Business Understanding

The company is expanding into both privatized and commercial aviation to diversify its portfolio. They would like to understand which aircraft types have the lowest risk. The "AviationData.csv" dataset provided by the NTSB, that will be explored in this notebook, contains information on selected accidents from 1962 to 2023. These are incidents that have taken place within the United States, its territories and possessions, and in international waters.

Key/focus questions:

- Which aircraft types have the lowest accident severity?
- Is a private or commercial flight riskier?
- Are certain conditions (e.g., weather, location) more associated with severe accidents?

Audience: Aviation division team and the company's stakeholders eg managers

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

In [2]:
```
#importing the dataset
df = pd.read_csv("C:/Users/PC/Desktop/School work/Projects/Phase1/Phase-1-Aviation-
```

```
C:\Users\PC\AppData\Local\Temp\ipykernel_13692\4218076357.py:2: DtypeWarning: Column
s (6,7,28) have mixed types. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv("C:/Users/PC/Desktop/School work/Projects/Phase1/Phase-1-Aviation
-Project/data/AviationData.csv", index_col = 0, encoding='cp1252')
```

Understanding the Dataset

In [3]:
```
#Looking into the datasets shape
df.shape
```

Out[3]: (88889, 30)

In [4]:
```
#information on the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 88889 entries, 20001218X45444 to 20221230106513
Data columns (total 30 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Investigation.Type      88889 non-null  object 
 1   Accident.Number         88889 non-null  object 
 2   Event.Date              88889 non-null  object 
 3   Location                88837 non-null  object 
 4   Country                 88663 non-null  object 
 5   Latitude                34382 non-null  object 
 6   Longitude               34373 non-null  object 
 7   Airport.Code            50132 non-null  object 
 8   Airport.Name            52704 non-null  object 
 9   Injury.Severity         87889 non-null  object 
 10  Aircraft.damage         85695 non-null  object 
 11  Aircraft.Category       32287 non-null  object 
 12  Registration.Number     87507 non-null  object 
 13  Make                    88826 non-null  object 
 14  Model                   88797 non-null  object 
 15  Amateur.Built           88787 non-null  object 
 16  Number.of.Engines       82805 non-null  float64
 17  Engine.Type             81793 non-null  object 
 18  FAR.Description         32023 non-null  object 
 19  Schedule                12582 non-null  object 
 20  Purpose.of.flight       82697 non-null  object 
 21  Air.carrier             16648 non-null  object 
 22  Total.Fatal.Injuries    77488 non-null  float64
 23  Total.Serious.Injuries  76379 non-null  float64
 24  Total.Minor.Injuries    76956 non-null  float64
 25  Total.Uninjured         82977 non-null  float64
 26  Weather.Condition       84397 non-null  object 
 27  Broad.phase.of.flight   61724 non-null  object 
 28  Report.Status           82505 non-null  object 
 29  Publication.Date        75118 non-null  object 
dtypes: float64(5), object(25)
memory usage: 21.0+ MB
```

In [5]:

```
#data types of the columns
df.dtypes
```

Out[5]:
```
Investigation.Type         object
Accident.Number            object
Event.Date                 object
Location                   object
Country                    object
Latitude                   object
Longitude                  object
Airport.Code               object
Airport.Name               object
Injury.Severity            object
Aircraft.damage            object
Aircraft.Category          object
Registration.Number        object
Make                       object
Model                      object
Amateur.Built              object
Number.of.Engines         float64
Engine.Type                object
FAR.Description            object
Schedule                   object
Purpose.of.flight          object
Air.carrier                object
Total.Fatal.Injuries      float64
Total.Serious.Injuries    float64
Total.Minor.Injuries      float64
Total.Uninjured           float64
Weather.Condition          object
Broad.phase.of.flight      object
Report.Status              object
Publication.Date           object
dtype: object
```

In [6]:
```
#looking into the first 5 rows of the dataset to get an idea of the data
df.head()
```

Out[6]:

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

5 rows × 30 columns

In [7]:

```
df.describe()
```

Out[7]:

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Tot
count	82805.000000	77488.000000	76379.000000	76956.000000	8
mean	1.146585	0.647855	0.279881	0.357061	
std	0.446510	5.485960	1.544084	2.235625	
min	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	0.000000	0.000000	0.000000	
50%	1.000000	0.000000	0.000000	0.000000	
75%	1.000000	0.000000	0.000000	0.000000	
max	8.000000	349.000000	161.000000	380.000000	

Cleaning the dataset

Using the head function and looking at the different columns of the dataset, some columns are not required moving forward.

Why? This is because they are not part/helpful in the analysis and will not interfere when forming a data driven conclusion. The columns such as Event Id and Accident number are just for administration purposes and Report status and publication date would be desired for a different type of analysis

In [8]:
```
#Getting the column names in the dataset

df.columns
```

Out[8]:
```
Index(['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 [9]:
```
#forming a list of the unrequired columns

unwanted_columns = ['Latitude', 'Longitude', 'Airport.Code',
       'Airport.Name', 'Registration.Number', 'Accident.Number', 'Report.Status',
       'Publication.Date']
df = df.drop(columns = unwanted_columns)
```

In [10]:
```
df.head()
```

Out[10]:

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

5 rows × 22 columns

In [11]:
```
# checking for columns with missing values
missing_count = df.isna().sum()
missing_count
```

Out[11]:
```
Investigation.Type            0
Event.Date                    0
Location                     52
Country                     226
Injury.Severity            1000
Aircraft.damage            3194
Aircraft.Category         56602
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
dtype: int64
```

In [12]:
```
#checking for the percentages of columns with missing values
#if it is greater than 50%, the columns are to be dropped

row_number = len(df)

missing_percentage = (missing_count / row_number) * 100
missing_percentage.sort_values(ascending = True)
```

Out[12]:
```
Investigation.Type         0.000000
Event.Date                 0.000000
Location                   0.058500
Make                       0.070875
Model                      0.103500
Amateur.Built              0.114750
Country                    0.254250
Injury.Severity            1.124999
Aircraft.damage            3.593246
Weather.Condition          5.053494
Total.Uninjured            6.650992
Number.of.Engines          6.844491
Purpose.of.flight          6.965991
Engine.Type                7.982990
Total.Fatal.Injuries      12.826109
Total.Minor.Injuries      13.424608
Total.Serious.Injuries    14.073732
Broad.phase.of.flight     30.560587
Aircraft.Category         63.677170
FAR.Description           63.974170
Air.carrier               81.271023
Schedule                  85.845268
dtype: float64
```

In [13]:
```
#dropping the columns with high percentage of missing values

df = df.drop(columns = ['Schedule', 'Air.carrier', 'FAR.Description'])
df.head()
```

Out[13]:

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

In [14]:
```
df.shape
```

Out[14]:
```
(88889, 19)
```

In [15]:
```
#Checking for duplicates in the data

df.duplicated().value_counts()
```

Out[15]:
```
False    88854
True        35
Name: count, dtype: int64
```

In [16]:
```
#dropping the duplicates

df = df.drop_duplicates()
df.shape
```

Out[16]:
```
(88854, 19)
```

In [17]:
```
#rechecking duplicates
df.duplicated().value_counts()
```

Out[17]:
```
False    88854
Name: count, dtype: int64
```

Handling Missing Values

Working according to the data types i.e, categorical or numerical, and the outliers.

In [18]:
```
df.dtypes
```

Out[18]:
```
Investigation.Type         object
Event.Date                 object
Location                   object
Country                    object
Injury.Severity            object
Aircraft.damage            object
Aircraft.Category          object
Make                       object
Model                      object
Amateur.Built              object
Number.of.Engines         float64
Engine.Type                object
Purpose.of.flight          object
Total.Fatal.Injuries      float64
Total.Serious.Injuries    float64
Total.Minor.Injuries      float64
Total.Uninjured           float64
Weather.Condition          object
Broad.phase.of.flight      object
dtype: object
```

In [19]:
```
df.isna().sum().sort_values(ascending = True)
```

Out[19]:
```
Investigation.Type            0
Event.Date                    0
Location                     52
Make                         63
Model                        92
Amateur.Built               102
Country                     226
Injury.Severity             998
Aircraft.damage            3191
Weather.Condition          4490
Total.Uninjured            5908
Number.of.Engines          6080
Purpose.of.flight          6189
Engine.Type                7093
Total.Fatal.Injuries      11398
Total.Minor.Injuries      11926
Total.Serious.Injuries    12503
Broad.phase.of.flight     27158
Aircraft.Category         56577
dtype: int64
```

Numerical columns

- First step will be describing the numerical columns and see if their mean and any outliers
- Fill the missing values using an appropriate and logical manner

After handling the missing data:

- Plotting graphs to visualise these outliers
- Handling the outliers if present
- Plot a graph to indicate the difference

In [20]:
```
df.columns
```

Out[20]:
```
Index(['Investigation.Type', 'Event.Date', 'Location', 'Country',
       'Injury.Severity', 'Aircraft.damage', 'Aircraft.Category', 'Make',
       'Model', 'Amateur.Built', 'Number.of.Engines', 'Engine.Type',
       'Purpose.of.flight', 'Total.Fatal.Injuries', 'Total.Serious.Injuries',
       'Total.Minor.Injuries', 'Total.Uninjured', 'Weather.Condition',
       'Broad.phase.of.flight'],
      dtype='object')
```

In [21]:
```
#creating a list of the columns which are float as indicated above
float_columns = ['Number.of.Engines', 'Total.Fatal.Injuries', 'Total.Serious.Injuri
float_columns
```

Out[21]:
```
['Number.of.Engines',
 'Total.Fatal.Injuries',
 'Total.Serious.Injuries',
 'Total.Minor.Injuries',
 'Total.Uninjured']
```

- Due to an error faced later as your filling in the missing values, converting to numeric is required since the columns are float
- This means using the pd.to_numeric function

In [22]:
```
for col in float_columns:
    df[col] = pd.to_numeric(df[col], errors='coerce')
```

In [23]:
```
for col in float_columns:
    print(df[col].dtype)
```

```
float64
float64
float64
float64
float64
```

In [24]:
```
#use a for loop to describe each of the columns in the above list to see their prop

for col in float_columns:
    print(f"{col} description:")
    print(df[col].describe())
    print("\n") #having line between each descruption
```

```
Number.of.Engines description:
count    82774.000000
mean         1.146556
std          0.446518
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          8.000000
Name: Number.of.Engines, dtype: float64


Total.Fatal.Injuries description:
count    77456.000000
mean         0.647826
std          5.487038
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max        349.000000
Name: Total.Fatal.Injuries, dtype: float64


Total.Serious.Injuries description:
count    76351.000000
mean         0.279892
std          1.544285
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max        161.000000
Name: Total.Serious.Injuries, dtype: float64


Total.Minor.Injuries description:
count    76928.000000
mean         0.357061
std          2.235891
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max        380.000000
Name: Total.Minor.Injuries, dtype: float64


Total.Uninjured description:
count    82946.000000
mean         5.318159
std         27.891441
min          0.000000
25%          0.000000
50%          1.000000
75%          2.000000
```

```
max        699.000000
Name: Total.Uninjured, dtype: float64
```

In [25]:
```
#calculating the median of the float columns

for col in float_columns:
    print(f"Median for {col}:")
    print(df[col].median())
    print("\n")
```

```
Median for Number.of.Engines:
1.0


Median for Total.Fatal.Injuries:
0.0


Median for Total.Serious.Injuries:
0.0


Median for Total.Minor.Injuries:
0.0


Median for Total.Uninjured:
1.0
```

From the results above:

- The number of engines is mostly 1. This is the suitable number to use to fill in the missing values in the rows for the Number of engine column. The outliers being 8 for example are for aircrafts which are used in the military. In this case, we are analysing for commercial or private aircrafts hence not considered.
- For injury based columns (the other 4 float columns), missing values means that the injuries were not collected/noted down. Therefore cannot fill in the missing values using the median/mean as it will not be accurate/correct assumption.

In [26]:
```
#filling in the missing values

#filling in the no.of.engines column
df['Number.of.Engines'] = df['Number.of.Engines'].fillna(df['Number.of.Engines'].me
```

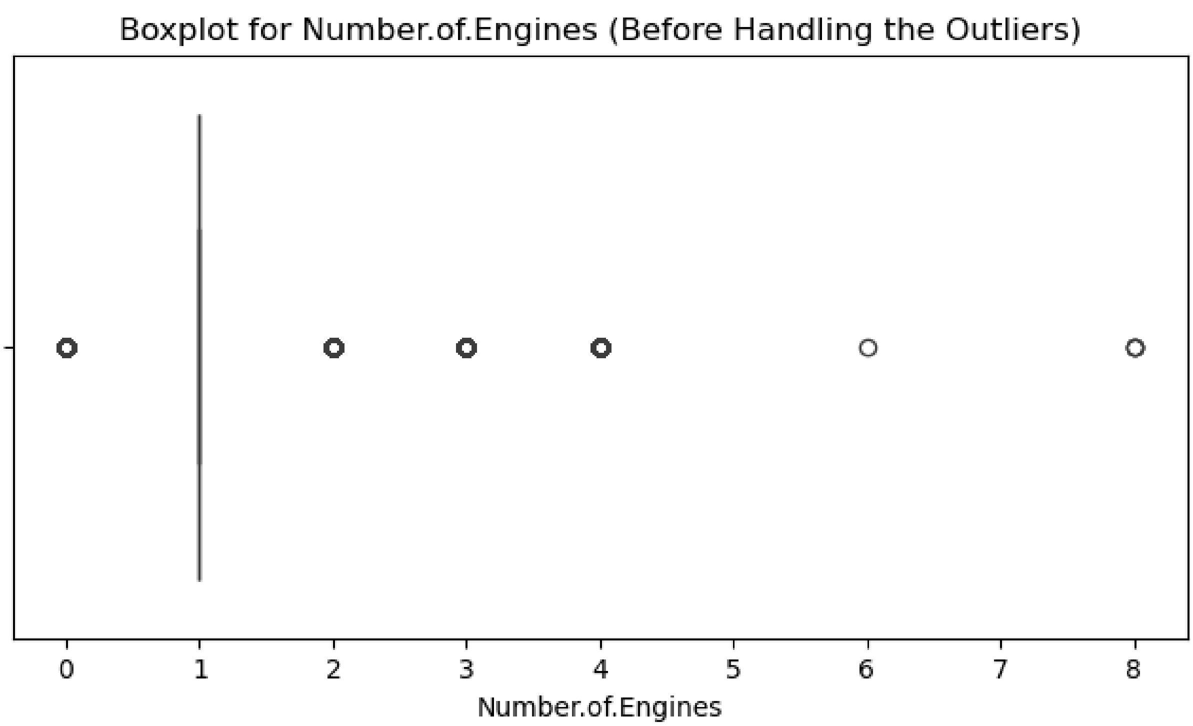
In [27]:
```
# other 4 columns that are to be filled with 0
four_columns = ['Total.Fatal.Injuries', 'Total.Serious.Injuries', 'Total.Minor.Inju
for col in four_columns:
    df[col] = df[col].fillna(0)
```

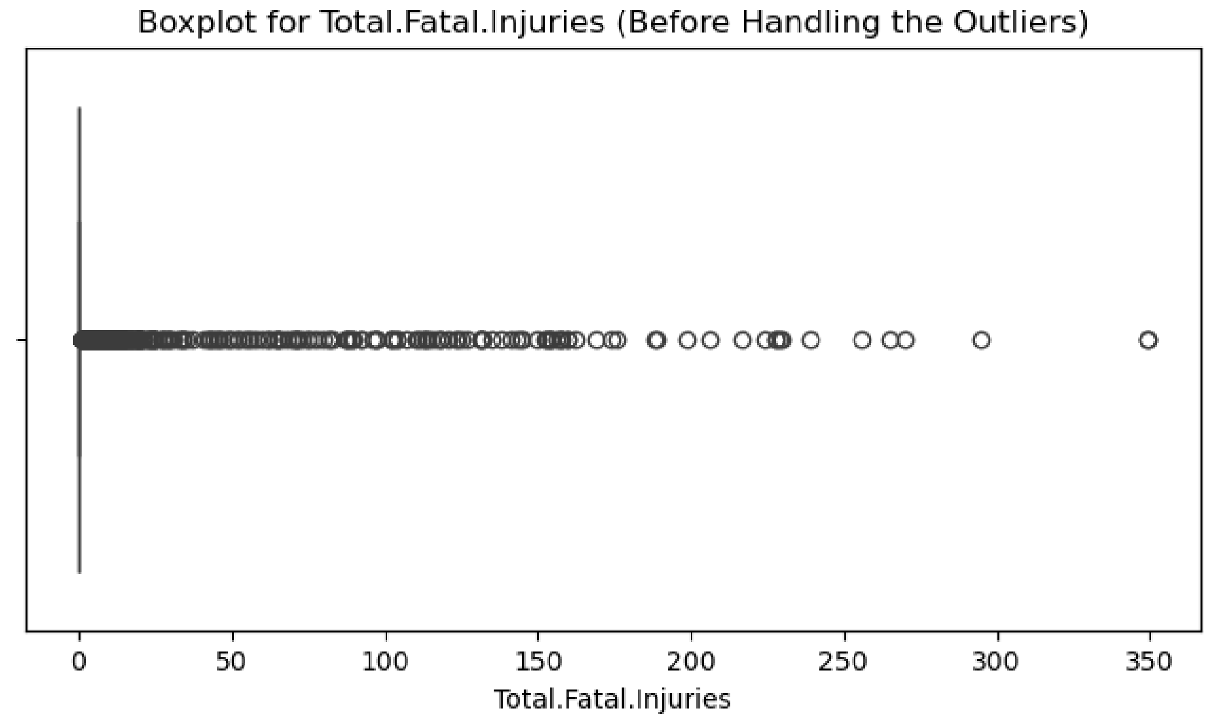
In [28]:
```
#checking if they have been filled
df[float_columns].isnull().sum()
```

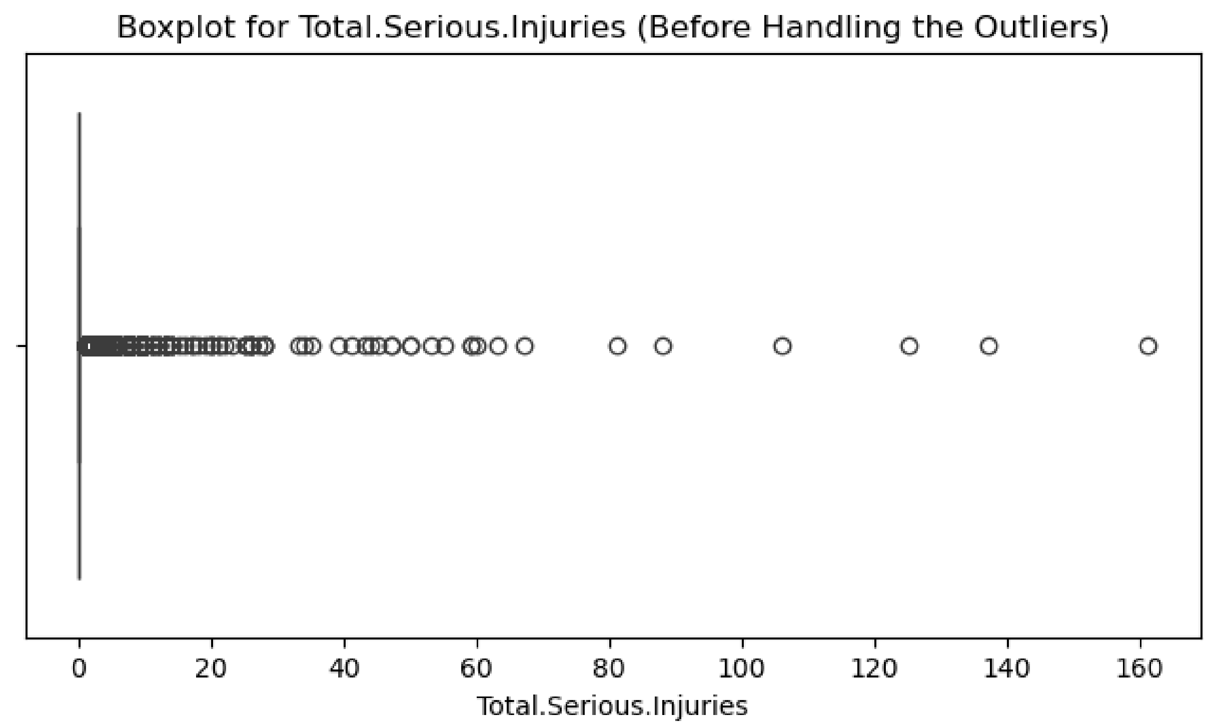
Out[28]:
```
Number.of.Engines         0
Total.Fatal.Injuries      0
Total.Serious.Injuries    0
Total.Minor.Injuries      0
Total.Uninjured           0
dtype: int64
```

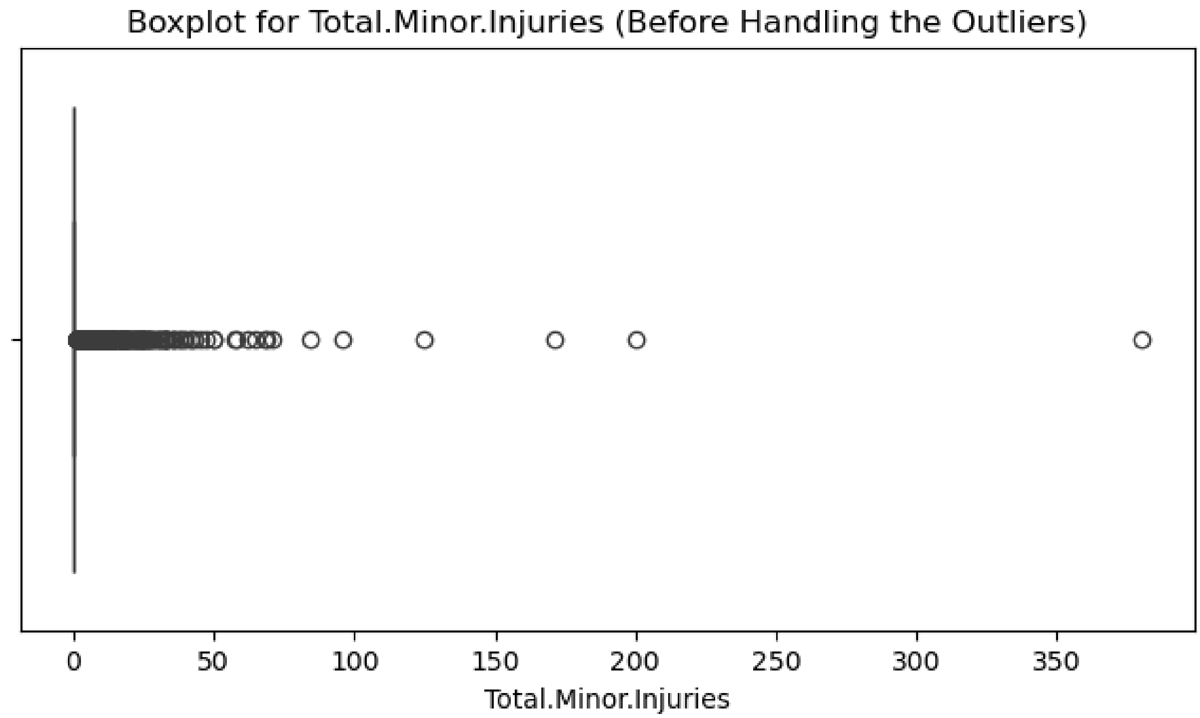
- Able to handle the missing values in the numerical columns and now proceed to handle the outliers based on the results from the describe function

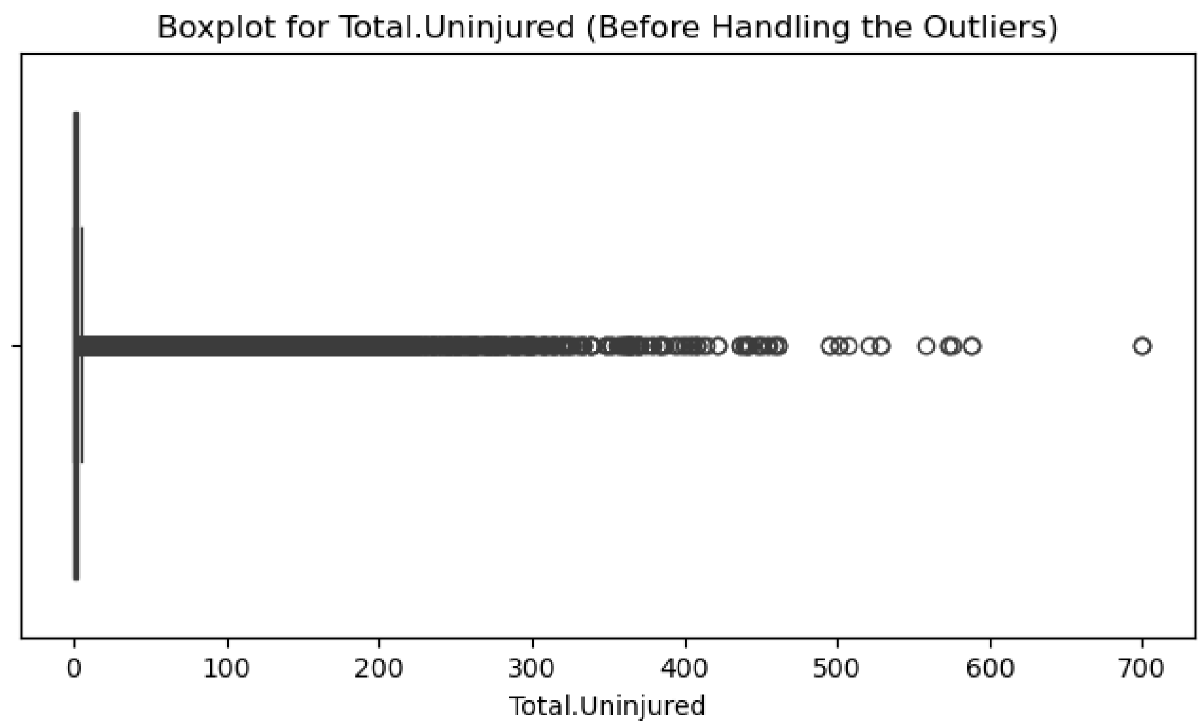
In [29]:
```
# create a boxplot to visualise the outliers in each of the float columns in the li
for col in float_columns:
    fig, ax = plt.subplots(figsize=(8,4))
    sns.boxplot(x=df[col], ax=ax)
    ax.set_title(f'Boxplot for {col} (Before Handling the Outliers)')
    plt.show()
```




Boxplot for Total.Fatal.Injuries (Before Handling the Outliers)
0
50
100
150
200
250
300
350
Total.Fatal.Injuries


Boxplot for Total.Serious.Injuries (Before Handling the Outliers)
0
20
40
60
80
100
120
140
160
Total.Serious.Injuries





- We can now visually notice that there are outliers present in the numerical columns that need to be dealt with

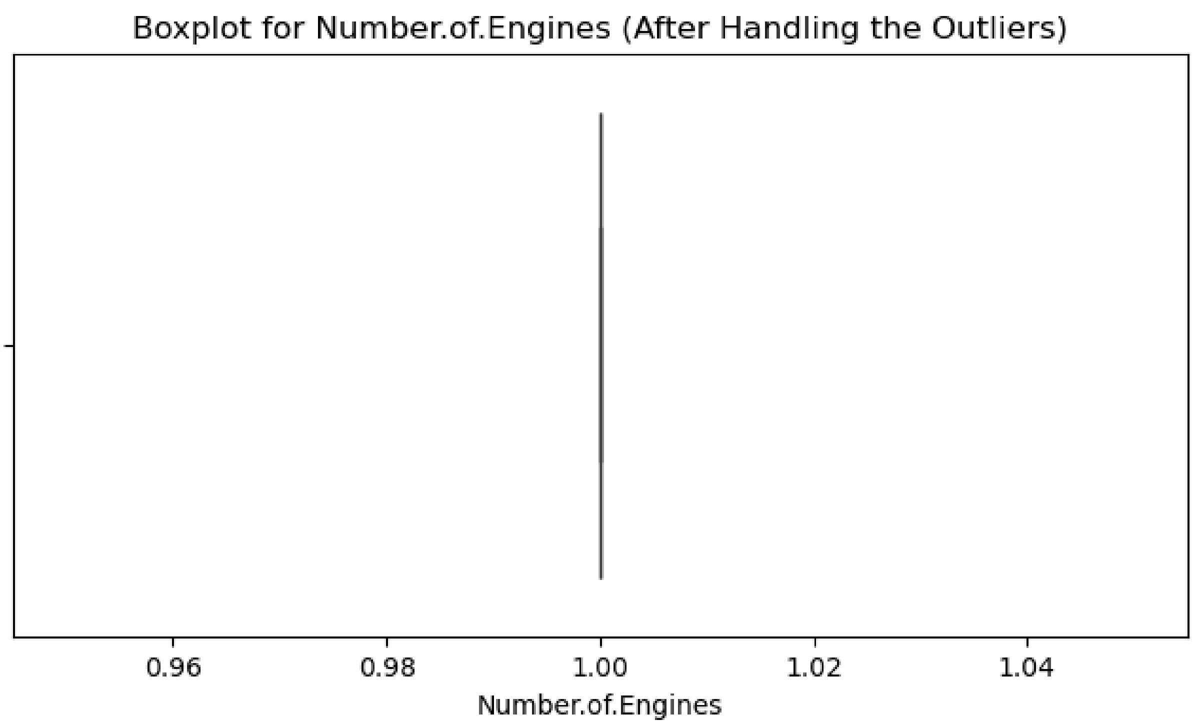
In [30]:
```
# removing the outliers in the float columns

for col in float_columns:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
```

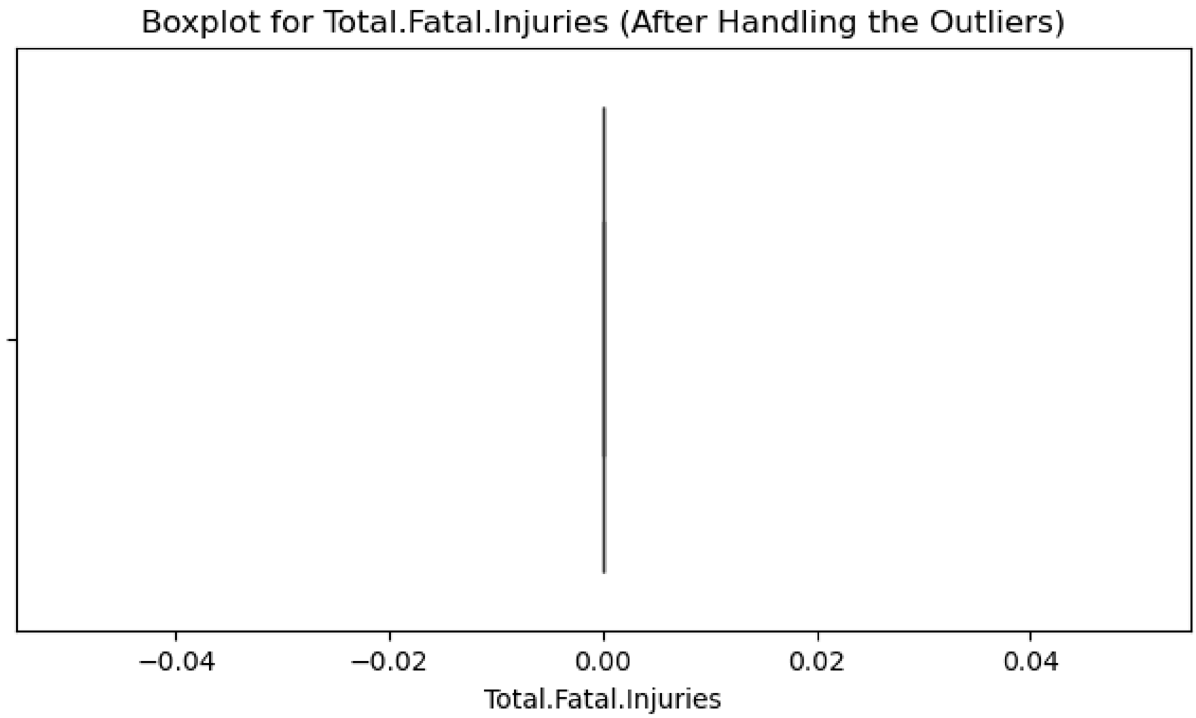
```
# for correcting the dataframe without outliers present
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    df = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]
```

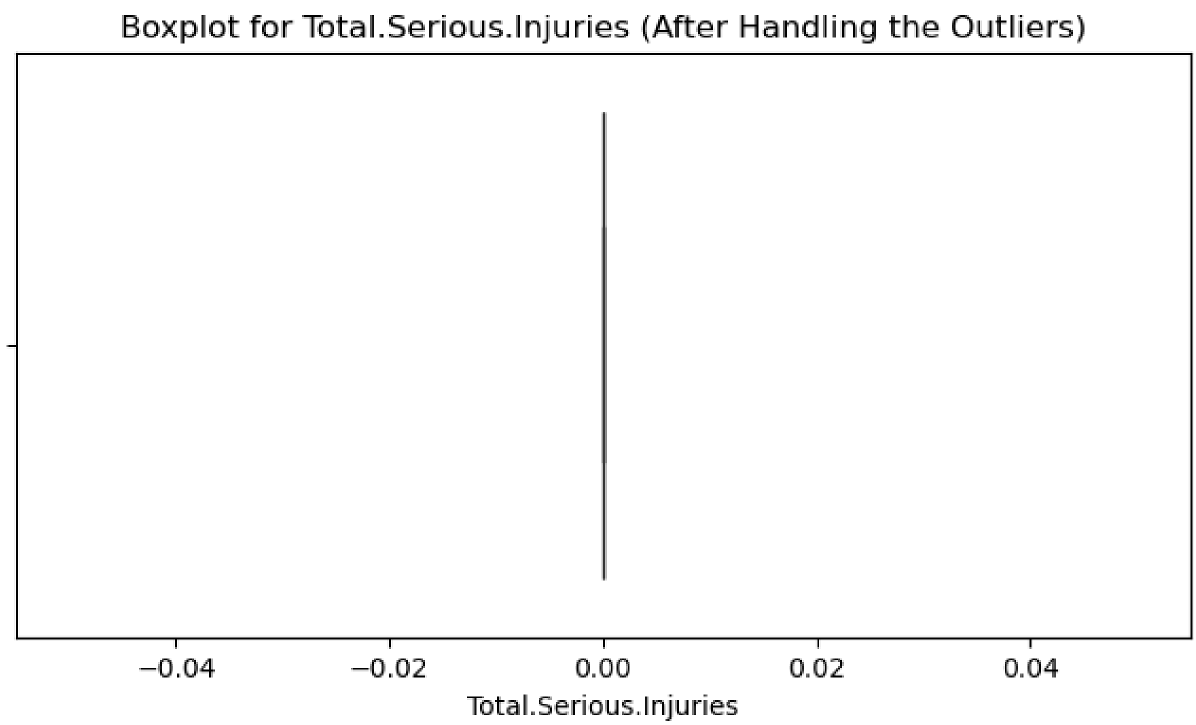
In [31]:
```
df.shape
```

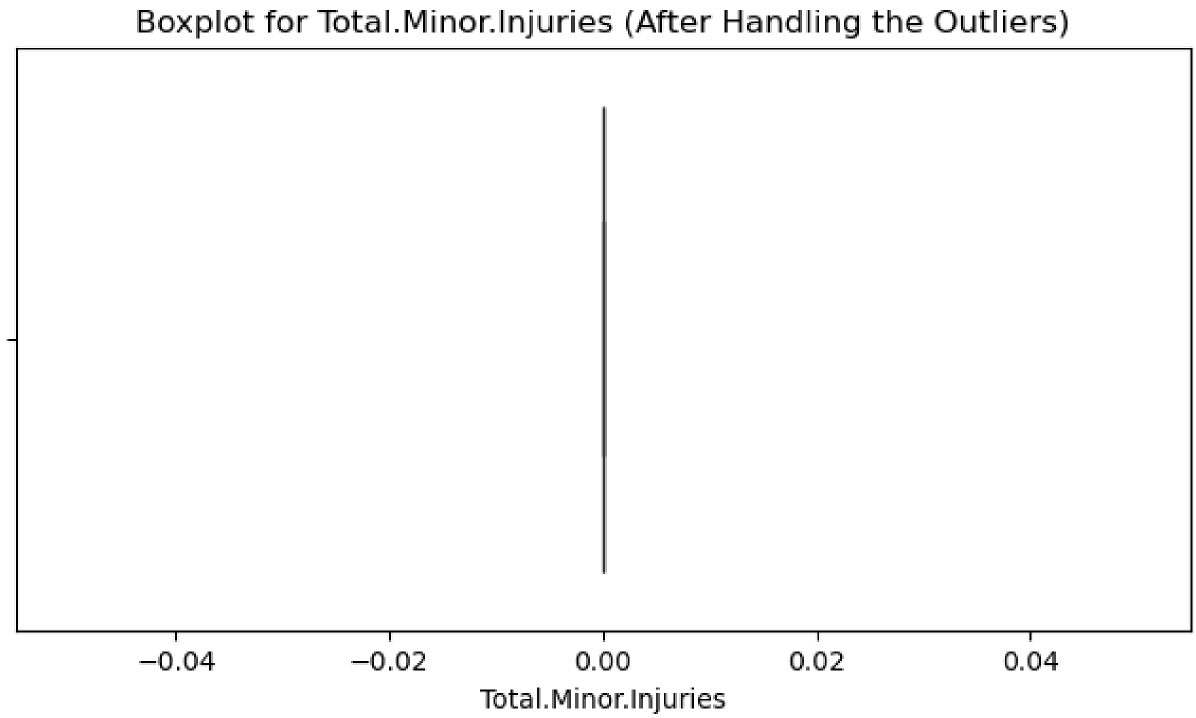
Out[31]: (37805, 19)

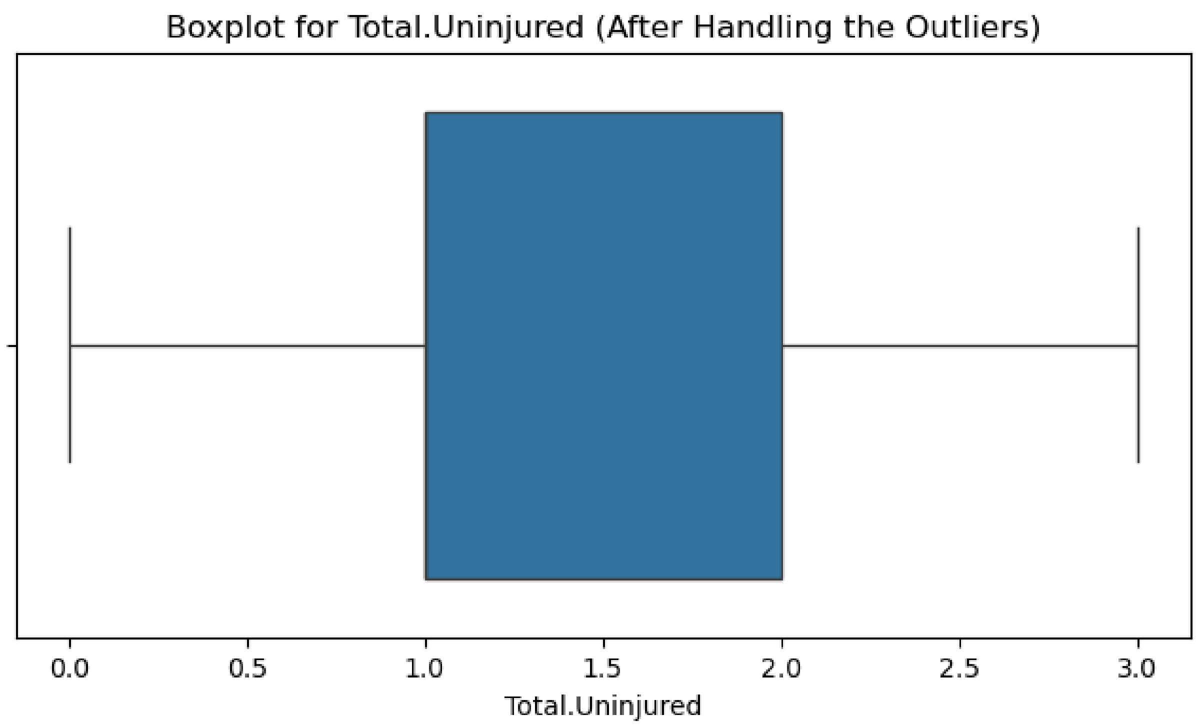
In [32]:
```
# plotting after handling the colums outliers

for col in float_columns:
    fig, ax = plt.subplots(figsize=(8,4))
    sns.boxplot(x=df[col], ax=ax)
    ax.set_title(f'Boxplot for {col} (After Handling the Outliers)')
    plt.show()
```




Boxplot for Total.Fatal.Injuries (After Handling the Outliers)
−0.04
−0.02
0.00
0.02
0.04
Total.Fatal.Injuries


Boxplot for Total.Serious.Injuries (After Handling the Outliers)
−0.04
−0.02
0.00
0.02
0.04
Total.Serious.Injuries





In [33]:
```
# lastly can deescribe and see if the outliers are still present

for col in float_columns:
    print(f"{col} description:")
    print(df[col].describe())
    print("\n") #having line between each descruption
```

```
Number.of.Engines description:
count    37805.0
mean         1.0
std          0.0
min          1.0
25%          1.0
50%          1.0
75%          1.0
max          1.0
Name: Number.of.Engines, dtype: float64


Total.Fatal.Injuries description:
count    37805.0
mean         0.0
std          0.0
min          0.0
25%          0.0
50%          0.0
75%          0.0
max          0.0
Name: Total.Fatal.Injuries, dtype: float64


Total.Serious.Injuries description:
count    37805.0
mean         0.0
std          0.0
min          0.0
25%          0.0
50%          0.0
75%          0.0
max          0.0
Name: Total.Serious.Injuries, dtype: float64


Total.Minor.Injuries description:
count    37805.0
mean         0.0
std          0.0
min          0.0
25%          0.0
50%          0.0
75%          0.0
max          0.0
Name: Total.Minor.Injuries, dtype: float64


Total.Uninjured description:
count    37805.000000
mean         1.480122
std          0.677462
min          0.000000
25%          1.000000
50%          1.000000
75%          2.000000
```

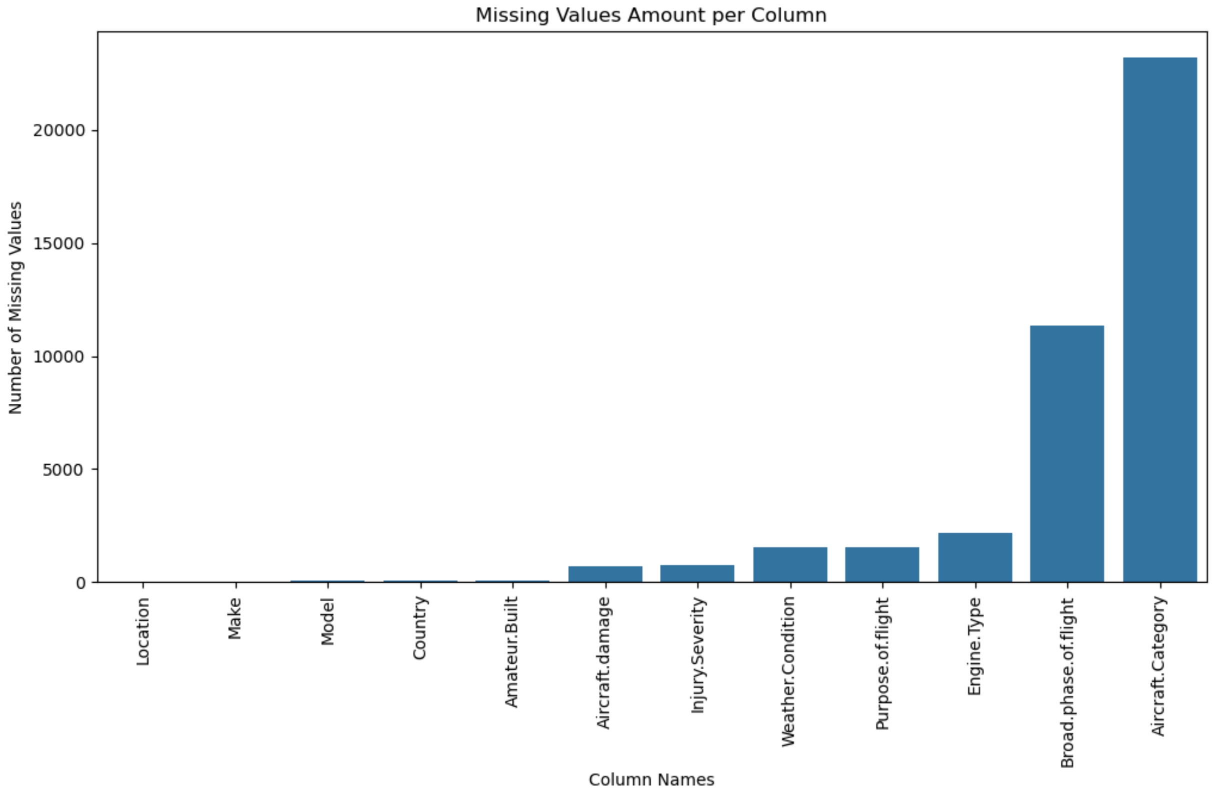
```
max           3.000000
Name: Total.Uninjured, dtype: float64
```

Categorical data

In [34]:
```python
# checking the columns again

df.isna().sum().sort_values(ascending = True)
```

Out[34]:
```
Investigation.Type          0
Event.Date                  0
Total.Uninjured             0
Total.Minor.Injuries        0
Total.Serious.Injuries      0
Total.Fatal.Injuries        0
Number.of.Engines           0
Location                   16
Make                       31
Model                      39
Country                    50
Amateur.Built              54
Aircraft.damage           703
Injury.Severity           765
Weather.Condition        1515
Purpose.of.flight        1552
Engine.Type              2188
Broad.phase.of.flight   11372
Aircraft.Category       23196
dtype: int64
```

In [35]:
```python
# we can create a graph to visualise this

missing_counts = df.isna().sum()
missing_counts = missing_counts[missing_counts > 0].sort_values(ascending = True)

# Plot
plt.figure(figsize = (12,6))
sns.barplot(x = missing_counts.index, y = missing_counts.values)
plt.title('Missing Values Amount per Column')
plt.ylabel('Number of Missing Values')
plt.xlabel('Column Names')
plt.xticks(rotation = 90)
plt.show()
```



From the results above:

- The numerical columns with missing values have been handled and the categorical columns are yet to be handled
- The aircraft category column has a very high value of missing data, there needs to be dropped as it will not be helpful

In [36]:
```
# we first drop the aircraft category column
df = df.drop(columns=['Aircraft.Category'])
df.head(2)
```

Out[36]:

	Investigation.Type	Event.Date	Location	Country	Injury.Severity	Aircr
Event.Id						
20020909X01562	Accident	1982-01-01	PULLMAN, WA	United States	Non-Fatal	
20020909X01559	Accident	1982-01-01	HOBBS, NM	United States	Non-Fatal	

In [37]:
```
# after dropping the column, proceed to create a list of the columns that are objec

object_columns = list(df.select_dtypes(include='object'))
object_columns
```

Out[37]:
```
['Investigation.Type',
 'Event.Date',
 'Location',
 'Country',
 'Injury.Severity',
 'Aircraft.damage',
 'Make',
 'Model',
 'Amateur.Built',
 'Engine.Type',
 'Purpose.of.flight',
 'Weather.Condition',
 'Broad.phase.of.flight']
```

In [38]:
```
# from the list above get the columns which are missing values

missing_columns = []

for col in object_columns:
    if df[col].isna().any():
        missing_columns.append(col)

missing_columns
```

Out[38]:
```
['Location',
 'Country',
 'Injury.Severity',
 'Aircraft.damage',
 'Make',
 'Model',
 'Amateur.Built',
 'Engine.Type',
 'Purpose.of.flight',
 'Weather.Condition',
 'Broad.phase.of.flight']
```

In [39]:
```
#now getting their unique values in the list above

for col in missing_columns:
    print(f"Unique values in {col}:")
    print(df[col].unique())
    print("\n")
```

```
Unique values in Location:
['PULLMAN, WA' 'HOBBS, NM' 'TUSKEGEE, AL' ... 'Kildare, '
 'Rancho Cordova, CA' 'San Manual, AZ']


Unique values in Country:
['United States' 'GULF OF MEXICO' 'Puerto Rico' nan 'Bahamas'
 'Netherlands Antilles' 'CARIBBEAN SEA' 'Philippines' 'Mexico'
 'ATLANTIC OCEAN' 'Northern Mariana Islands' 'Turks And Caicos Islands'
 'Japan' 'Panama' 'PACIFIC OCEAN' 'American Samoa' 'Germany' 'Sudan'
 'United Kingdom' 'Venezuela' 'Canada' 'Switzerland' 'Argentina'
 'West Indies' 'Brazil' 'Trinidad And Tobago' 'Colombia' 'Fiji'
 'Netherlands' 'Ireland' 'Peru' 'Central African Republic'
 'British Virgin Islands' 'China' 'Saudi Arabia' 'Mauritius' 'Thailand'
 'Belgium' 'Uruguay' 'Guatemala' 'France' 'Taiwan' 'Iceland' 'Kazakhstan'
 'Ethiopia' 'Australia' 'Egypt' 'India' 'Spain' 'Greece'
 'Korea, Republic Of' 'Ecuador' 'Mozambique' 'Italy' 'Singapore'
 'Indonesia' 'Portugal' 'Finland' 'Guyana' 'Turkey' 'New Zealand'
 'Zimbabwe' 'Costa Rica' 'Federated States Of Micronesia' 'Norway' 'Gabon'
 'South Africa' 'Angola' 'Kenya' 'Guadeloupe' 'Ivory Coast'
 'Dominican Republic' 'Vietnam' 'Nepal' 'Sweden' 'Nigeria' 'Malaysia'
 'Cuba' 'Austria' 'Namibia' 'Czech Republic' 'Martinique' 'Denmark'
 'Chile' 'Belize' 'Bolivia' 'Reunion' 'United Arab Emirates' 'Ukraine'
 'Jordan' 'Nicaragua' 'Pakistan' 'Qatar' 'Poland' 'Israel' 'Jamaica'
 'Bangladesh' 'Hungary' 'Sint Maarten' 'Central Africa' 'Seychelles'
 'Rwanda' 'Afghanistan' 'Russia' 'South Korea' 'Iran' 'Lithuania'
 'Barbados' 'Eswatini' 'Antigua and Barbuda' 'Maldives' 'AY' 'Latvia'
 'Ghana' 'Macao' 'Luxembourg' 'Tanzania' 'Senegal' 'Papua New Guinea'
 'Cayman Islands' 'Solomon Islands' 'Mali' 'Turks And Caicos' 'Slovenia'
 'Cameroon' 'Bahrain' 'Nauru' 'Niue' 'UN' 'Antarctica' 'Bulgaria'
 'Morocco' 'Hong Kong' 'Romania' 'Suriname' 'Saint Barthelemy' 'Somalia'
 'Honduras' 'Guinea' 'Greenland' 'Estonia' 'Kyrgyzstan' 'Albania'
 'Croatia' 'Malta' 'South Sudan' 'Virgin Islands' 'Wallis and Futuna'
 'Lebanon' 'Saint Pierre and Miquelon' 'Georgia' "Côte d'Ivoire"
 'French Polynesia' 'Serbia' 'MU' 'Great Britain']


Unique values in Injury.Severity:
['Non-Fatal' 'Incident' 'Unavailable' nan 'Fatal' 'Serious' 'Minor']


Unique values in Aircraft.damage:
['Substantial' 'Destroyed' 'Minor' nan 'Unknown']


Unique values in Make:
['Cessna' 'Piper' 'Beech' ... 'CHILDS MICHAEL  A' 'RUTAN'
 'JAMES R DERNOVSEK']


Unique values in Model:
['140' 'PA-28-161' 'V35B' ... 'KITFOX S5' '441' 'A330-243']


Unique values in Amateur.Built:
['No' 'Yes' nan]
```

```
Unique values in Engine.Type:
['Reciprocating' 'Turbo Shaft' 'Turbo Prop' 'Unknown' 'Turbo Jet'
 'Turbo Fan' nan 'Electric' 'Geared Turbofan']


Unique values in Purpose.of.flight:
['Personal' 'Instructional' 'Unknown' 'Ferry' 'Business'
 'Aerial Application' 'Executive/corporate' 'Aerial Observation'
 'Public Aircraft' 'Other Work Use' 'Positioning' nan 'Skydiving'
 'Flight Test' 'Air Race/show' 'Air Drop' 'Glider Tow'
 'Public Aircraft - Local' 'External Load' 'Banner Tow'
 'Public Aircraft - Federal' 'Public Aircraft - State' 'Firefighting'
 'Air Race show' 'PUBS' 'ASHO' 'PUBL']


Unique values in Weather.Condition:
['VMC' 'IMC' 'UNK' nan 'Unk']


Unique values in Broad.phase.of.flight:
['Takeoff' 'Approach' 'Landing' 'Taxi' 'Cruise' 'Climb' 'Descent'
 'Go-around' 'Maneuvering' 'Standing' 'Other' 'Unknown' nan]
```

In [40]:

```python
#getting the mode of the unique values in the missing columns data

for col in missing_columns:
    print(f"Mode for {col}: {df[col].mode()[0]}")
    print("\n")
```

```
Mode for Location: ANCHORAGE, AK

Mode for Country: United States

Mode for Injury.Severity: Non-Fatal

Mode for Aircraft.damage: Substantial

Mode for Make: Cessna

Mode for Model: 152

Mode for Amateur.Built: No

Mode for Engine.Type: Reciprocating

Mode for Purpose.of.flight: Personal

Mode for Weather.Condition: VMC

Mode for Broad.phase.of.flight: Landing
```

From the results above:

- We notice that the amateur built column has 2 options which is boolean (yes or no) therefore replace missing values with the mode
- The other columns have multiple options, hence will not be suitable to replace with the mode but rather "missing"

In [41]:
```
#handling the missing data for the missing columns

for col in missing_columns:
    if col == 'Amateur.Built':
        df[col] = df[col].fillna(df[col].mode()[0])
    else:
        df[col] = df[col].fillna('Missing')
```

In [42]:
```
df.isna().any()
```

Out[42]:
```
Investigation.Type        False
Event.Date                False
Location                  False
Country                   False
Injury.Severity           False
Aircraft.damage           False
Make                      False
Model                     False
Amateur.Built             False
Number.of.Engines         False
Engine.Type               False
Purpose.of.flight         False
Total.Fatal.Injuries      False
Total.Serious.Injuries    False
Total.Minor.Injuries      False
Total.Uninjured           False
Weather.Condition         False
Broad.phase.of.flight     False
dtype: bool
```

In [43]:
```
# ensuring the columns which are object are the same with the all the letters upper
#avoiding Boeing and BOEING
# Loop through all object columns and clean
for col in df.select_dtypes(include='object').columns:
    df[col] = df[col].str.strip().str.upper()
```

In [44]:
```
#converting the dataset that's been cleaned to csv to use for tableau

df.to_csv('cleaned_aviation_data.csv', index=False)
```

Data Analysis

- In this section the dataset will be narrowed down to the top 10 for filtering purposes
- This is to guide into drawing a well informed conclusion on which airplanes and approach is best for the company
- There will be use of diagrams such as bar graphs to form a visual conclusion
- Functions such as groupby will be used to combine/filter the dataset

In [45]:
```
df.columns
```

Out[45]:
```
Index(['Investigation.Type', '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',
       'Broad.phase.of.flight'],
      dtype='object')
```

In [46]:
```
df.head(2)
```

Out[46]:

Event.Id	Investigation.Type	Event.Date	Location	Country	Injury.Severity	Aircr
20020909X01562	ACCIDENT	1982-01-01	PULLMAN, WA	UNITED STATES	NON-FATAL	SU
20020909X01559	ACCIDENT	1982-01-01	HOBBS, NM	UNITED STATES	NON-FATAL	SU

In [47]:
```
# number of makes of aircrafts
number_of_makes = df['Make'].nunique()
print(f"Number of unique aircraft makes: {number_of_makes}")
```

```
Number of unique aircraft makes: 3311
```

In [48]:
```
# number of models of aircrafts
number_of_models = df['Model'].nunique()
print(f"Number of unique aircraft models: {number_of_models}")
```

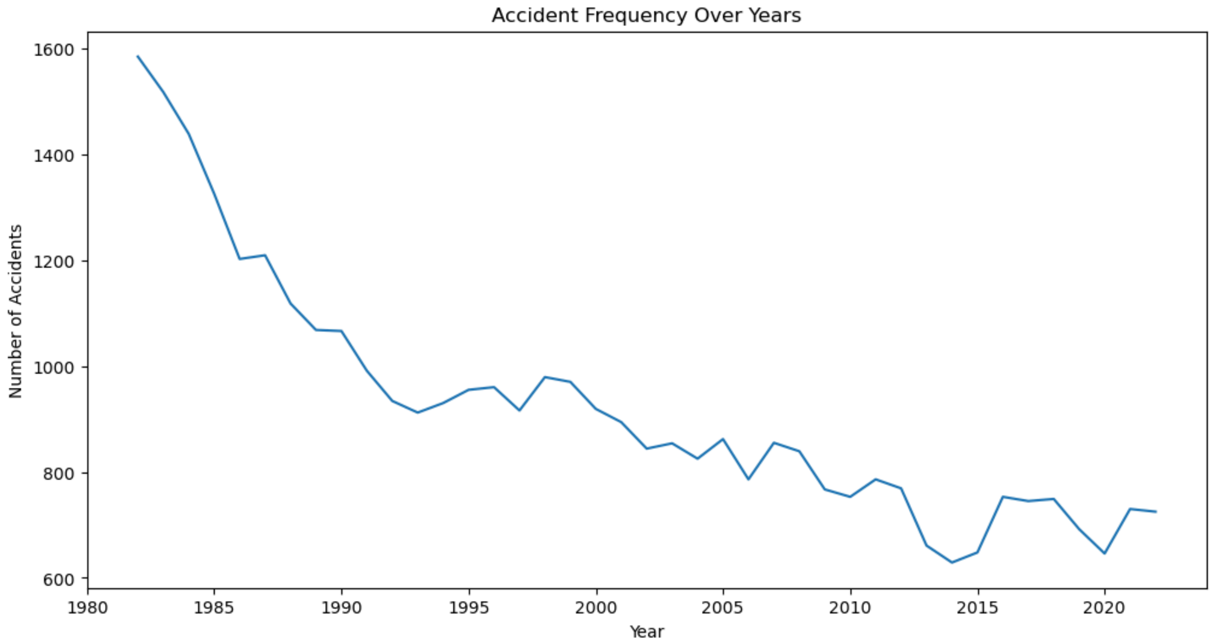
```
Number of unique aircraft models: 5365
```

Frequency of accident over the years

- This will show and help us understand the trend from 1962-2023

In [49]:
```
# the column Event Date needs to be converted to datetime
df['Event.Date'] = pd.to_datetime(df['Event.Date'], errors='coerce')
# need to create a column with just the year on its own which would be 1962 for exa
df['Year'] = df['Event.Date'].dt.year
```

In [50]:
```
# for the plot, it needs to be grouped by year
accidents_per_year = df.groupby('Year').size()

plt.figure(figsize = (12,6))
sns.lineplot(x = accidents_per_year.index, y = accidents_per_year.values)
plt.title('Accident Frequency Over Years')
plt.xlabel('Year')
plt.ylabel('Number of Accidents')
plt.show()
```



From the line graph above you are able to notice that over the years, the number of accidents have decreased. This is possibly due to the imporvements in technology, communication systems and safety protocls over the years. For the company, it would be an indication that investing in aviation is not a bad idea.

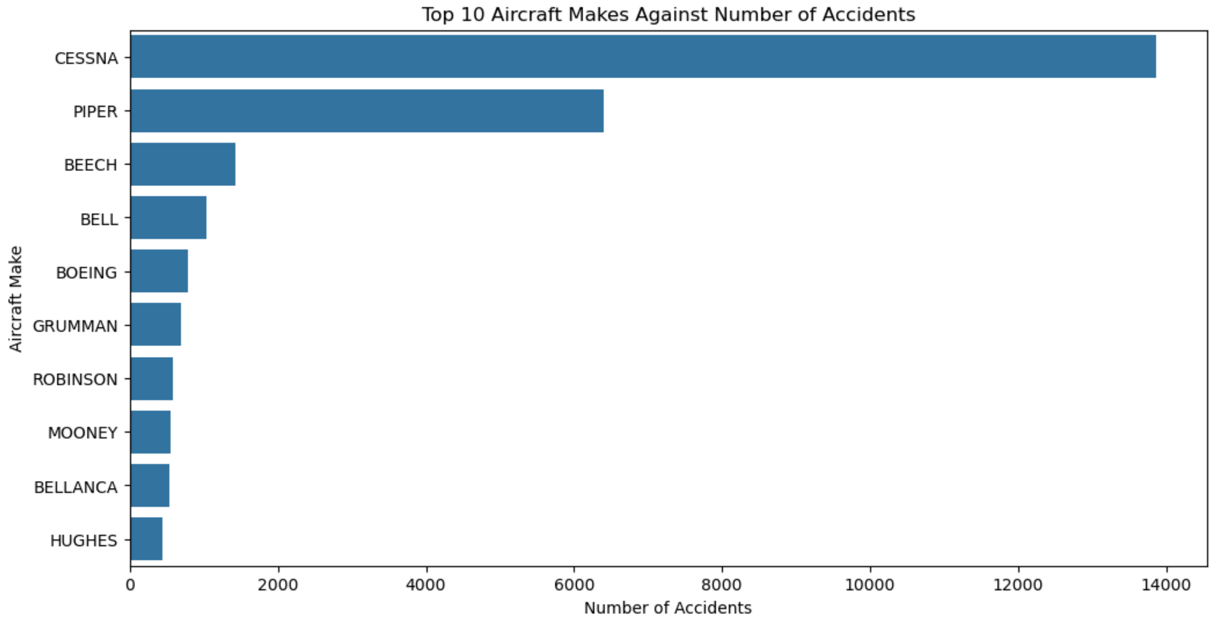
Top 10 Makes of aircrafts involved in accidents

- This will help understand which makes to avoid

In [51]:
```
top_makes = df['Make'].value_counts().head(10)
top_makes
```

Out[51]:
```
Make
CESSNA      13858
PIPER        6406
BEECH        1422
BELL         1030
BOEING        779
GRUMMAN       692
ROBINSON      581
MOONEY        548
BELLANCA      531
HUGHES        441
Name: count, dtype: int64
```

In [52]:
```
#plotting the graph for visualising

plt.figure(figsize = (12,6))
sns.barplot(x = top_makes.values, y = top_makes.index)
plt.title('Top 10 Aircraft Makes Against Number of Accidents')
plt.xlabel('Number of Accidents')
plt.ylabel('Aircraft Make')
plt.show()
```



From the horizontal graph above, it would make most sense to espeially avoid Cessna with the highest followed by Piper. These makes makes (the top 2 mentioned) have averagely had the largest number of accidents which would not be a good investment for the company. It would put them and clientel at risk.

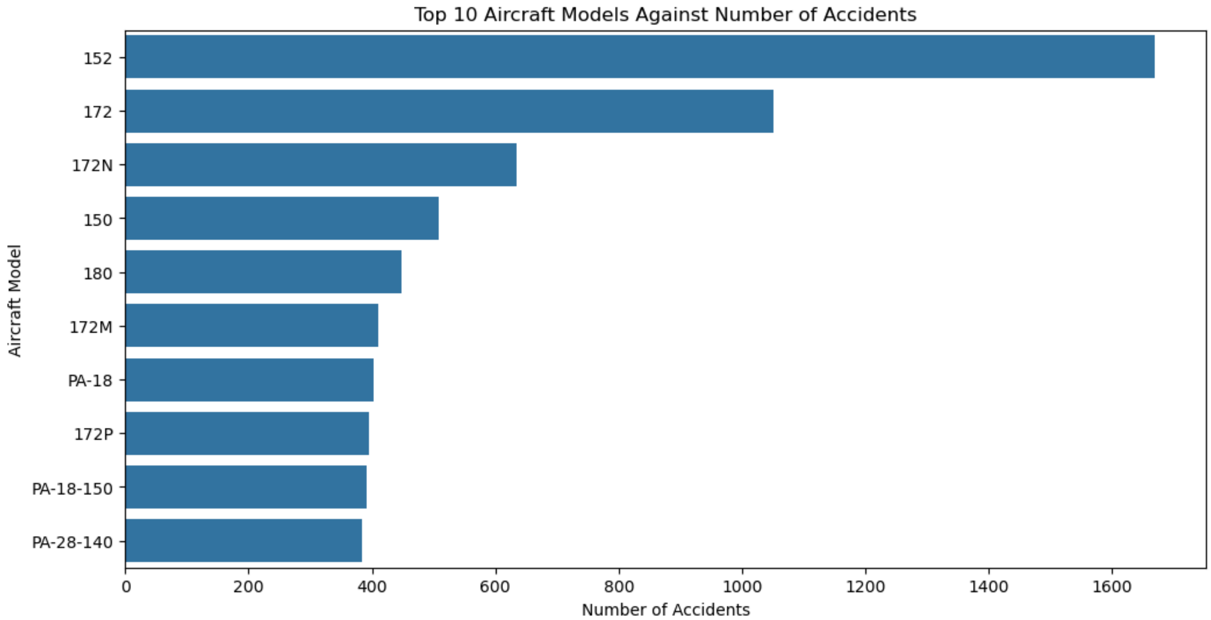
Top 10 Models against the number of accident

- Helps us understand the models to avoid

In [53]:
```
top_models = df['Model'].value_counts().head(10)
top_models
```

Out[53]:
```
Model
152          1669
172          1051
172N          635
150           508
180           448
172M          410
PA-18         403
172P          396
PA-18-150     391
PA-28-140     383
Name: count, dtype: int64
```

In [54]:
```
#plotting the graph for visualising

plt.figure(figsize = (12,6))
sns.barplot(x = top_models.values, y = top_models.index)
plt.title('Top 10 Aircraft Models Against Number of Accidents')
plt.xlabel('Number of Accidents')
plt.ylabel('Aircraft Model')
plt.show()
```



The 152, 172 and 172N models would be be the riskiest and worst options to invest in as a company. This is because they hold the highest number of accidents. The last 5 models hold averagely the same amount of accidents; 172M - PA-28-140.

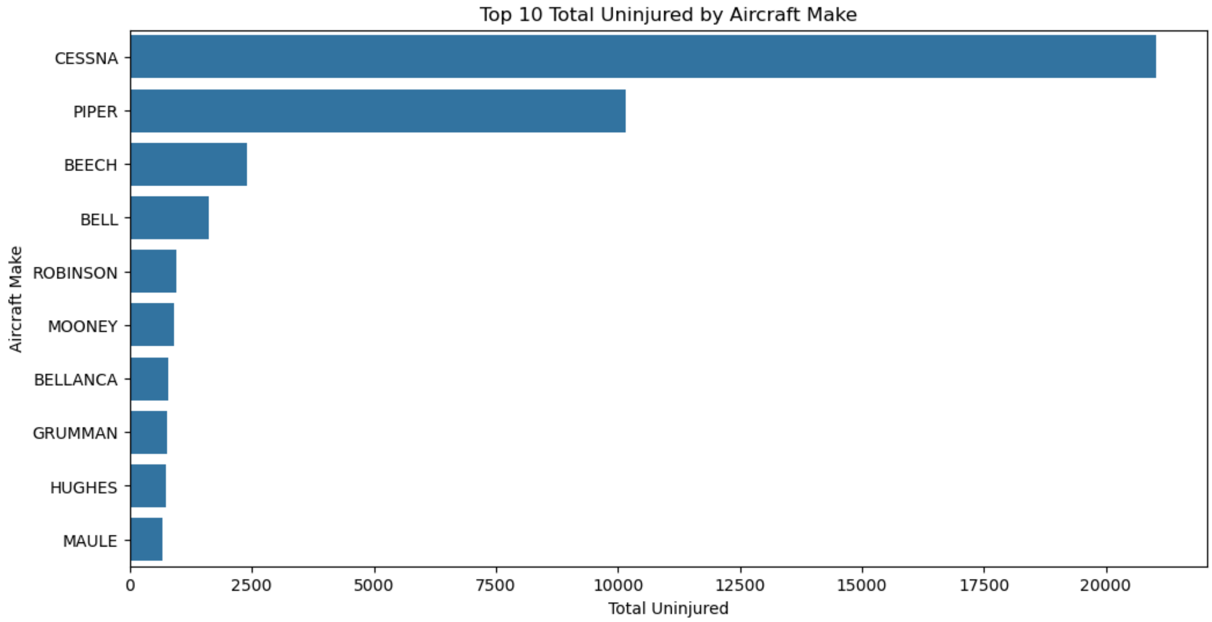
Top 10 Total Uninjured by Aircraft Make

- This is grouping under the make and will indicate the the safest make to invest in/ make that holds a high capacity of passengers

In [55]:
```
top_uninjured_make = df.groupby('Make')['Total.Uninjured'].sum().sort_values(ascend
top_uninjured_make
```

Out[55]:
```
Make
CESSNA      21023.0
PIPER       10170.0
BEECH        2403.0
BELL         1606.0
ROBINSON      961.0
MOONEY        911.0
BELLANCA      791.0
GRUMMAN       766.0
HUGHES        740.0
MAULE         663.0
Name: Total.Uninjured, dtype: float64
```

In [56]:
```
#graph to visualise

plt.figure(figsize = (12,6))
sns.barplot(x = top_uninjured_make.values, y = top_uninjured_make.index)
plt.title('Top 10 Total Uninjured by Aircraft Make')
plt.xlabel('Total Uninjured')
plt.ylabel('Aircraft Make')
plt.show()
```



From the results above, the Cessna brand is the safest make to invest as a company for an aircraft. This is because compared to the rest, it has the largest difference in the number of uninjured people after an accident.

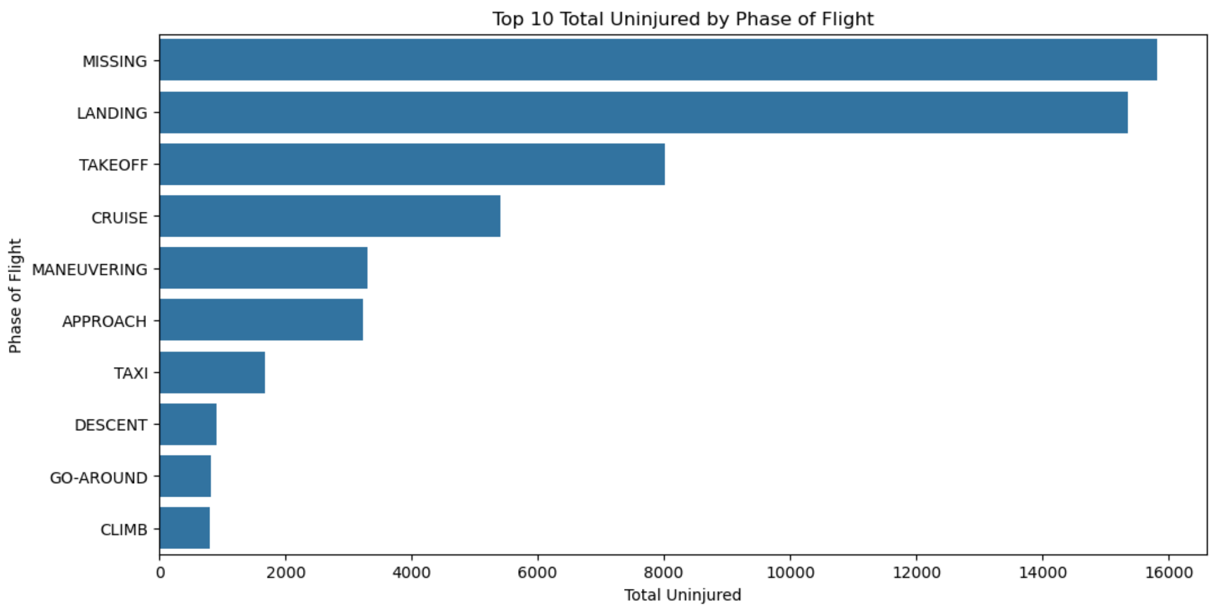
Broad Phase of Flight against Total Uninjured

- This is will help draw a conclusion on what the company should focus on (aviation team). This is whether when landing, cruising, etc

In [57]:
```
uninjured_by_phase = df.groupby('Broad.phase.of.flight')['Total.Uninjured'].sum().s
uninjured_by_phase
```

Out[57]:
```
Broad.phase.of.flight
MISSING        15818.0
LANDING        15362.0
TAKEOFF         8016.0
CRUISE          5402.0
MANEUVERING     3305.0
APPROACH        3230.0
TAXI            1668.0
DESCENT          901.0
GO-AROUND        819.0
CLIMB            795.0
Name: Total.Uninjured, dtype: float64
```

In [58]:
```
#graph for visualising

plt.figure(figsize = (12,6))
sns.barplot(x = uninjured_by_phase.values, y = uninjured_by_phase.index)
plt.title('Top 10 Total Uninjured by Phase of Flight')
plt.xlabel('Total Uninjured')
plt.ylabel('Phase of Flight')
plt.show()
```



According to research, there are multiple phases of flight that can be present in aviation. These include the landing, takeoff, cruise and etc. In the case of the results above, we can assume that the results for "MISSING" is Standing phase of flight because it would mean that it is stationary (the aircraft), hence would have the least uninjured individuals out of all the other phases. Out of the 10 featured, the riskiest phases are descent, go around and climb. Visualising and recognising this can help the company pilots be aware.

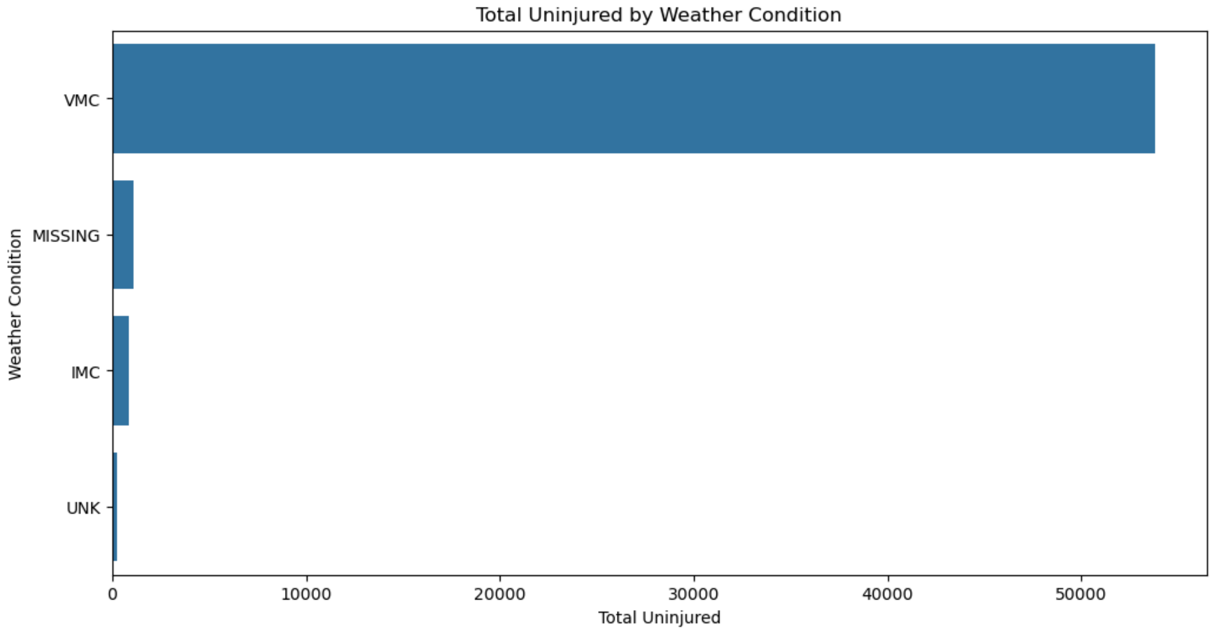
Weather Condition Impact on Total Uninjured

- This is to indicate which is the safest weather condition, or rather which weather condition holds the least risk

In [59]:
```
uninjured_by_weather = df.groupby('Weather.Condition')['Total.Uninjured'].sum().sor
uninjured_by_weather
```

Out[59]:
```
Weather.Condition
VMC        53784.0
MISSING     1076.0
IMC          860.0
UNK          236.0
Name: Total.Uninjured, dtype: float64
```

In [60]:
```
#plotting for visuals
plt.figure(figsize = (12,6))
sns.barplot(x = uninjured_by_weather.values, y = uninjured_by_weather.index)
plt.title('Total Uninjured by Weather Condition')
plt.xlabel('Total Uninjured')
plt.ylabel('Weather Condition')
plt.show()
```



The safest weather to travel in based on the results above is VMC which means there is clear weather and good visibility for the pilots. This means that the company would take note of when it is best to have flights taking place and when to avoid flying which would be UNK, meaning unknown i.e, weather is not recorded and unknown.

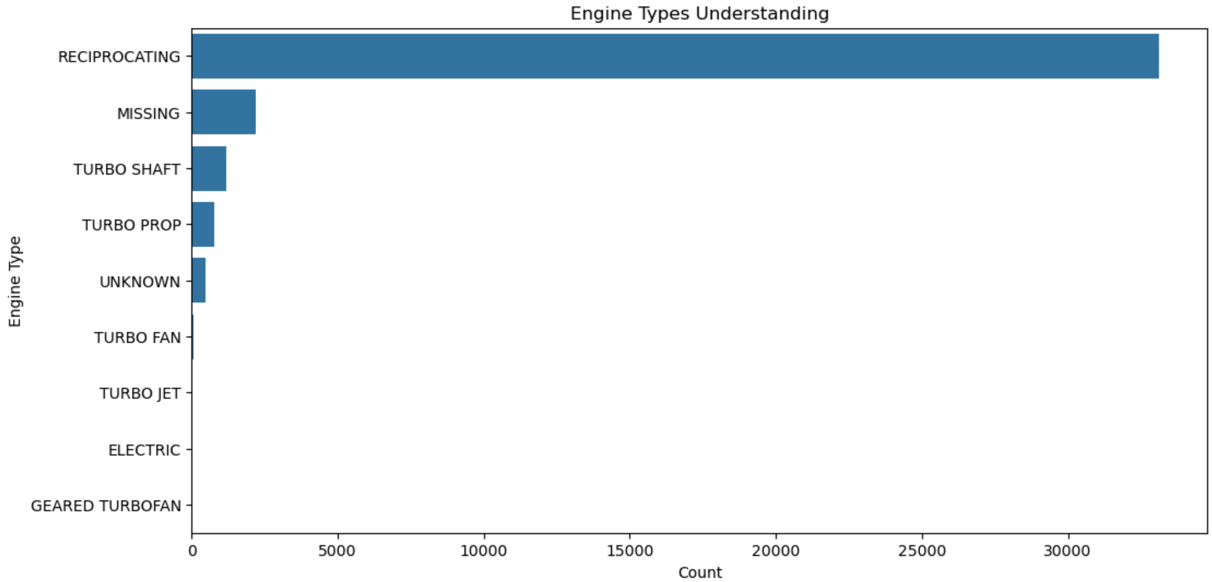
Engine Type

- Understanding the engines involved in accidents

In [61]:
```
engine_type_counts = df['Engine.Type'].value_counts()
engine_type_counts
```

Out[61]:
```
Engine.Type
RECIPROCATING      33124
MISSING             2188
TURBO SHAFT         1181
TURBO PROP           766
UNKNOWN              454
TURBO FAN             57
TURBO JET             31
ELECTRIC               3
GEARED TURBOFAN        1
Name: count, dtype: int64
```

In [62]:
```
#visuals
plt.figure(figsize = (12,6))
sns.barplot(x = engine_type_counts.values, y = engine_type_counts.index)
plt.title('Engine Types Understanding')
plt.xlabel('Count')
plt.ylabel('Engine Type')
plt.show()
```



The results indicate that Reciprocating engine type is one to be avoided as it has the highest count in the number of accidents it is involved in. The safest options for the company to invest is; turbo fan, turbo jet, electric and geared turbofan

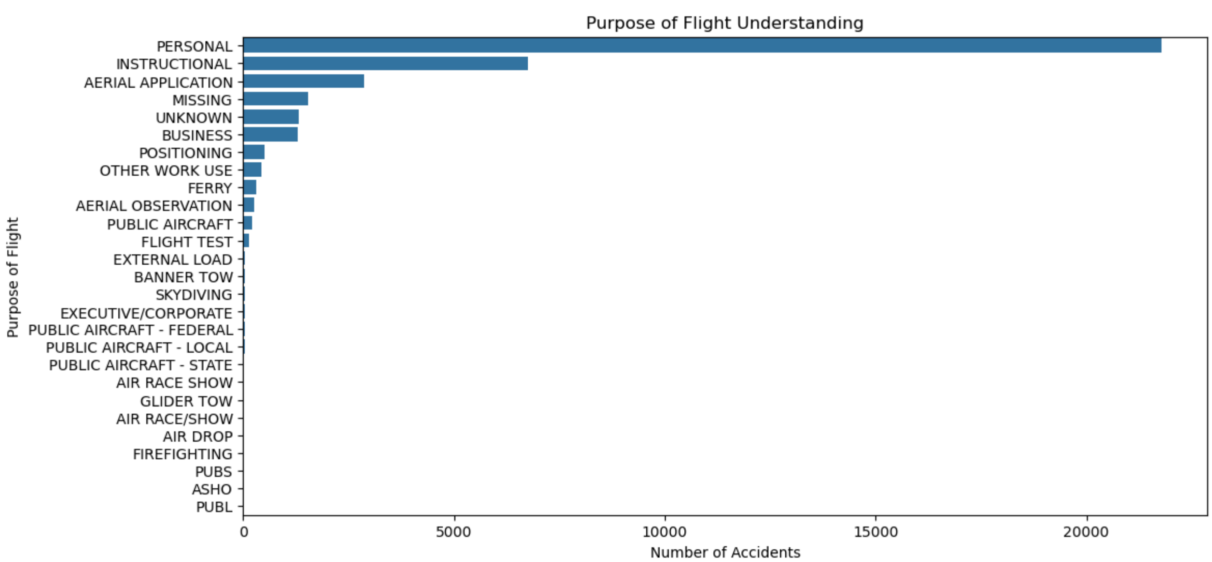
Flight purpose

- This will help draw a conclusion on the best purpose to invest in as a company venturing into the aviation sector.

In [63]:
```
purpose_counts = df['Purpose.of.flight'].value_counts()
purpose_counts
```

Out[63]:
```
Purpose.of.flight
PERSONAL                      21781
INSTRUCTIONAL                  6752
AERIAL APPLICATION             2860
MISSING                        1552
UNKNOWN                        1318
BUSINESS                       1299
POSITIONING                     519
OTHER WORK USE                  443
FERRY                           302
AERIAL OBSERVATION              256
PUBLIC AIRCRAFT                 224
FLIGHT TEST                     153
EXTERNAL LOAD                    49
BANNER TOW                       47
SKYDIVING                        45
EXECUTIVE/CORPORATE              38
PUBLIC AIRCRAFT - FEDERAL        38
PUBLIC AIRCRAFT - LOCAL          31
PUBLIC AIRCRAFT - STATE          30
AIR RACE SHOW                    27
GLIDER TOW                       18
AIR RACE/SHOW                     9
AIR DROP                          5
FIREFIGHTING                      5
PUBS                              2
ASHO                              1
PUBL                              1
Name: count, dtype: int64
```

In [64]:
```python
# a visual representation of the data above

plt.figure(figsize = (12,6))
sns.barplot(x = purpose_counts.values, y = purpose_counts.index)
plt.title('Purpose of Flight Understanding')
plt.xlabel('Number of Accidents')
plt.ylabel('Purpose of Flight')
plt.show()
```



From the results above, it is risky for the company to invest in personal/privatised flights. This is because it has the highest count of accidents compared to all the other purposes.

Conclusion and Recommendations

Conclusion

In the analysis above, we explored aviation accident data from 1962 to 2023 to identify insights for aircraft purchase and operational safety recommendations. The data was collected from Kaggle and presented by NTSB. From the cleaning and analysis we have been abke to form visuals to help form recommendations for the company.

The dataset was cleaned by:

- Handling missing values strategically (mode or 'Missing')
- Removing or capping outliers using IQR
- Narrowing to top makes and models for focused insights
- Understanding the engine types, weather, and purpose of the flight

Key findings include:

- The frequency of accidents over the years has decreased
- Certain makes and models have higher accident frequencies but also higher uninjured counts, which uggests relative safety in accidents.
- Weather conditions and flight phases significantly impact safety outcomes.
- The type of engine matters based on the number of accidents as well as the purpose on the frequency of accidents that take place

Recommendations

1. Aircraft Selection: Note and prioritse the makes, engine types and models with high uninjured passenger counts, this indicates that the aircrafts have robust safety features.

2. Operational Focus: Strengthen pilot training and protocols for high-risk phases such as approach and landing as well as handling the unpredictable weather and how to overcome them.

3. Purpose of flight: It's important to invest in flights that have less accident frequency such as the public/commercial flights to avoid any business risk on the company