Data Driven Recommendations: Aviation Business

Overview

The objective of this analysis is to Come up with Actionable Insights that informs a company that wants to venture into aviation business on the Areas of focus(operating airplanes for commercial and private enterprises). We want to get the less risky Aircraft in the aviation Business. The data set used is from the National Transportation Safety Board that includes aviation accident data from 1962 to 2023 about civil aviation accidents and selected incidents in the United States and international waters.

Business Understanding

We will be using the National Transportation Safety Board data to identify the aircraft that is associated with the lowest accident rates and has the highest safety record by assessing factors like make, category, Engine types by the number of accidents. we will come up with actionable insights for the company to select the safest aircraft and give effective risk management

Technologies used

1. pandas - for manipulation and analysis
2. numpy - for numerical operations and calculations
3. matplotlib - for interactive visuals
4. seaborn - Data visualizations

The analysis will cover the following features

1. loading the aviation data set and getting the required information
2. Data cleaning
3. Exploratory data analysis(visualizations)

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

1. Loading dataset and getting the required information

In [2]:
```
#reading the csv file
#the data is encoded in latin encoding style hence the specification (encoding
#low_memory = False helps pandas read file and to infer the correct data type
df = pd.read_csv("AviationData.csv", encoding = 'latin1', low_memory = False)
```

In [3]:
```
#df.head() gives the first five rows of the data
df.head()
```

Out[3]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	L
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.!
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	

5 rows × 31 columns

In [4]:
```
# the .tail()retrieves the last five rows from the data
#it's used to ensure that the data is uniform from top to bottom
df.tail()
```

Out[4]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Lat
88884	20221227106491	Accident	ERA23LA093	2022-12-26	Annapolis, MD	United States	
88885	20221227106494	Accident	ERA23LA095	2022-12-26	Hampton, NH	United States	
88886	20221227106497	Accident	WPR23LA075	2022-12-26	Payson, AZ	United States	341
88887	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	
88888	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	

5 rows × 31 columns

In [5]:
```
#checking the number of columns and rows in the aviation data
shape = df.shape
print(shape)
print(f'the data set contains {shape[0]} rows and {shape[1]} columns')
```

```
(88889, 31)
the data set contains 88889 rows and 31 columns
```

In [6]:
```
# checking the colums in the data
df.columns
```

Out[6]:
```
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.Descriptio
n',
       'Schedule', 'Purpose.of.flight', 'Air.carrier', 'Total.Fatal.Injurie
s',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured',
       'Weather.Condition', 'Broad.phase.of.flight', 'Report.Status',
       'Publication.Date'],
      dtype='object')
```

In [7]:
```
#checking the data set information
df.info(verbose = False)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Columns: 31 entries, Event.Id to Publication.Date
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

In [8]:
```
#checking the data types
df.dtypes
```

Out[8]:
```
Event.Id                    object
Investigation.Type          object
Accident.Number             object
Event.Date                  object
Location                    object
Country                     object
Latitude                    object
Longitude                   object
Airport.Code                object
Airport.Name                object
Injury.Severity             object
Aircraft.damage             object
Aircraft.Category           object
Registration.Number         object
Make                        object
Model                       object
Amateur.Built               object
Number.of.Engines          float64
Engine.Type                 object
FAR.Description             object
Schedule                    object
Purpose.of.flight           object
Air.carrier                 object
Total.Fatal.Injuries       float64
Total.Serious.Injuries     float64
Total.Minor.Injuries       float64
Total.Uninjured            float64
Weather.Condition           object
Broad.phase.of.flight       object
Report.Status               object
Publication.Date            object
dtype: object
```

In [9]:
```
# changing Event.Date and Publication.Date  from objects to date_time
df['Event.Date'] = pd.to_datetime(df['Event.Date'])
df['Publication.Date'] = pd.to_datetime(df['Publication.Date'])
```

In [10]:
```
#running the dtypes again to confirm the type has changed
df.dtypes
```

Out[10]:
```
Event.Id                          object
Investigation.Type                object
Accident.Number                   object
Event.Date                datetime64[ns]
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          datetime64[ns]
dtype: object
```

In [11]:
```
#descriptive statistics for numerical data
df.describe().T
```

Out[11]:

	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 [12]:
```
#descriptive statistics for object data type
df.describe( include = 'O').T
```

Out[12]:

	count	unique	top	freq
Event.Id	88889	87951	20001214X45071	3
Investigation.Type	88889	2	Accident	85015
Accident.Number	88889	88863	DCA22LA135	2
Location	88837	27758	ANCHORAGE, AK	434
Country	88663	219	United States	82248
Latitude	34382	25589	332739N	19
Longitude	34373	27154	0112457W	24
Airport.Code	50249	10375	NONE	1488
Airport.Name	52790	24871	Private	240
Injury.Severity	87889	109	Non-Fatal	67357
Aircraft.damage	85695	4	Substantial	64148
Aircraft.Category	32287	15	Airplane	27617
Registration.Number	87572	79105	NONE	344
Make	88826	8237	Cessna	22227
Model	88797	12318	152	2367
Amateur.Built	88787	2	No	80312
Engine.Type	81812	13	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	82508	17075	Probable Cause	61754

In [13]:
```
#creating a copy of data to be used in data cleaning
df0 = df.copy (deep = True)
```

In [14]:
```
df0.head()
```

Out[14]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	L
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.!
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	

5 rows × 31 columns

In [15]:
```
#getting unique values in a column called name
df0['Make'].nunique()
```

Out[15]:
```
8237
```

Problem statement

For a company that wants to venture into aviation business, it is crucial for the company to investigate several factors before purchasing planes; The industry is always faced with various challenges some of which affects the reputation of a company. Such challenges include, planes having accidents and injuring or causing fatalities. Therefore, this analysis aims to investigate several factors that should be considerd before purchasing aircrafts, these factors in this case are;

1. The model and make that is involved in least number of accidents/injuries
2. The Engine type that is least involved
3. whether Amature built aircrafts are safe
4. The aircraft category that is least involved in accidents/injuries

Metrics of Success

My project will be successful if I am able to investigate the factors listed above and come up with reccomendations on what the company should consider doing in order to be successful in the Aviation Business

2 Data cleaning

2.1 Checking columns to see if there are mispelt columns

In [16]:
```
#checking the columns
df0.columns
```

Out[16]:
```
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.Descriptio
n',
       'Schedule', 'Purpose.of.flight', 'Air.carrier', 'Total.Fatal.Injurie
s',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured',
       'Weather.Condition', 'Broad.phase.of.flight', 'Report.Status',
       'Publication.Date'],
      dtype='object')
```

In [17]:
```
#Removing the white spaces
df0.columns = df0.columns.str.replace(' ', '')
df0.columns
```

Out[17]:
```
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.Descriptio
n',
       'Schedule', 'Purpose.of.flight', 'Air.carrier', 'Total.Fatal.Injurie
s',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured',
       'Weather.Condition', 'Broad.phase.of.flight', 'Report.Status',
       'Publication.Date'],
      dtype='object')
```

In [18]:
```
df0.groupby('Weather.Condition')['Weather.Condition'].count()
```

Out[18]:
```
Weather.Condition
IMC     5976
UNK      856
Unk      262
VMC    77303
Name: Weather.Condition, dtype: int64
```

In [19]:
```
#weather condation has unknown named in various forms; UNK, unk and Unknown, tl
df0['Weather.Condition'] = df0['Weather.Condition'].str.replace('UNK','unknown
df0['Weather.Condition'] = df0['Weather.Condition'].str.replace('Unk','unknown
df0['Weather.Condition'].unique()
```

Out[19]:
```
array(['unknown', 'IMC', 'VMC', nan], dtype=object)
```

In [20]:
```
df0.groupby('Make')['Make'].nunique()
```

Out[20]:
```
Make
107.5 Flying Corporation    1
1200                        1
177MF LLC                   1
1977 Colfer-chan            1
1st Ftr Gp                  1
                           ..
Zukowski                    1
Zwart                       1
de Havilland                1
drone                       1
unknown                     1
Name: Make, Length: 8237, dtype: int64
```

In [21]:
```
# combining aircrafts with the same name but writen diffferently
df0['Make'] = df0['Make'].str.replace('Cessna','CESSNA')
df0['Make'] = df0['Make'].str.replace('Boeing','BOEING')
df0['Make'] = df0['Make'].str.replace('Piper','PIPER')
df0['Make'] = df0['Make'].str.replace('Bell','BELL')
df0['Make'] = df0['Make'].str.replace('Beech','BEECH')
df0['Make'] = df0['Make'].str.replace('Airbus','AIRBUS')
df0['Make'] = df0['Make'].str.replace('Mooney','MOONEY')

df0['Make'].unique()
```

Out[21]:
```
array(['Stinson', 'PIPER', 'CESSNA', ..., 'JAMES R DERNOVSEK',
       'ORLICAN S R O', 'ROYSE RALPH L'], dtype=object)
```

2.2 droping the unnecessary columns

In [22]:
```
# the purpose of this project is to inform the company on what aircraft is safe
# dropping unnecessary columns
df0.drop(columns = 'Airport.Name', axis=1, inplace=True)
df0.drop(columns = 'Airport.Code', axis=1, inplace=True)
df0.drop(columns = 'FAR.Description', axis=1, inplace=True)
df0.drop(columns = 'Schedule', axis=1, inplace=True)
df0.drop(columns = 'Report.Status', axis=1, inplace=True)
df0.drop(columns = 'Event.Date', axis=1, inplace=True)
df0.drop(columns = 'Publication.Date', axis=1, inplace=True)
df0.drop(columns = 'Registration.Number', axis=1, inplace=True)
df0.drop(columns = 'Accident.Number', axis=1, inplace=True)
df0.drop(columns = 'Event.Id', axis=1, inplace=True)
df0.drop(columns = 'Investigation.Type', axis=1, inplace=True)
```

In [23]:
```
#checking if the columns has been droped
df0.columns
```

Out[23]:
```
Index(['Location', 'Country', 'Latitude', 'Longitude', 'Injury.Severity',
       'Aircraft.damage', 'Aircraft.Category', 'Make', 'Model',
       'Amateur.Built', 'Number.of.Engines', 'Engine.Type',
       'Purpose.of.flight', 'Air.carrier', 'Total.Fatal.Injuries',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured',
       'Weather.Condition', 'Broad.phase.of.flight'],
      dtype='object')
```

2.3checking for missing values in the data and working on them

In [24]:
```
#check the missing values
df0.isnull().sum()
```

Out[24]:
```
Location                     52
Country                     226
Latitude                  54507
Longitude                 54516
Injury.Severity            1000
Aircraft.damage            3194
Aircraft.Category         56602
Make                         63
Model                        92
Amateur.Built               102
Number.of.Engines          6084
Engine.Type                7077
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
```

2.4 dealing with missing data

2.41 dealing with missing numerical data using mean and mode

Here, various method of dealing with missing numerical data are employed. First is using the mode method which replaces the missing values with the mode of the data in a particular column The mean also works the same as the mode, replaces the missing values with the mean values of a particular colum.

In [25]:
```
#getting the mode for number of engines
df0['Number.of.Engines'].mode()[0]
# filling using the mode
df0['Number.of.Engines'].fillna(df0['Number.of.Engines'].mode()[0], inplace=Tr
```

In [26]:
```
#using the mean
df0['Total.Fatal.Injuries'].mean()
#filling in the missing values using the mean
df0['Total.Fatal.Injuries'].fillna(df0['Total.Fatal.Injuries'].mean(), inplace
```

In [27]:
```
#using the mean for serious injuries
df0['Total.Serious.Injuries'].mean()
#filling in the missing values using the mean
df0['Total.Serious.Injuries'].fillna(df0['Total.Serious.Injuries'].mean(), inp
```

In [28]:
```
#using the mean for total minor injuries
df0['Total.Minor.Injuries'].mean()
#filling in the missing values using the means
df0['Total.Minor.Injuries'].fillna(df0['Total.Minor.Injuries'].mean(), inplace
```

In [29]:
```
#using the mean for total uninjured
df0['Total.Uninjured'].mean()
#filling in the missing values using the means
df0['Total.Uninjured'].fillna(df0['Total.Uninjured'].mean(), inplace=True)
```

In [30]:
```
#check if the missing values are removed for categorical data
df0.isnull().sum()
```

Out[30]:
```
Location                      52
Country                      226
Latitude                   54507
Longitude                  54516
Injury.Severity             1000
Aircraft.damage             3194
Aircraft.Category          56602
Make                          63
Model                         92
Amateur.Built                102
Number.of.Engines              0
Engine.Type                 7077
Purpose.of.flight           6192
Air.carrier                72241
Total.Fatal.Injuries           0
Total.Serious.Injuries         0
Total.Minor.Injuries           0
Total.Uninjured                0
Weather.Condition           4492
Broad.phase.of.flight      27165
dtype: int64
```

2.42 dealing with missing non-numeric data

In this case, several methods of dealing with missing non-numeric data are used. The .mode method is used to replace missing values with the most occuring value The .fillna method is used to fill the Nan values with 'Unknown'. The .dropna method is also used to drop the null values for columns that has few number of missing values

In [31]:
```
# injury severity can be dealt with using the mode, since there are few outcome
df_cleaned = df0['Injury.Severity'].mode()[0]
df_cleaned= df0['Injury.Severity'].fillna(df0['Injury.Severity'].mode()[0], in
```

In [32]:
```
df_cleaned = df0['Aircraft.Category'].mode()[0]
df_cleaned= df0['Aircraft.Category'].fillna(df0['Aircraft.Category'].mode()[0]
```

In [33]:
```
df_cleaned = df0['Air.carrier'].mode()[0]
df_cleaned= df0['Air.carrier'].fillna(df0['Air.carrier'].mode()[0], inplace=Tr
```

In [34]:
```
df_cleaned = df0['Broad.phase.of.flight'].mode()[0]
df_cleaned= df0['Broad.phase.of.flight'].fillna(df0['Broad.phase.of.flight'].m
```

In [35]:
```
df_cleaned = df0['Engine.Type'].mode()[0]
df_cleaned= df0['Engine.Type'].fillna(df0['Engine.Type'].mode()[0], inplace=Tr
```

In [36]:
```
df_cleaned = df0['Weather.Condition'].mode()[0]
df_cleaned= df0['Weather.Condition'].fillna(df0['Weather.Condition'].mode()[0]
```

In [37]:
```
# replacing missing values with unknown
df_cleaned = df0['Latitude'].fillna('unknown', inplace=True)
df_cleaned = df0['Longitude'].fillna('unknown', inplace=True)
df_cleaned = df0['Country'].fillna('unknown', inplace=True)
df_cleaned = df0['Aircraft.damage'].fillna('unknown', inplace=True)
df_cleaned = df0['Purpose.of.flight'].fillna('unknown', inplace=True)
```

In [38]:
```

# since make,Model,Location and Amateur.Build has few missing values the dropna
df_cleaned = df0.dropna(subset=['Make', 'Model', 'Location', 'Amateur.Built'])
```

In [39]:
```
#all the columns have no missing values
df_cleaned.isnull().sum()
```

Out[39]:
```
Location                  0
Country                   0
Latitude                  0
Longitude                 0
Injury.Severity           0
Aircraft.damage           0
Aircraft.Category         0
Make                      0
Model                     0
Amateur.Built             0
Number.of.Engines         0
Engine.Type               0
Purpose.of.flight         0
Air.carrier               0
Total.Fatal.Injuries      0
Total.Serious.Injuries    0
Total.Minor.Injuries      0
Total.Uninjured           0
Weather.Condition         0
Broad.phase.of.flight     0
dtype: int64
```

In [40]:
```
#checking for duplicates
df0.duplicated().sum()
```

Out[40]:
```
289
```

In [41]:
```
#droping duplicates
df0.drop_duplicates(inplace=True)

#check
df0.duplicated().sum()
```

Out[41]:
```
0
```

In [42]:
```
#checking the shape to see whether the rows and some columns have been droped9
df_cleaned.shape
```

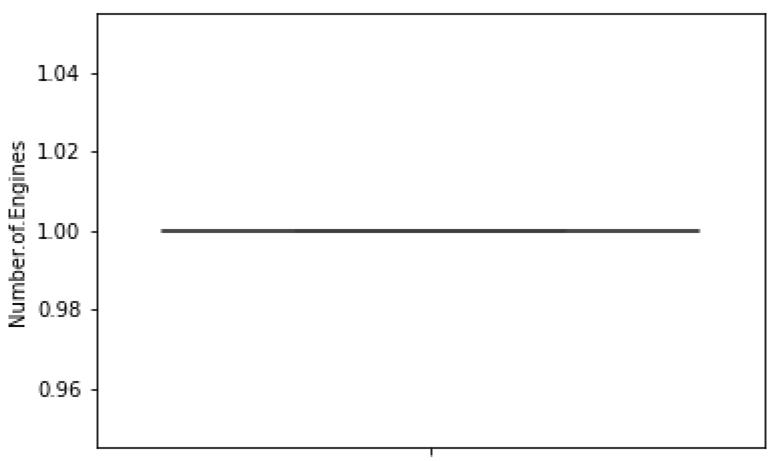
Out[42]:
```
(88630, 20)
```

2.43 Checking for outliers and dealing with them

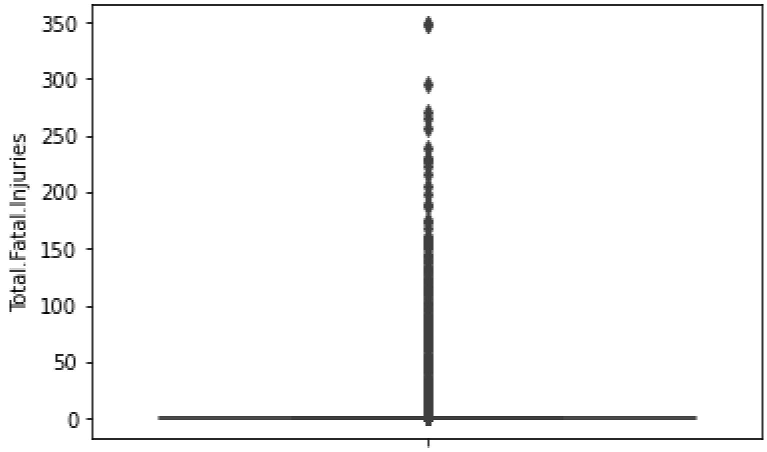
In this case, outliers for the numerical data will be dealt with using the Interquartile Range method to ensure smooth analysis of the data

In [43]:
```
#checking for outliers in the Number of Engines data type using a box plot

sns.boxplot(data=df_cleaned, y="Number.of.Engines");
```

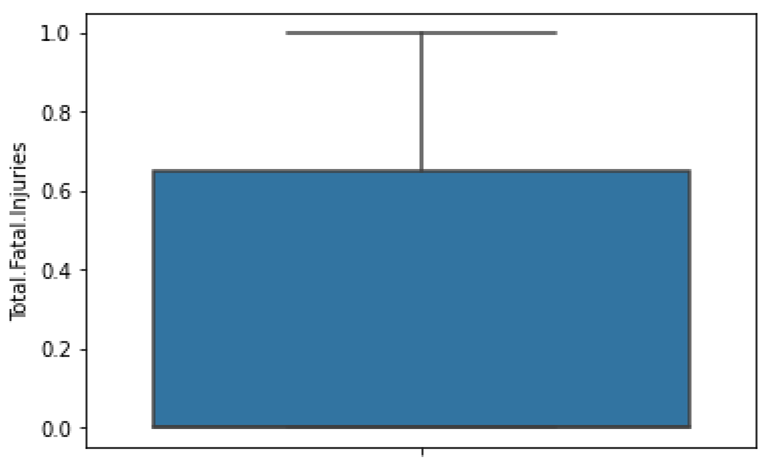
In [44]:
```
# removing number of Engines outliers
# interquartile range (IQR)
q1 = df_cleaned['Number.of.Engines'].quantile(0.25)
q3 = df_cleaned['Number.of.Engines'].quantile(0.75)
iqr = q3 - q1

lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

# remove outliers
df1 = df_cleaned[(df_cleaned['Number.of.Engines'] >= lower_bound) & (df_cleane

# Checking the boxplot again
sns.boxplot(y='Number.of.Engines', data=df1);
```



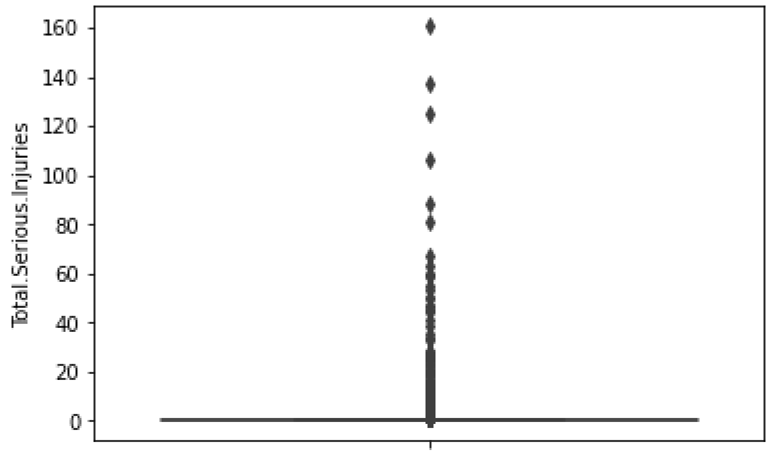
In [45]:
```
#checking for outliers in the Total.Fatal.Injuries data using a box plot

sns.boxplot(data=df_cleaned, y="Total.Fatal.Injuries");
```



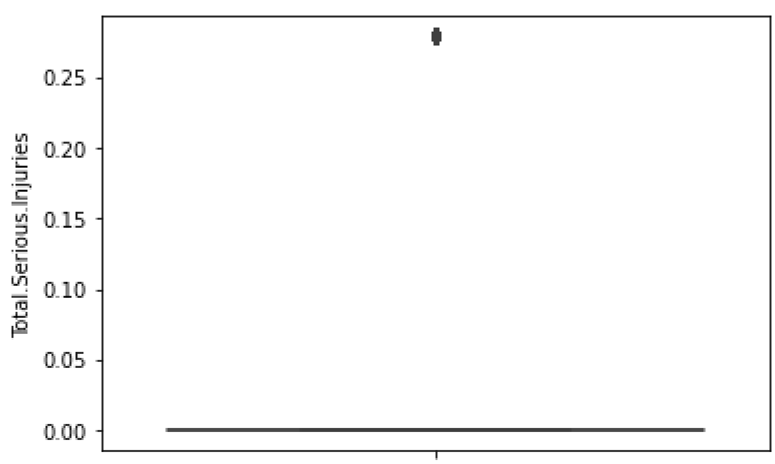
In [46]:
```
# revoving Total.Fatal.Injuries outliers
# interquartile range (IQR)
q1 = df_cleaned['Total.Fatal.Injuries'].quantile(0.25)
q3 = df_cleaned['Total.Fatal.Injuries'].quantile(0.75)
iqr = q3 - q1

lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

# to remove outliers
df1 = df_cleaned[(df_cleaned['Total.Fatal.Injuries'] >= lower_bound) & (df_clea

# Checking the boxplot again
sns.boxplot(y='Total.Fatal.Injuries', data=df1);
```



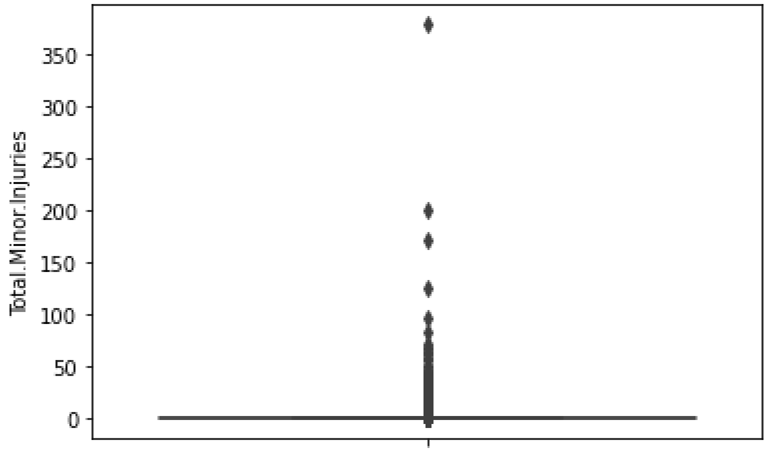
In [47]:
```
#checking for outliers in the Total.Serious.Injuries data using a box plot

sns.boxplot(data=df_cleaned, y="Total.Serious.Injuries");
```



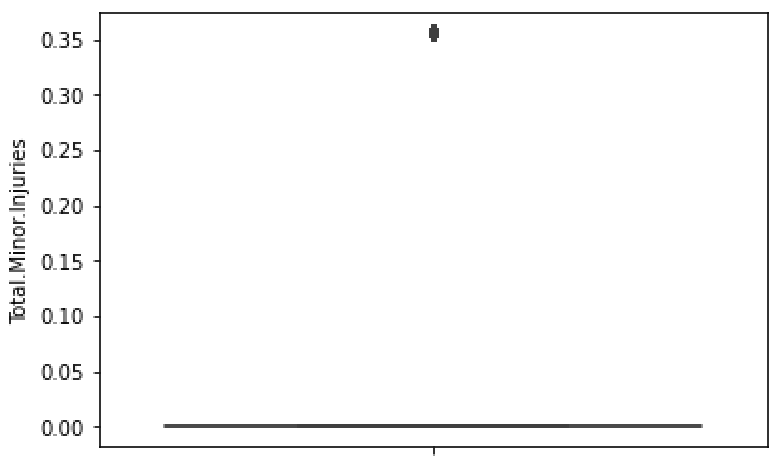
In [48]:
```
# revoving Total.Serious.Injuries outliers
#interquartile range (IQR)
q1 = df_cleaned['Total.Serious.Injuries'].quantile(0.25)
q3 = df_cleaned['Total.Serious.Injuries'].quantile(0.75)
iqr = q3 - q1

lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

# remove outliers
df1 = df_cleaned[(df_cleaned['Total.Serious.Injuries'] >= lower_bound) & (df_c

# Checking the boxplot again
sns.boxplot(y='Total.Serious.Injuries', data=df1);
```



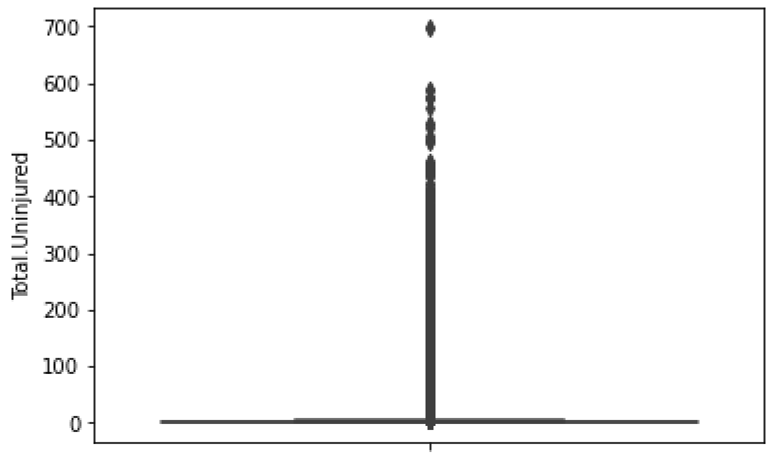
In [49]:
```
#checking for outliers in the Total.Minor.Injuries data using a box plot

sns.boxplot(data=df_cleaned, y="Total.Minor.Injuries");
```



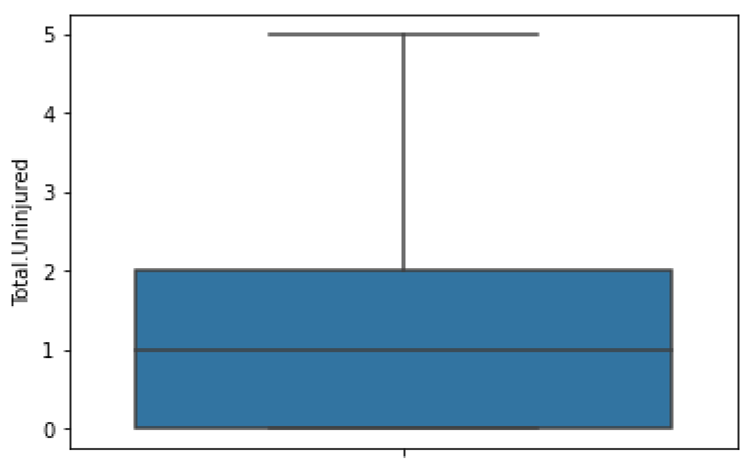
In [50]:
```
# revoving Total.Minor.Injuries outliers
#interquartile range (IQR)
q1 = df_cleaned['Total.Minor.Injuries'].quantile(0.25)
q3 = df_cleaned['Total.Minor.Injuries'].quantile(0.75)
iqr = q3 - q1

lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

#remove outliers
df1 = df_cleaned[(df_cleaned['Total.Minor.Injuries'] >= lower_bound) & (df_cle

# Checking the boxplot again
sns.boxplot(y='Total.Minor.Injuries', data=df1);
```



In [51]:
```
#checking for outliers in the Total.Uninjured data using a box plot

sns.boxplot(data=df_cleaned, y="Total.Uninjured");
```



In [52]:
```
# revoving Total.Uninjured outliers
# interquartile range (IQR)
q1 = df_cleaned['Total.Uninjured'].quantile(0.25)
q3 = df_cleaned['Total.Uninjured'].quantile(0.75)
iqr = q3 - q1


lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

# remove outliers
df1 = df_cleaned[(df_cleaned['Total.Uninjured'] >= lower_bound) & (df_cleaned[

# Checking the boxplot again
sns.boxplot(y='Total.Uninjured', data=df1);
```



2.43 saving the new dataframe

In [53]:
```
#save the new dataframe in cvs format
df1.to_csv('clean_aviationdata.csv', index=False)
```

3 Exploratory Data Analysis

In [54]:
```
#loading the clean Dataset and creating a adataframe
data = pd.read_csv('clean_aviationdata.csv')
data.head()
```

Out[54]:

	Location	Country	Latitude	Longitude	Injury.Severity	Aircraft.damage	Aircraft.Category
0	MOOSE CREEK, ID	United States	unknown	unknown	Fatal(2)	Destroyed	Airplane
1	BRIDGEPORT, CA	United States	unknown	unknown	Fatal(4)	Destroyed	Airplane
2	EUREKA, CA	United States	unknown	unknown	Fatal(2)	Destroyed	Airplane
3	Canton, OH	United States	unknown	unknown	Fatal(1)	Destroyed	Airplane
4	COTTON, MN	United States	unknown	unknown	Fatal(4)	Destroyed	Airplane

In [55]:
```
#adding a column (Total Injuries)
data['Total.Injuries'] = data['Total.Fatal.Injuries']+data['Total.Serious.Inju
data.tail()
```

Out[55]:

	Location	Country	Latitude	Longitude	Injury.Severity	Aircraft.damage	Aircraft.Category
78685	Annapolis, MD	United States	unknown	unknown	Minor	unknown	Airplane
78686	Hampton, NH	United States	unknown	unknown	Non-Fatal	unknown	Airplane
78687	Payson, AZ	United States	341525N	1112021W	Non-Fatal	Substantial	Airplane
78688	Morgan, UT	United States	unknown	unknown	Non-Fatal	unknown	Airplane
78689	Athens, GA	United States	unknown	unknown	Minor	unknown	Airplane

5 rows × 21 columns

3.1 Univariate analysis

This is used to describe and summarize the distribution of a single variable

In [56]:
```
data.describe (include = 'O').T
```

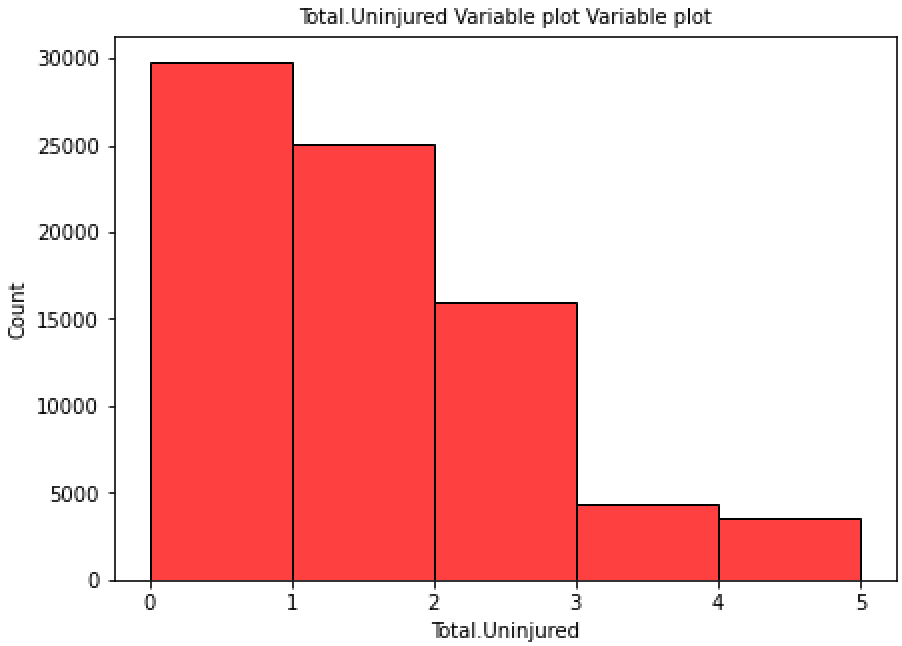
Out[56]:

	count	unique	top	freq
Location	78690	25336	ANCHORAGE, AK	401
Country	78690	194	United States	73977
Latitude	78690	21295	unknown	50429
Longitude	78690	22527	unknown	50437
Injury.Severity	78690	66	Non-Fatal	62777
Aircraft.damage	78690	5	Substantial	59382
Aircraft.Category	78690	15	Airplane	74316
Make	78690	7432	CESSNA	25342
Model	78690	10787	152	2298
Amateur.Built	78690	2	No	71223
Engine.Type	78690	13	Reciprocating	70093
Purpose.of.flight	78690	27	Personal	45675
Air.carrier	78690	12346	Pilot	64767
Weather.Condition	78690	3	VMC	73014
Broad.phase.of.flight	78690	12	Landing	39044

From the above descriptive statistics and in line with our analysis, we can be able to tell;

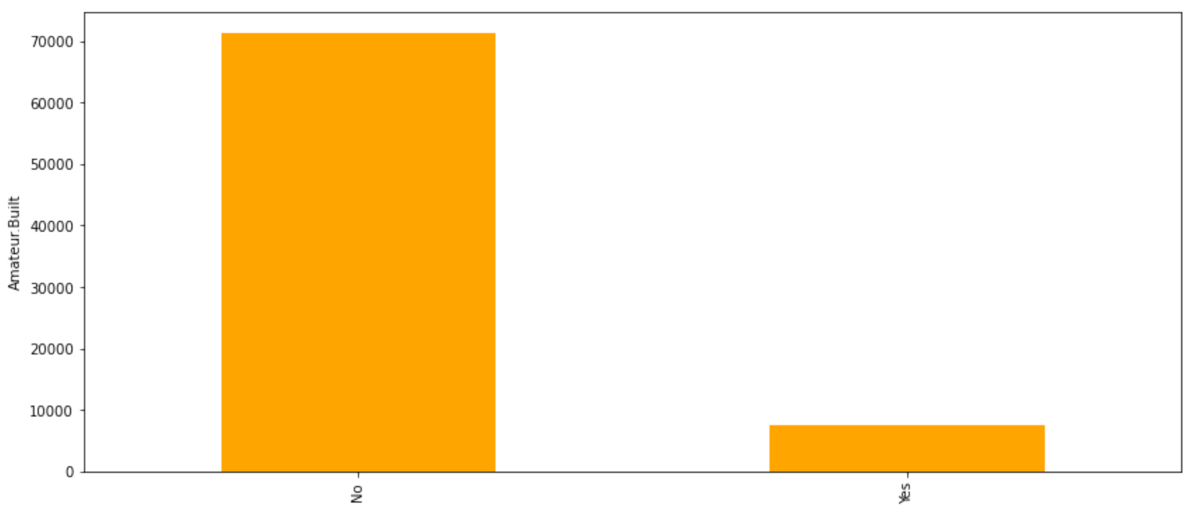
1. The airplane is the aircraft category involved in most accidents.
2. The Cessna make is the make that is involved in most accidents
3. Model 152 is also the most plane involved in accidents
4. The Reciprocating engine type is the most engine type involved in accidents
5. Private flights are the most involved in accidents
6. VMC weather condition is the worst to fly in and
7. Most accidents occurs during landing phase of the flight

In [57]:
```
# histogram to show the  frequency of the Total uninjured
plt.figure(figsize=(7,5))
sns.histplot(x=data['Total.Uninjured'], bins=5, color = 'red')
plt.title('Total.Uninjured Variable plot Variable plot', fontsize=10)
plt.show()
```

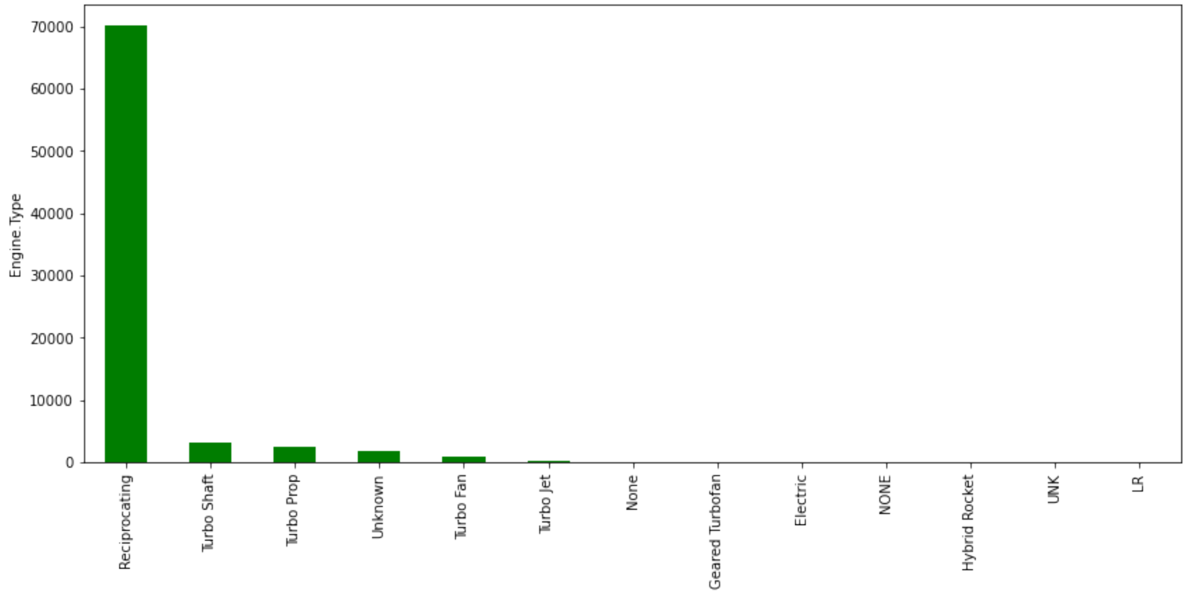


Cessna is the most involved make in accidents

In [58]:
```
#bar graph count of amateur built aircrafts
ax = data['Amateur.Built'].value_counts().plot(kind='bar', figsize=(14,6), col
ax.set_ylabel('Amateur.Built');
```



In [59]:
```
# count of Engine.types
ax = data['Engine.Type'].value_counts().plot(kind='bar', figsize=(14,6), color
ax.set_ylabel('Engine.Type');
```



In [60]:
```
#skewness and kurtosis

columns = [['Location', 'Country', 'Latitude', 'Longitude', 'Injury.Severity',
       'Aircraft.damage', 'Aircraft.Category', 'Make', 'Model',
       'Amateur.Built', 'Number.of.Engines', 'Engine.Type',
       'Purpose.of.flight', 'Air.carrier', 'Total.Fatal.Injuries',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured',
       'Weather.Condition', 'Broad.phase.of.flight']]

for column in columns:
  print("skew is:\n " + str(data[column].skew()))
  print("\n\n")
  print("kurtosis is:\n " + str(data[column].kurtosis()))
```

```
skew is:
 Number.of.Engines          2.802123
Total.Fatal.Injuries      41.530744
Total.Serious.Injuries    72.536424
Total.Minor.Injuries      14.624500
Total.Uninjured            1.097882
dtype: float64



kurtosis is:
 Number.of.Engines           16.407268
Total.Fatal.Injuries      2111.551241
Total.Serious.Injuries    9352.831282
Total.Minor.Injuries       777.633704
Total.Uninjured              0.988117
dtype: float64
```

3.2 Bivariate analysis

In [61]:
```
corr = data.corr()
corr
```

Out[61]:

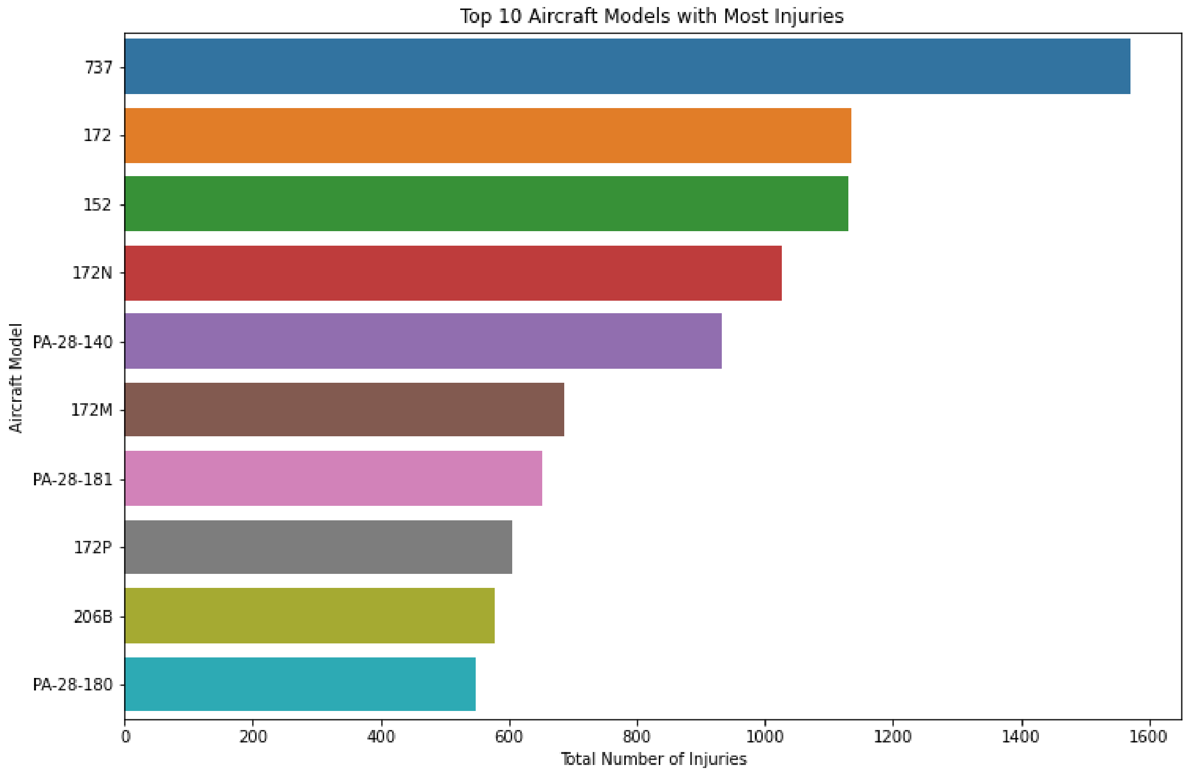
	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injur
Number.of.Engines	1.000000	0.076348	0.010162	0.0026
Total.Fatal.Injuries	0.076348	1.000000	0.069753	0.0388
Total.Serious.Injuries	0.010162	0.069753	1.000000	0.1438
Total.Minor.Injuries	0.002678	0.038834	0.143869	1.0000
Total.Uninjured	0.091528	-0.096402	-0.132733	-0.1812
Total.Injuries	0.073637	0.950108	0.326836	0.2425

1.A correlation value close to +1 indicates a strong positive correlation between the variables

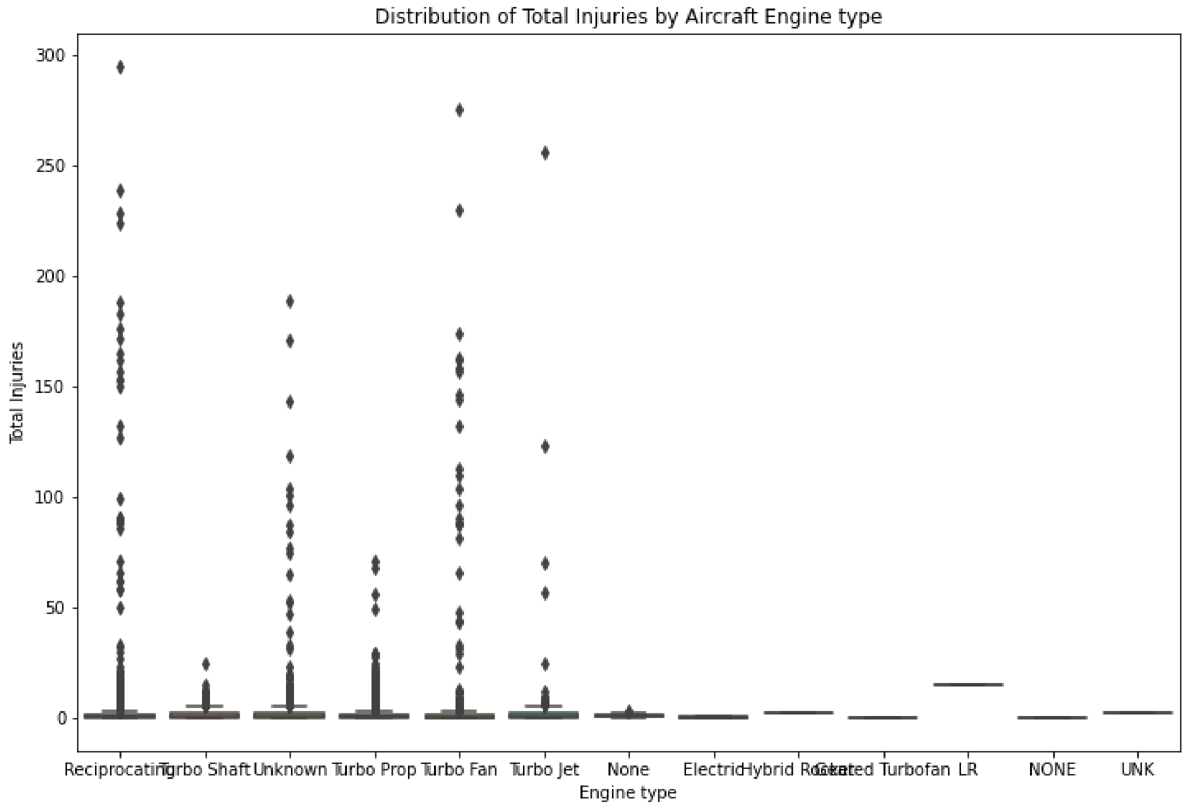
2.A correlation value close to 0(zero) indicates a weak positive correlation

3.A negative value indicates a negative correlation

In [62]:
```
# since model has many unique values, we use the top 10 most occuring model
grouped_data = data.groupby('Model')['Total.Injuries'].sum().reset_index()
top_10_data = grouped_data.sort_values(by='Total.Injuries', ascending=False).h
plt.figure(figsize=(12, 8))
bar_plot = sns.barplot(x='Total.Injuries', y='Model', data=top_10_data)
bar_plot.set_xlabel('Total Number of Injuries')
bar_plot.set_ylabel('Aircraft Model')
bar_plot.set_title('Top 10 Aircraft Models with Most Injuries')

plt.show()
```



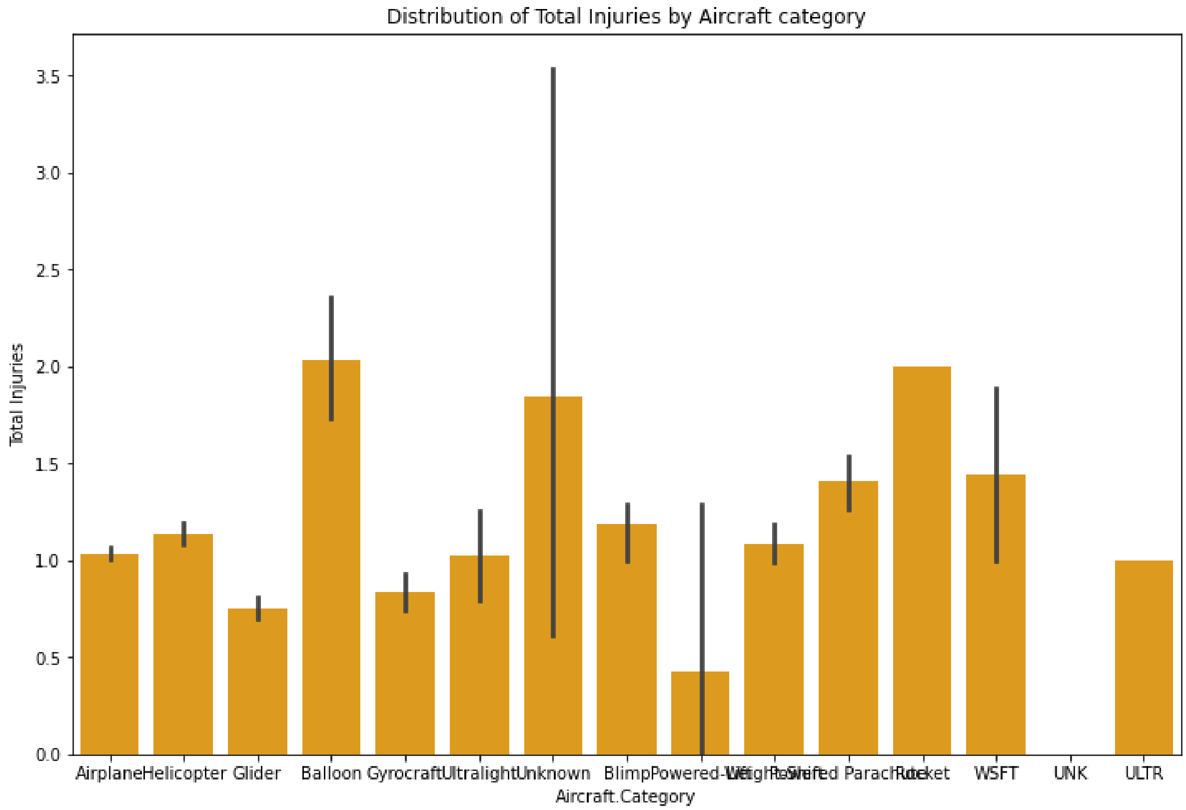
In [63]:
```
# boxplot of Engine type by total injuries caused
plt.figure(figsize=(12, 8))
sns.boxplot(data=data, x='Engine.Type', y='Total.Injuries')
plt.title('Distribution of Total Injuries by Aircraft Engine type')
plt.xlabel('Engine type')
plt.ylabel('Total Injuries')
plt.show()
```



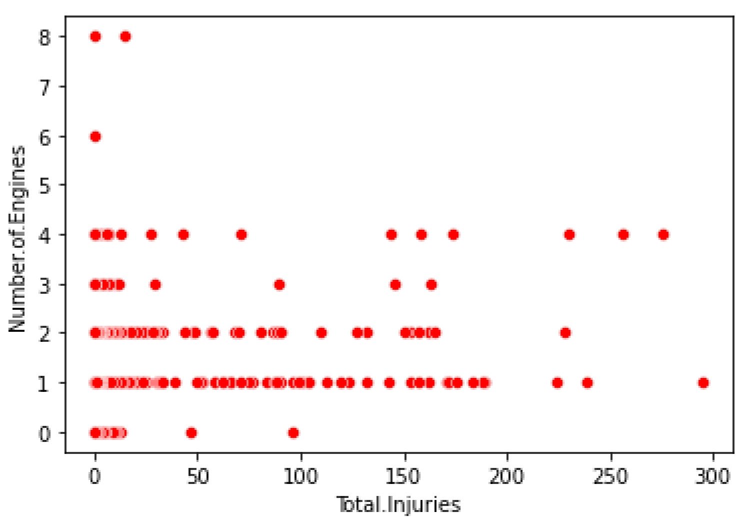
Receprocating Engine type appears to be the Engine type that causes the most accidents with injuries

while the LR Engine type appears to have caused no accidents

In [64]:
```
#barplot of distribution of total injuries by aircraft category
plt.figure(figsize=(12, 8))
sns.barplot(data=data, x='Aircraft.Category', y='Total.Injuries', color = 'orar
plt.title('Distribution of Total Injuries by Aircraft category')
plt.xlabel('Aircraft.Category')
plt.ylabel('Total Injuries')
plt.show()
```

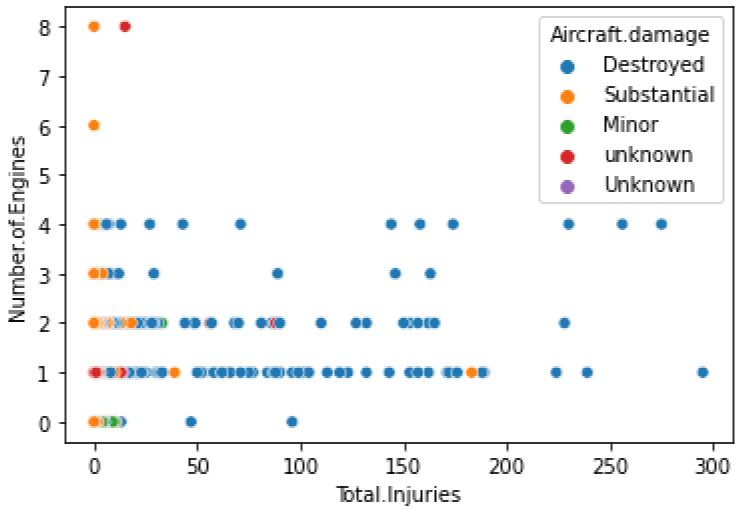


In [65]:
```
# number of engines by Total injuries
sns.scatterplot(y=data['Number.of.Engines'], x=data['Total.Injuries'], color =
```

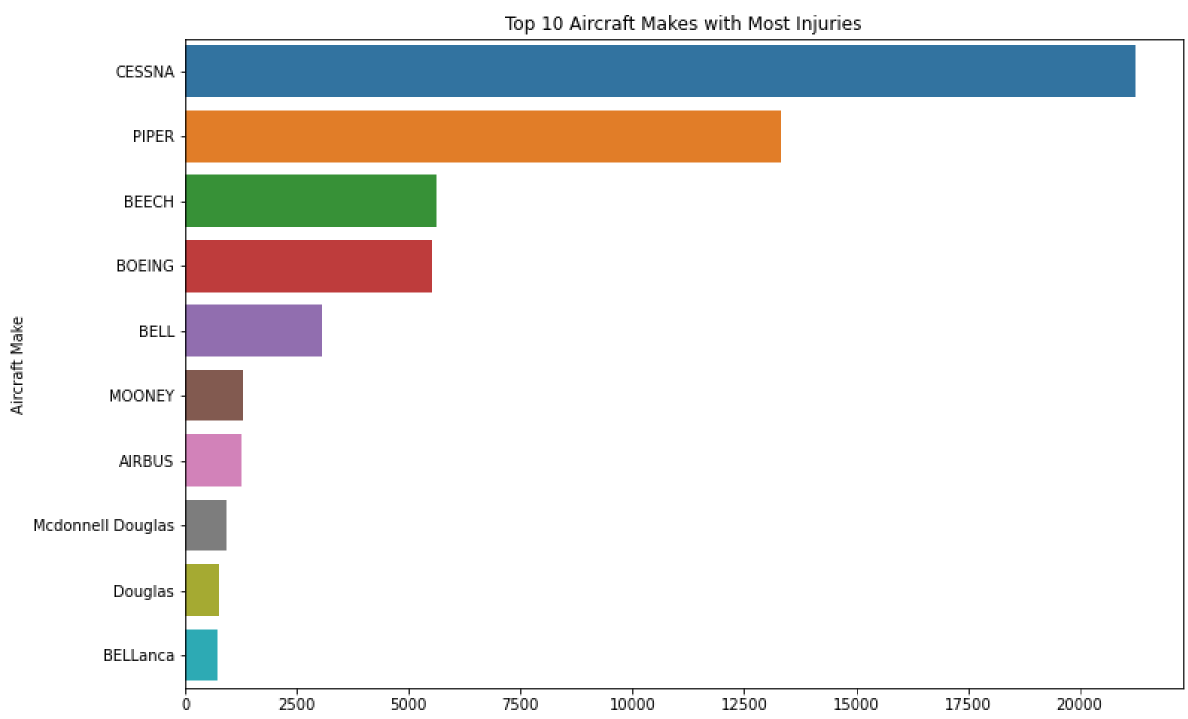


3.3 Multivariate Analysis

In [66]:
```
# Showing how aircraft damage is associated with injuries
sns.scatterplot(x=data['Total.Injuries'], y=data['Number.of.Engines'], hue=dat
```



In [67]:
```
# Top 10 Aircraft makes/models with the most number of injuries
make_data = data.groupby('Make')['Total.Injuries'].sum().reset_index()
model_data = data.groupby('Model')['Total.Injuries'].sum().reset_index()
top_10_data = make_data.sort_values(by='Total.Injuries', ascending=False).head
plt.figure(figsize=(12, 8))
bar_plot =sns.barplot(x='Total.Injuries', y='Make', data=top_10_data)
bar_plot.set_xlabel('Total Number of Injuries')
bar_plot.set_ylabel('Aircraft Make')
bar_plot.set_title('Top 10 Aircraft Makes with Most Injuries')
plt.show()
```



Conclusion

From the above analysis, we can be able to conclude that;

1. The Airbus Make is the one which is less involved in accidents
2. LR engine type carries the least number of injuries
3. The aircraft category that is least involved in injury incidences is the powerd-Lift
4. The higher the number of Engines an aircaft has, the less the damage and the less the number of accidents.
5. Amateur built aircrafts cause least number of accidents compared to those not amateur built.

Recomendations

When purchasing Aircraft, the company should consider the following;

1. Multi- engine aircrafts should be prioritized. As observed, aircrafts with fewer engines tend to cause most accidents and injury incidences as well
2. LR(Long Range) engines should also be considerd into the fleet. LR engines have shown to have caused the least number of injury incidences probably due to their reliability
3. Power- Lift air craft category and the AirBus Make should also be given the first priority as they have shown to cause less injury incidences
4. If the company plans to include Cessna, safety measures and training of pilots on handling Cessna aircraft should be prioritized.
5. The company should consider purchasing amateur built planes.