
# checking the event dates and see whether they date back to irrelevant years
df['Event_Date'].head(20)
```

Out[32]:

```
0     1948-10-24
1     1962-07-19
2     1974-08-30
3     1977-06-19
4     1979-08-02
5     1979-09-17
6     1981-08-01
7     1982-01-01
8     1982-01-01
9     1982-01-01
10    1982-01-01
11    1982-01-01
12    1982-01-02
13    1982-01-02
14    1982-01-02
15    1982-01-02
16    1982-01-02
17    1982-01-02
18    1982-01-02
19    1982-01-02
Name: Event_Date, dtype: object
```

In [33]:

```
# since the year 1982 is the most frequent, we can drop the records before 1982

# convert Event_Date to a datetime formart
```

```python
df['Event_Date'] = pd.to_datetime(df['Event_Date'])

# creating another column for years
df['Year'] = df['Event_Date'].dt.year

# df['Year']

# removing records before 1982
df = df[df['Year'] >= 1982]
```

```
/tmp/ipykernel_43300/907466565.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
r_guide/indexing.html#returning-a-view-versus-a-copy
  df['Event_Date'] = pd.to_datetime(df['Event_Date'])
/tmp/ipykernel_43300/907466565.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
r_guide/indexing.html#returning-a-view-versus-a-copy
  df['Year'] = df['Event_Date'].dt.year
```

In [34]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 82125 entries, 7 to 88888
Data columns (total 26 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event_Id                82125 non-null  object
 1   Investigation_Type      82125 non-null  object
 2   Accident_Number         82125 non-null  object
 3   Event_Date              82125 non-null  datetime64[ns]
 4   Location                82125 non-null  object
 5   Country                 82125 non-null  object
 6   Airport_Code            49017 non-null  object
 7   Airport_Name            51513 non-null  object
 8   Injury_Severity         82125 non-null  object
 9   Aircraft_damage         82125 non-null  object
 10  Registration_Number     82125 non-null  object
 11  Make                    82125 non-null  object
 12  Model                   82125 non-null  object
 13  Amateur_Built           82125 non-null  object
 14  Number_of_Engines       82125 non-null  float64
 15  Engine_Type             82125 non-null  object
 16  Purpose_of_flight       82125 non-null  object
 17  Total_Fatal_Injuries    82125 non-null  float64
 18  Total_Serious_Injuries  82125 non-null  float64
 19  Total_Minor_Injuries    82125 non-null  float64
 20  Total_Uninjured         82125 non-null  float64
 21  Weather_Condition       82125 non-null  object
 22  Broad_phase_of_flight   82125 non-null  object
 23  Report_Status           82125 non-null  object
 24  Publication_Date        69445 non-null  object
 25  Year                    82125 non-null  int32
dtypes: datetime64[ns](1), float64(5), int32(1), object(19)
memory usage: 16.6+ MB
```

In [35]:

```python
df.describe(include = 'O').T
```

Out[35]:

	count	unique	top	freq
Event_Id	82125	81246	20001212X19172	3
Investigation_Type	82125	2	Accident	79831
Accident_Number	82125	82107	CEN23MA034	2
Location	82125	23014	ANCHORAGE, AK	434
Country	82125	1	United States	82125
Airport_Code	49017	9627	NONE	1472
Airport_Name	51513	23875	Private	238
Injury_Severity	82125	57	Non-Fatal	64829
Aircraft_damage	82125	4	Substantial	61624
Registration_Number	82125	74044	NONE	342
Make	82125	7968	Cessna	21567
Model	82125	11395	152	2323
Amateur_Built	82125	3	No	73833
Engine_Type	82125	11	Reciprocating	71431
Purpose_of_flight	82125	26	Personal	48477
Weather_Condition	82125	5	VMC	75210
Broad_phase_of_flight	82125	12	Unknown	21574
Report_Status	82125	16966	Probable Cause	61084
Publication_Date	69445	2027	25-09-2020	15405

Merging and spliting values in columns

In [36]:

```
# Merge different capitalizations of Make togheter
df['Make'] = df['Make'].str.title()
df['Make'].value_counts().nlargest(10)
```

Out[36]:

```
Make
Cessna      25847
Piper       14166
Beech        5059
Bell         2285
Boeing       1471
Mooney       1293
Grumman      1142
Bellanca     1040
Robinson      919
Hughes        874
Name: count, dtype: int64
```

In [37]:

```
# Merge same registration numbers togheter
df['Registration_Number'].replace(to_replace = '(?i)none', value = 'NONE', inplace =
df['Registration_Number'].value_counts().nlargest(10)
```

Out[37]:
```
Registration_Number
NONE       343
UNREG      115
USAF         9
N20752       8
UNK          7
N121CC       6
N5408Y       6
N4101E       6
N53893       6
N8402K       6
Name: count, dtype: int64
```

In [38]:
```
# lets split the location into city and states
df['City'] = df['Location'].str.split(',').str[0]
df['State'] = df['Location'].str.split(',').str[1]

df[['City','State']].head()
```

Out[38]:

	City	State
7	PULLMAN	WA
8	EAST HANOVER	NJ
9	JACKSONVILLE	FL
10	HOBBS	NM
11	TUSKEGEE	AL

In [39]:
```
# Merge weather condition unknowns
df['Weather_Condition'].replace(to_replace = ['Unk', 'UNK'], value = 'Unknown', inpla
df['Weather_Condition'].value_counts()
```

Out[39]:
```
Weather_Condition
VMC        75210
IMC         5611
Unknown     1304
Name: count, dtype: int64
```

In [40]:
```
# fill missing values in states with unknown
df['State'].fillna("Unknown", inplace=True)
```

In [41]:
```
# Remove amount of injuries as this is aleady in another column
df['Injury_Severity'] = df['Injury_Severity'].str.split('(').str[0]
df['Injury_Severity'].value_counts()
```

Out[41]:
```
Injury_Severity
Non-Fatal      64829
Fatal          14987
Incident        1836
Minor            203
Serious          153
Unknown          102
Unavailable       15
Name: count, dtype: int64
```

In [42]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 82125 entries, 7 to 88888
Data columns (total 28 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event_Id                82125 non-null  object
 1   Investigation_Type      82125 non-null  object
 2   Accident_Number         82125 non-null  object
 3   Event_Date              82125 non-null  datetime64[ns]
 4   Location                82125 non-null  object
 5   Country                 82125 non-null  object
 6   Airport_Code            49017 non-null  object
 7   Airport_Name            51513 non-null  object
 8   Injury_Severity         82125 non-null  object
 9   Aircraft_damage         82125 non-null  object
 10  Registration_Number     82125 non-null  object
 11  Make                    82125 non-null  object
 12  Model                   82125 non-null  object
 13  Amateur_Built           82125 non-null  object
 14  Number_of_Engines       82125 non-null  float64
 15  Engine_Type             82125 non-null  object
 16  Purpose_of_flight       82125 non-null  object
 17  Total_Fatal_Injuries    82125 non-null  float64
 18  Total_Serious_Injuries  82125 non-null  float64
 19  Total_Minor_Injuries    82125 non-null  float64
 20  Total_Uninjured         82125 non-null  float64
 21  Weather_Condition       82125 non-null  object
 22  Broad_phase_of_flight   82125 non-null  object
 23  Report_Status           82125 non-null  object
 24  Publication_Date        69445 non-null  object
 25  Year                    82125 non-null  int32
 26  City                    82125 non-null  object
 27  State                   82125 non-null  object
dtypes: datetime64[ns](1), float64(5), int32(1), object(21)
memory usage: 17.9+ MB
```

In [43]:

```
df.head().T
```

Out[43]:

	7	8	9	1
Event_Id	20020909X01562	20020909X01561	20020909X01560	20020909X015
Investigation_Type	Accident	Accident	Accident	Accide
Accident_Number	SEA82DA022	NYC82DA015	MIA82DA029	FTW82DA0
Event_Date	1982-01-01 00:00:00	1982-01-01 00:00:00	1982-01-01 00:00:00	1982-01- 00:00:
Location	PULLMAN, WA	EAST HANOVER, NJ	JACKSONVILLE, FL	HOBBS, N
Country	United States	United States	United States	United Stat
Airport_Code	NaN	N58	JAX	N
Airport_Name	BLACKBURN AG STRIP	HANOVER	JACKSONVILLE INTL	N
Injury_Severity	Non-Fatal	Non-Fatal	Non-Fatal	Non-Fa
Aircraft_damage	Substantial	Substantial	Substantial	Substant
Registration_Number	N2482N	N7967Q	N3906K	N448
Make	Cessna	Cessna	North American	Pip
Model	140	401B	NAVION L-17B	PA-28-1
Amateur_Built	No	No	No	
Number_of_Engines	1.0	2.0	1.0	1
Engine_Type	Reciprocating	Reciprocating	Reciprocating	Reciprocati
Purpose_of_flight	Personal	Business	Personal	Persor
Total_Fatal_Injuries	0.0	0.0	0.0	(
Total_Serious_Injuries	0.0	0.0	0.0	(
Total_Minor_Injuries	0.0	0.0	3.0	(
Total_Uninjured	2.0	2.0	0.0	1
Weather_Condition	VMC	IMC	IMC	VI
Broad_phase_of_flight	Takeoff	Landing	Cruise	Approa
Report_Status	Probable Cause	Probable Cause	Probable Cause	Probable Cau
Publication_Date	01-01-1982	01-01-1982	01-01-1982	01-01-19
Year	1982	1982	1982	19
City	PULLMAN	EAST HANOVER	JACKSONVILLE	HOB
State	WA	NJ	FL	N

In [44]:

```
df.isna().sum()
```

Out[44]:
```
Event_Id                    0
Investigation_Type          0
Accident_Number             0
Event_Date                  0
Location                    0
Country                     0
Airport_Code            33108
Airport_Name            30612
Injury_Severity             0
Aircraft_damage             0
Registration_Number         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
Broad_phase_of_flight       0
Report_Status               0
Publication_Date        12680
Year                        0
City                        0
State                       0
dtype: int64
```

3. Drop Unecessary columns that would not be needed in the DA

In [45]:
```python
# lets drop unnecessary columns like airport code and airport name and publication da
df.drop(['Airport_Code', 'Airport_Name', 'Publication_Date'], axis=1, inplace=True)
```

4. Clearing outliers

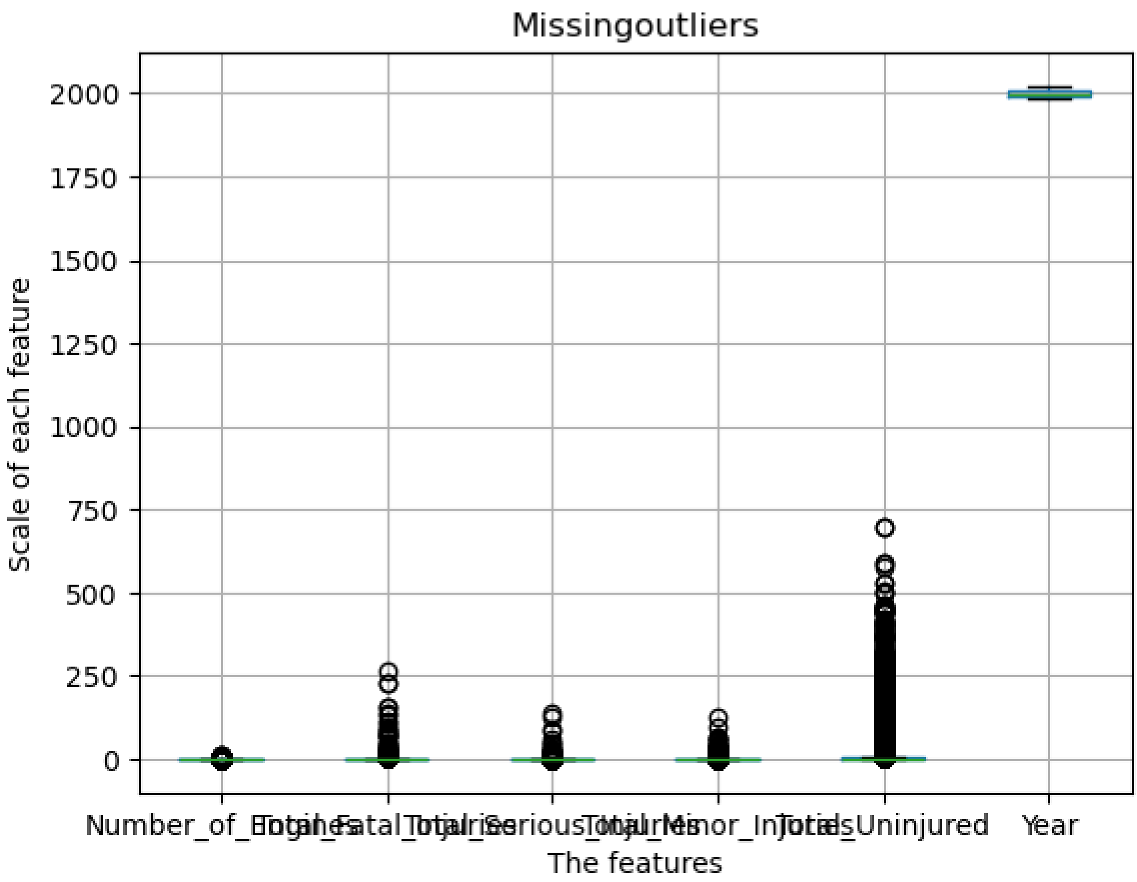
In [46]:
```python
df.describe().T
```

Out[46]:

	count	mean	min	25%	50%	75%
Event_Date	82125	1998-11-27 02:36:16.964383616	1982-01-01 00:00:00	1988-07-10 00:00:00	1997-06-11 00:00:00	2008-04-10 00:00:00
Number_of_Engines	82125.0	1.132505	0.0	1.0	1.0	1.0
Total_Fatal_Injuries	82125.0	0.436637	0.0	0.0	0.0	0.541084
Total_Serious_Injuries	82125.0	0.258182	0.0	0.0	0.0	0.265453
Total_Minor_Injuries	82125.0	0.333682	0.0	0.0	0.0	0.338968
Total_Uninjured	82125.0	4.303138	0.0	0.0	1.0	2.0
Year	82125.0	1998.399963	1982.0	1988.0	1997.0	2008.0

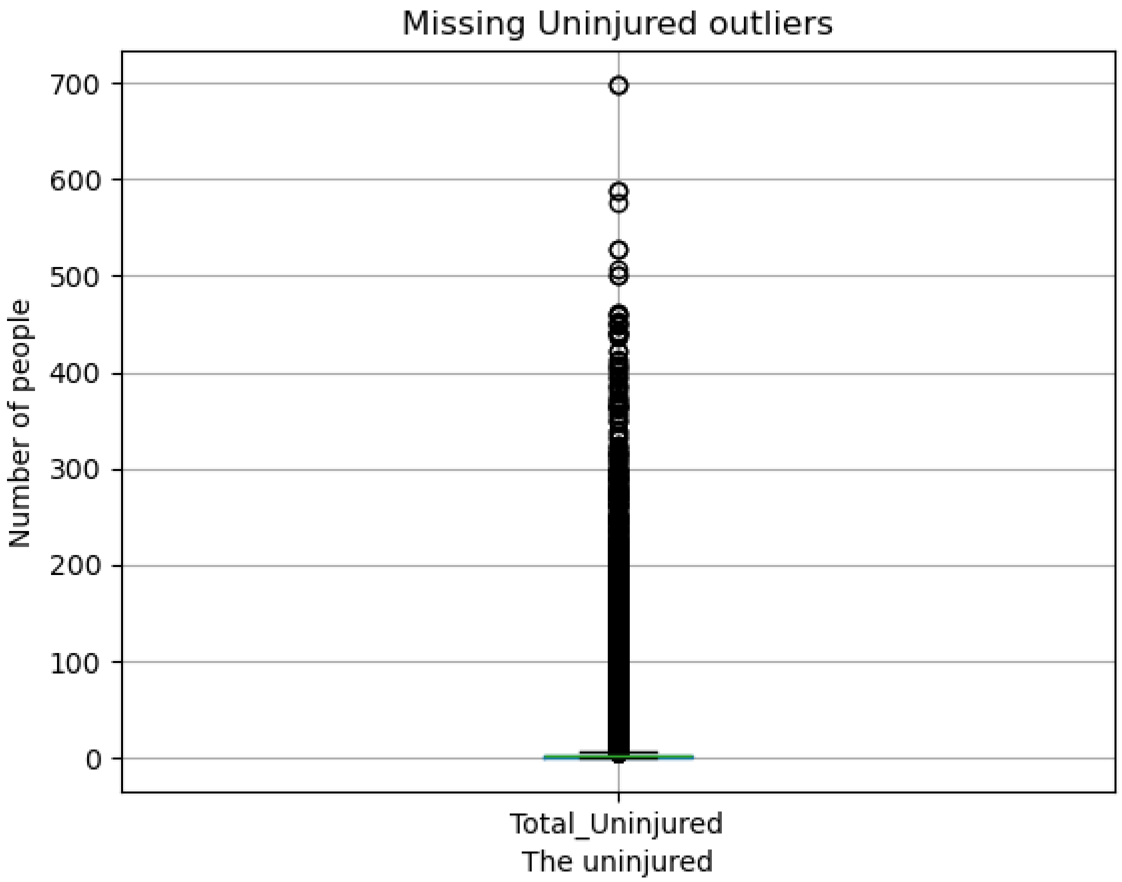
In [47]:
```python
# using matplotlib to check for the outliers
df.boxplot()

#plot title
plt.title('Missingoutliers')
```

```
plt.xlabel("The features")
plt.ylabel("Scale of each feature")

plt.show()
```



In [48]:

```
# Total uninjured people column has the most outliers
df.boxplot(column = ['Total_Uninjured'])

#plot title
plt.title('Missing Uninjured outliers')
#plot labels
plt.xlabel("The uninjured")
plt.ylabel("Number of people")

plt.show()
```



In [49]:
```
# to handle the outlier we would have used the interquatile method but since this is
```

In [50]:
```
# check if the key columns for the EDA are still present
'''
Event Details:
  Event.Id, Event.Date, Location, Country, Weather.Condition, Broad.phase.of.flight
Aircraft Details:
  Make, Model, Aircraft.damage, Aircraft.Category, Number.of.Engines, Engine.Type
Injury and Severity:
  Injury.Severity, Total.Fatal.Injuries, Total.Serious.Injuries, Total.Minor.Injuries
Operational Context:
  Purpose.of.flight
'''

df.columns
```

Out[50]:
```
Index(['Event_Id', 'Investigation_Type', 'Accident_Number', 'Event_Date',
       'Location', 'Country', 'Injury_Severity', 'Aircraft_damage',
       'Registration_Number', 'Make', 'Model', 'Amateur_Built',
       'Number_of_Engines', 'Engine_Type', 'Purpose_of_flight',
       'Total_Fatal_Injuries', 'Total_Serious_Injuries',
       'Total_Minor_Injuries', 'Total_Uninjured', 'Weather_Condition',
       'Broad_phase_of_flight', 'Report_Status', 'Year', 'City', 'State'],
      dtype='object')
```

Exporting the cleaned Dataset

In [51]:
```
# Let's export our dataframe into a csv file as shown
df.to_csv('AviationData_cleaned.csv')
```

Exploratory Data Analysis

1. Identifying Aircraft with the Lowest risk

In [52]:
```
#Load the cleaned Data
df = pd.read_csv('AviationData_cleaned.csv')
```

In [53]:
```
df.describe().T
```

Out[53]:

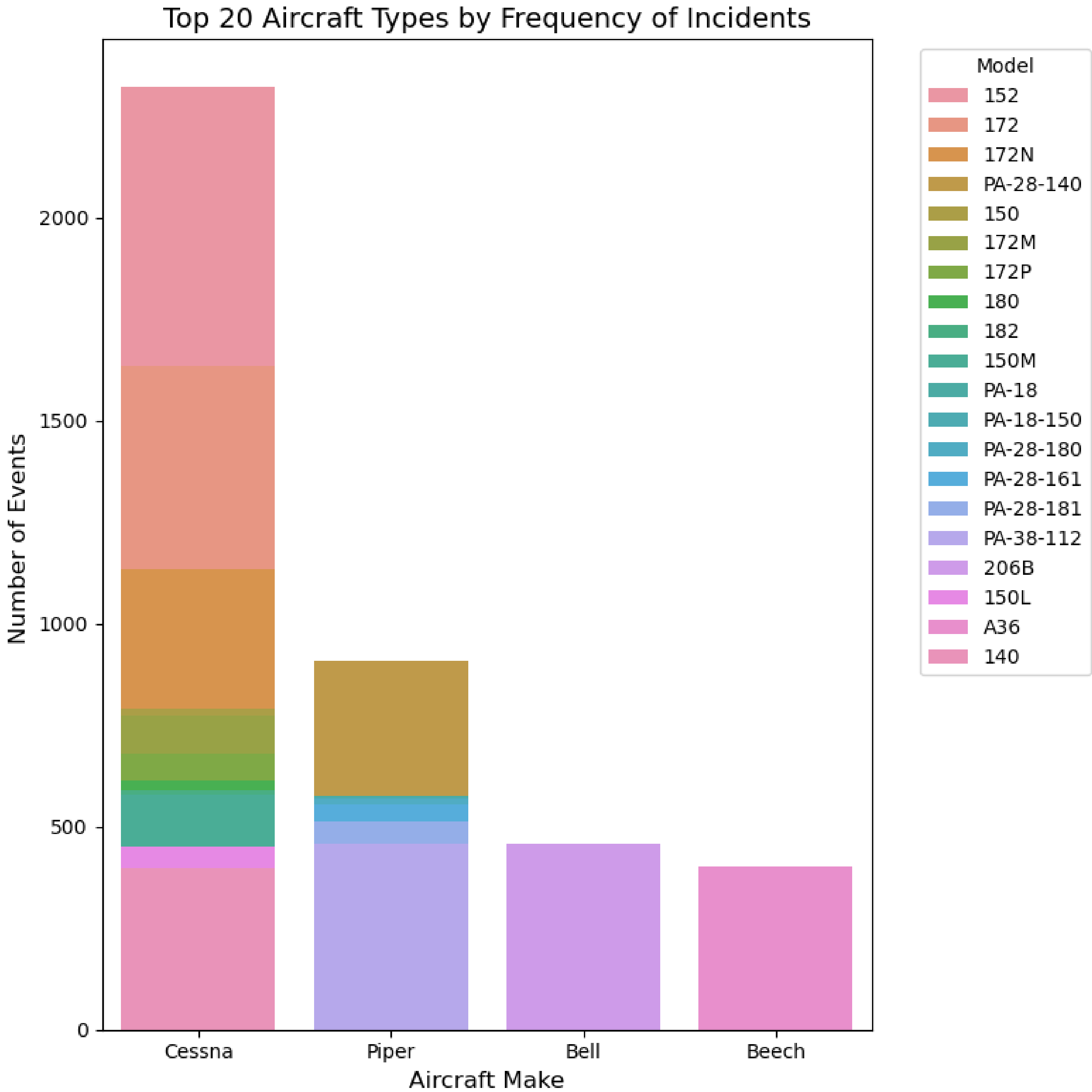
	count	mean	std	min	25%	50%	
Unnamed: 0	82125.0	42747.137023	25362.620997	7.0	20798.0	41953.0	64
Number_of_Engines	82125.0	1.132505	0.423053	0.0	1.0	1.0	
Total_Fatal_Injuries	82125.0	0.436637	2.272425	0.0	0.0	0.0	
Total_Serious_Injuries	82125.0	0.258182	1.062820	0.0	0.0	0.0	
Total_Minor_Injuries	82125.0	0.333682	1.219245	0.0	0.0	0.0	
Total_Uninjured	82125.0	4.303138	22.852245	0.0	0.0	1.0	
Year	80668.0	1998.055809	11.481453	1982.0	1988.0	1997.0	2

In [54]:
```
df.describe(include = 'O')
```

Out[54]:

	Event_Id	Investigation_Type	Accident_Number	Event_Date	Location	Cour
count	83582	83582	83580	82125	82125	82
unique	81260	1102	82161	14600	23014	
top	2018	Accident	TX	1982-05-16	ANCHORAGE, AK	Un Sta
freq	202	79831	160	25	434	82

In [55]:
```
# We can identify the aircrafts by their make and model
# using matplotlib, lets have bar plots of the make and model against the events

# Aggregate the data: count the number of incidents per Make and Model
event_counts = df.groupby(['Make', 'Model']).size().reset_index(name='Event_Count')

# Sort the data for better visualization (e.g., top 20 by event count)
top_event_counts = event_counts.sort_values(by='Event_Count', ascending=False).head(2

# Plot the bar chart
plt.figure(figsize=(8, 8))
sns.barplot(
    x='Make',
    y='Event_Count',
    hue='Model',
    data=top_event_counts,
    dodge=False,
)

# Labels and title
plt.title('Top 20 Aircraft Types by Frequency of Incidents', fontsize=14)
plt.xlabel('Aircraft Make', fontsize=12)
plt.ylabel('Number of Events ', fontsize=12)
plt.legend(title='Model', bbox_to_anchor=(1.05, 1), loc='upper left', fontsize=10)
plt.tight_layout()

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



In [56]:

```
# we need to know the number of events that occured for each aircraft category and th
purpose_counts = df.groupby('Purpose_of_flight').size().reset_index(name='Event_Count

# Bar plot for Purpose of Flight
plt.figure(figsize=(8, 10))
sns.barplot(
    x='Purpose_of_flight',
    y='Event_Count',
    data=purpose_counts,
    palette='viridis'
)

# Adding labels and title
plt.title('Event Counts by Purpose of Flight', fontsize=16)
plt.xlabel('Purpose of Flight', fontsize=14)
plt.ylabel('Event Count', fontsize=14)
plt.xticks(rotation=45)
plt.tight_layout()

plt.show()
```

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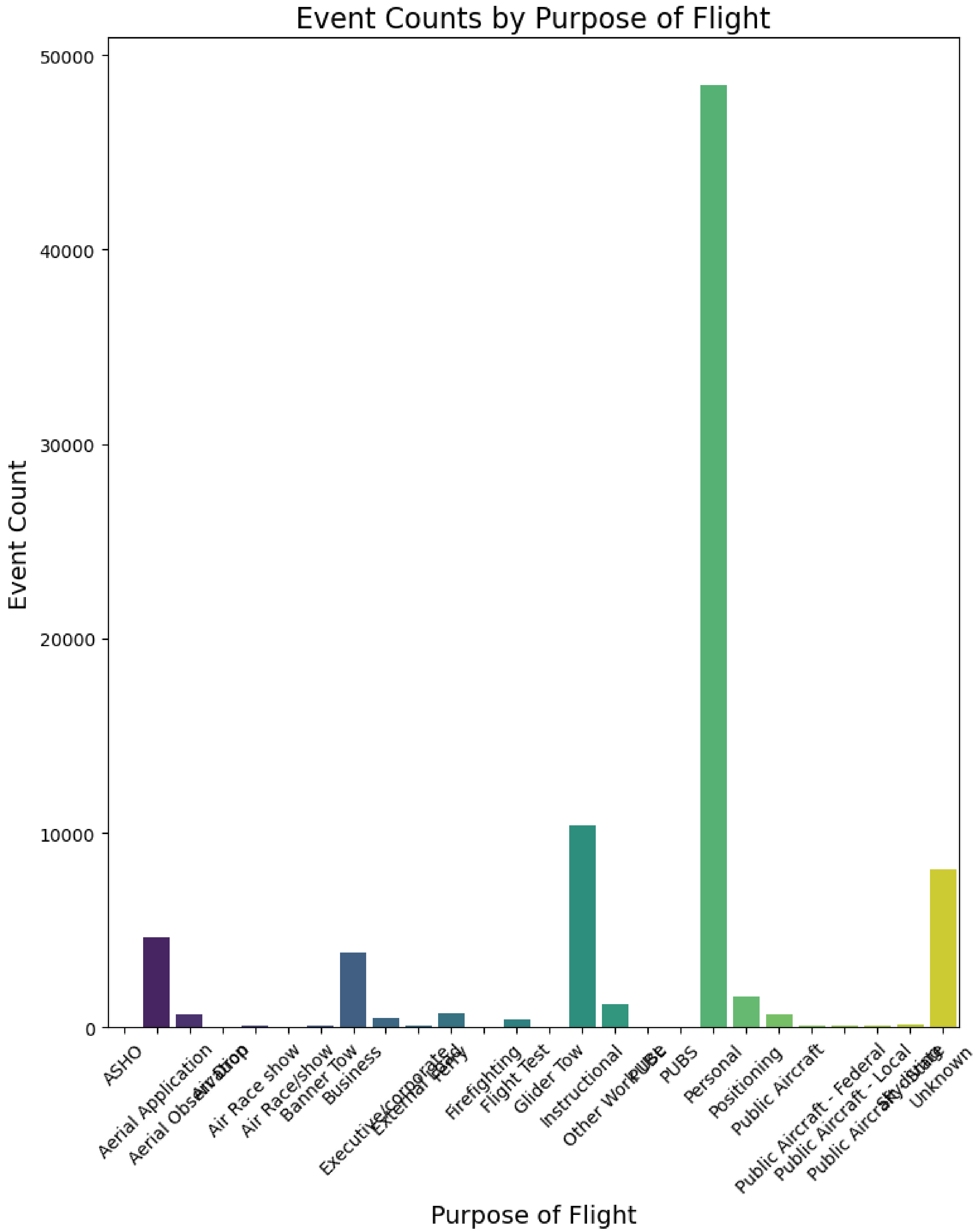


In [57]:

```
# Lets check on the number of accidents/ events per year

events_per_year = df.groupby(['Year'], as_index = False)['Event_Id'].count()
events_per_year
```

Out[57]:

	Year	Event_Id
0	1982.0	3564
1	1983.0	3524
2	1984.0	3418
3	1985.0	3066
4	1986.0	2845
5	1987.0	2770
6	1988.0	2660
7	1989.0	2495
8	1990.0	2464
9	1991.0	2404
10	1992.0	2293
11	1993.0	2250
12	1994.0	2186
13	1995.0	2214
14	1996.0	2106
15	1997.0	2032
16	1998.0	2067
17	1999.0	2073
18	2000.0	2043
19	2001.0	1898
20	2002.0	1866
21	2003.0	1932
22	2004.0	1779
23	2005.0	1842
24	2006.0	1648
25	2007.0	1804
26	2008.0	1688
27	2009.0	1601
28	2010.0	1552
29	2011.0	1587
30	2012.0	1509
31	2013.0	1209
32	2014.0	1171
33	2015.0	1242
34	2016.0	1261
35	2017.0	1204
36	2018.0	1145
37	2019.0	1158
38	2020.0	979
39	2021.0	1069

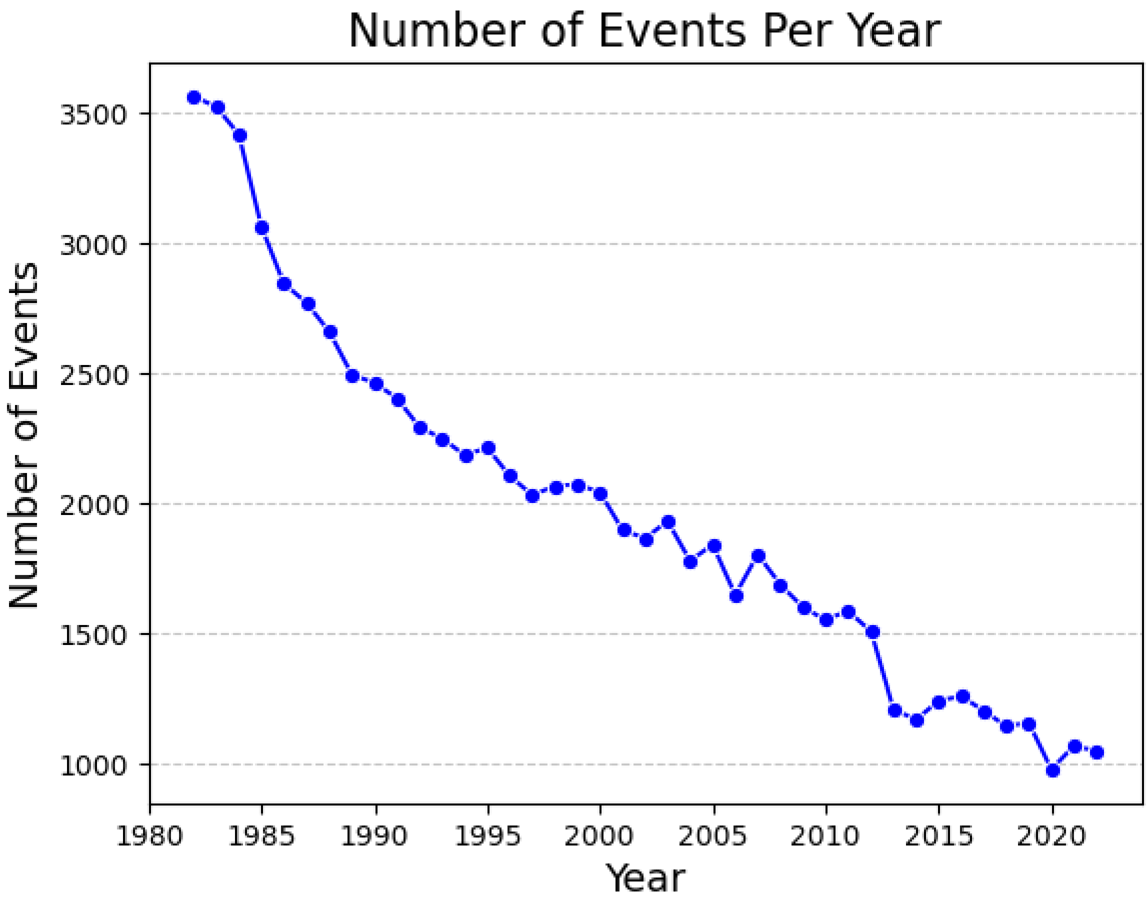
	Year	Event_Id
40	2022.0	1050

In [58]:
```
# we can have a line plot for the number of events per year using seaborn and matplot
# Plotting the line plot
# plt.figure(figsize=(12, 6))
sns.lineplot(
    x='Year',
    y='Event_Id',
    data=events_per_year,
    marker='o',
    color='blue',
)

# Adding labels and title
plt.title('Number of Events Per Year', fontsize=16)
plt.xlabel('Year', fontsize=14)
plt.ylabel('Number of Events', fontsize=14)
plt.grid(axis='y', linestyle='--', alpha=0.7)

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

```
/home/bev/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119: FutureWarni
ng: use_inf_as_na option is deprecated and will be removed in a future version. Conver
t inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/home/bev/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119: FutureWarni
ng: use_inf_as_na option is deprecated and will be removed in a future version. Conver
t inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



In [59]:
```
# finding pattern related to the phase of flight, weather conditiond and injury sever
# lets first group the broad phase of flight and the number of incidents then examine
# after we can compare how the weather conditions affected each event count and sever
```

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js

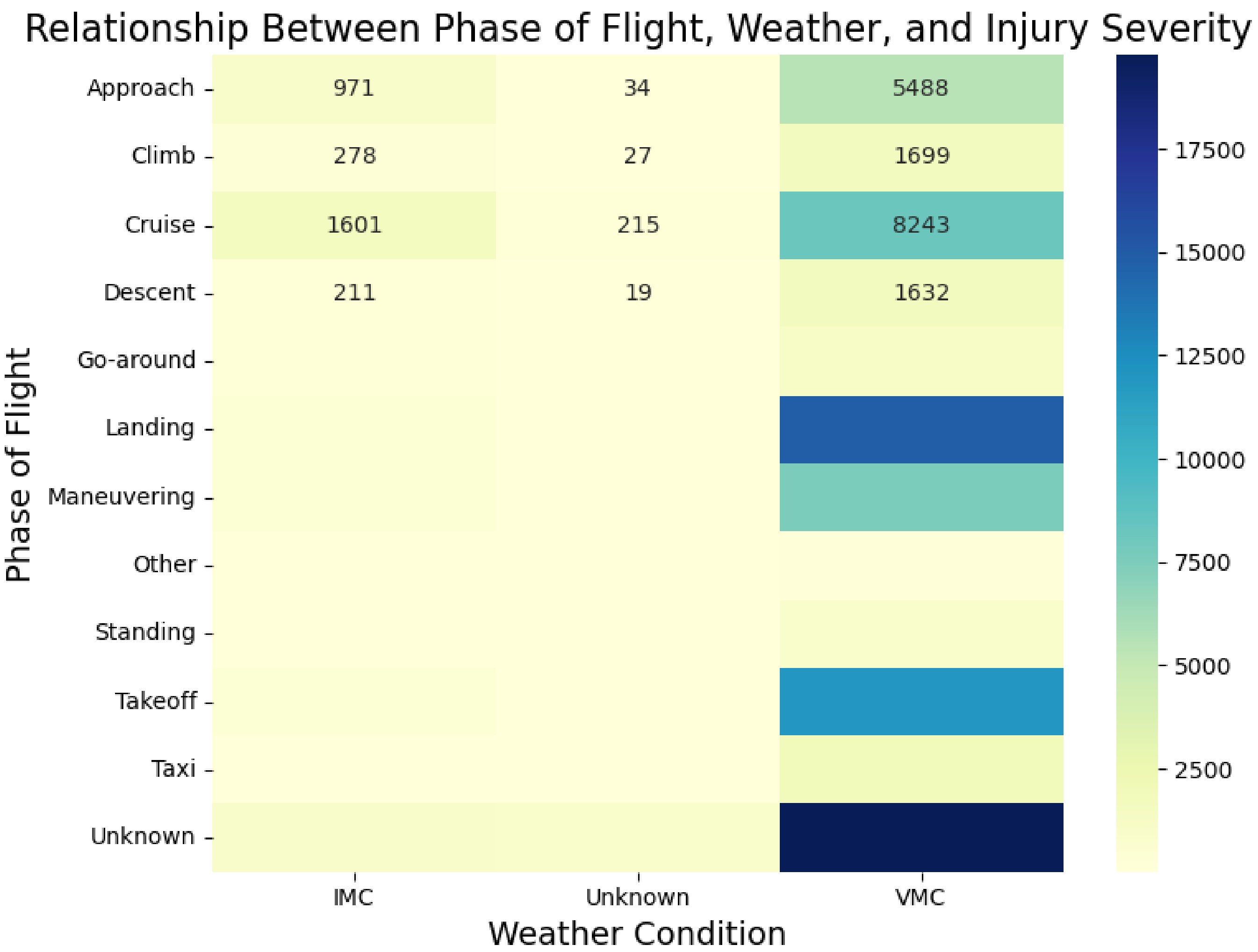
```
phase_weather_injury = df.pivot_table(
    index='Broad_phase_of_flight',
    columns='Weather_Condition',
    values='Injury_Severity',
    aggfunc='count'
)

# ploting
plt.figure(figsize=(8, 6))
sns.heatmap(phase_weather_injury, annot=True, fmt='d', cmap='YlGnBu')

# plot labels
plt.title('Relationship Between Phase of Flight, Weather, and Injury Severity', fonts
plt.xlabel('Weather Condition', fontsize=14)
plt.ylabel('Phase of Flight', fontsize=14)
plt.tight_layout()

plt.show()

# to note
'''
Instrument meteorological conditions (IMC)
are meteorological conditions expressed in terms of visibility, distance from cloud,
less than the minima specified for visual meteorological conditions (VMC)
'''
```



Out[59]: '\nInstrument meteorological conditions (IMC) \nare meteorological conditions expressed in terms of visibility, distance from cloud, and ceiling, \nless than the minima specified for visual meteorological conditions (VMC)\n'

In [60]:

```
# Examining the correlation between aircraft damage and make or model
# Create a copy of the subset of data for visualization
scatter_data = df[['Make', 'Model', 'Total_Fatal_Injuries', 'Aircraft_damage']].copy(
```

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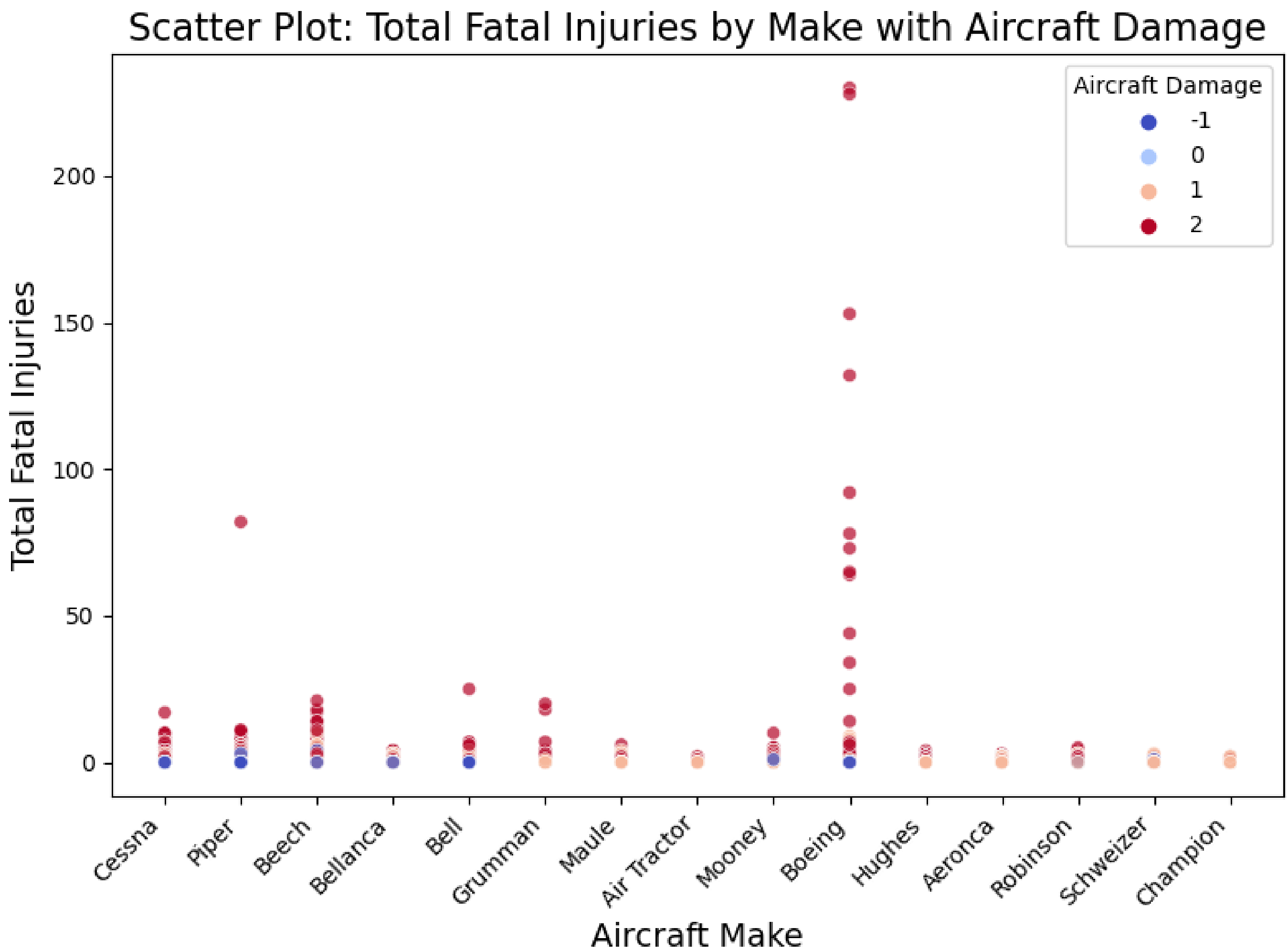
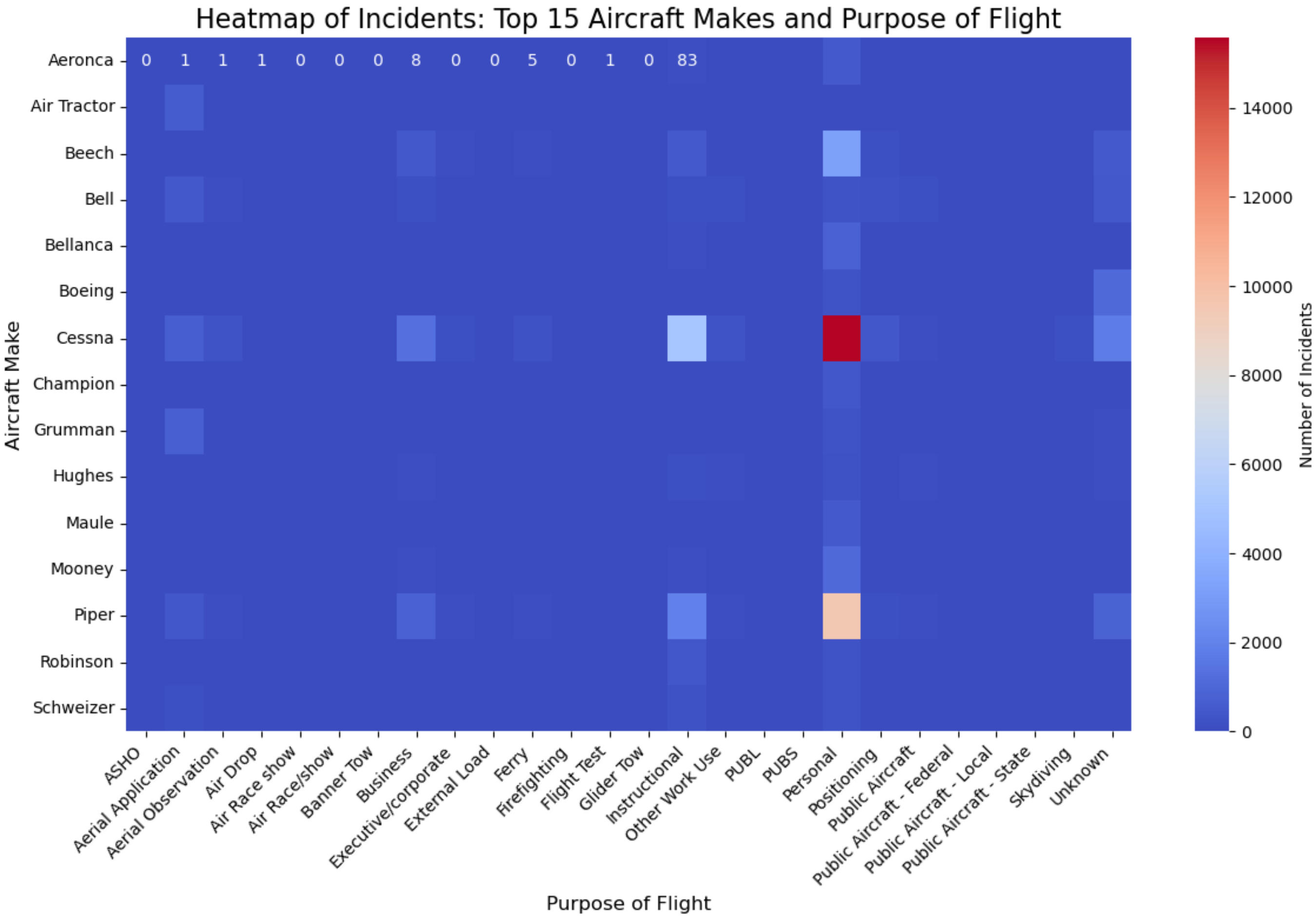
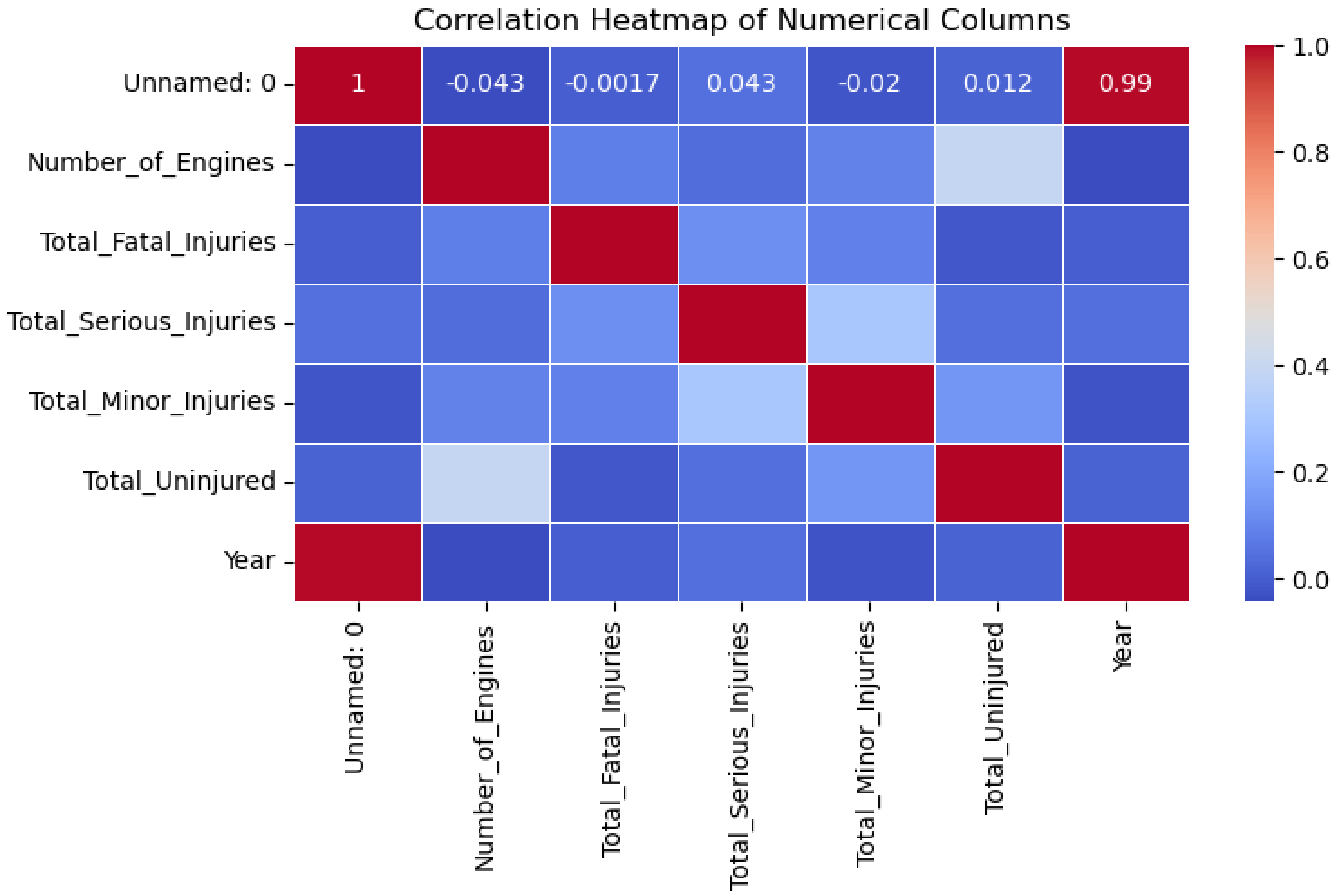
```python
top_makes = df['Make'].value_counts().nlargest(15).index

# Filter the data to include only the top 15 makes
scatter_data = scatter_data[scatter_data['Make'].isin(top_makes)]

# Convert 'Aircraft_damage' to numeric for better visualization
damage_mapping = {
    'Destroyed': 2,
    'Substantial': 1,
    'Minor': 0,
    'Unknown': -1  # Optional, for missing/unknown values
}
scatter_data['Aircraft_damage_numeric'] = scatter_data['Aircraft_damage'].map(damage_

# Create the scatter plot
plt.figure(figsize=(8, 6))
sns.scatterplot(
    data=scatter_data,
    x='Make',
    y='Total_Fatal_Injuries',
    hue='Aircraft_damage_numeric',
    palette='coolwarm',
    alpha=0.7
)

# Add labels and title
plt.title('Scatter Plot: Total Fatal Injuries by Make with Aircraft Damage', fontsize
plt.xlabel('Aircraft Make', fontsize=14)
plt.ylabel('Total Fatal Injuries', fontsize=14)
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for readability
plt.legend(title='Aircraft Damage')
plt.tight_layout()

plt.show()
```



In [61]:
```
# Heatmap of Incidents
# Filter the top 15 makes with the highest number of incidents
top_15_makes = df['Make'].value_counts().head(15).index
filtered_data = df[df['Make'].isin(top_15_makes)]

# Create a pivot table
heatmap_data = filtered_data.pivot_table(index='Make', columns='Purpose_of_flight',
                                         values='Event_Id', aggfunc='count', fill_val

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(heatmap_data, cmap='coolwarm', annot=True, fmt='d', cbar_kws={'label': 'N

# Add labels and title
plt.title('Heatmap of Incidents: Top 15 Aircraft Makes and Purpose of Flight', fontsi
plt.xlabel('Purpose of Flight', fontsize=12)
plt.ylabel('Aircraft Make', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.tight_layout()

plt.show()
```



In [62]:
```
# A correlation heatmap of numerical values
numerical_data = df.select_dtypes(include=['number'])

correlation_matrix = numerical_data.corr()

#plotting
plt.figure(figsize=(8, 4))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Heatmap of Numerical Columns')

plt.show()
```



Conclusion

Observations

1. **Most Common Aircraft Makes**: Top 15 aircraft makes account for 68.44% of the number of incidents. The Boeing Aircraft Make has the highest amount of fatal injuries with the aircraft being desroyed.
2. **Purpose of Flight**: Incidents are more frequent during personal flights compared to business or commercial operations.
3. **Flight Phases**: Takeoff, landing and maneuvering phases are the most critical, with higher probabilities of incidents.
4. **Weather Conditions**: Events are significantly higher during adverse weather conditions, particularly under Visual Meteorological Conditions (VMC).
5. **Severity Trends**: Fatalities and severe injuries are more likely in takeoff and maneuvering flight phases and during adverse weather.

Recommendations

1. **Aircraft Selection**:
   - Focus on acquiring aircraft with lower incident frequencies and lower severity ratings.
   - Prioritize makes and models with strong safety performance records.
   - Consider the aircraft make with the least amount of damage during the incidents.
2. **Safety Enhancements**:
   - Develop targeted training programs for pilots to handle takeoff, landing and maneuvering more effectively.

- Emphasize safety measures and emergency preparedness during adverse weather conditions.

3. **Operational Focus**:

   - Encourage the use of aircraft for commercial and business flights where risks are relatively lower.
   - Optimize flight schedules to minimize operations during high-risk weather conditions.

4. **Continuous Monitoring**:

   - Establish a framework to track and analyze incidents continuously to adapt to emerging trends and risks.
   - Invest in robust data systems for real-time risk assessment.

Final Thoughts

By leveraging historical aviation event data, we can make informed decisions about which aircraft to purchase and how to optimize safety operations. These insights empower stakeholders to minimize risks and align the new aviation division with long-term safety and performance goals.