1 Project Overview

1.0 Executive Summary

My company is desirous in venturing into a new airline operations business for commercial and private use. The business model targets regional short haul scheduled commercial flights as well as private charters. The financial investment for this project is huge, and significant analysis of the opportunities, risks and returns will need to be undertaken to determine technical, financial and commercial viability.This will require multiple analyses with multiple data sets and models to determine market opportunities in different regions, competitor analysis, profitability and return on investment(ROI), technical risks to name but a few. My role in this multi-disciplinary endeavor is to perform an analysis of potential risks associated with different aircraft makes and models in order to determine the safest models in the market and make a recommendation to the head of the aviation department on the make and models to consider for this investment.

1.1 Industry Overview

The airline industry is one of the riskiest businesses in the world. It requires significant capital outlays due to the huge fixed costs of acquiring equipment, huge maintenance costs to comply with the stringent safety standards, landing fees, parking and hanger costs; airline businesses also have to contend with strong labor unions and the cost of the main commodity - fuel and oil is affected negatively by various geopolitical factors.

This cannot be articulated better than this statement by Warren Buffet. *" The worst sort of business is one that grows rapidly, requires significant capital to engender the growth, and then earns little or no money. Think airlines. Here a durable competitive advantage has proven elusive ever since the days of the Wright Brothers. Indeed, if a farsighted capitalist had been present at Kitty Hawk, he would have done his successors a huge favor by shooting Orville down".* Kitty Hawk, North Craolina is where, after 4 years of scientific experimentation, Wilbur and Orville Wright achieved the first successful airplane flight on December 17, 1903.

However, with strategic cost cutting measures and a customer centric business model, some airlines have achieved success where others have failed. Our company is studying the Southwest Airlines model, one of the most success airline businesses in the USA. Founded in 1967 with the idea of providing affordable air travel to people who otherwise couldn't afford it,Southwest Airlines has a unique business model that is based on keeping costs low. They do this by flying only one type of plane, which makes maintenance and training easier, and by using a point-to-point system instead of a hub-and-spoke model, which reduces the need for expensive airport infrastructure. The point-to point system means they are able to offer flights for shorter routes with very few connecting flights. Their customer centric culture and speed of execution (eg. pilots helping in bag and cabin clearance) ensures quick plane turn around, more revenue and reduced costs. This is the model my company seeks to emurate and my task is to recommend the safest aircraft(s) for deployment.

2. The Data

2.0 The Data Set

For my analysis, I will use the National Transportation Safety Board(NTSB) aviation accident database that contains information from 1948 to 2023 about civil aviation accidents and selected incidents within the United States, its territories and possessions, and in international waters. [https://www.kaggle.com/datasets/khsamaha/aviation-accident-database-synopses (https://www.kaggle.com/datasets/khsamaha/aviation-accident-database-synopses)](https://www.kaggle.com/datasets/khsamaha/aviation-accident-database-synopses)

This data has documented details about aviation accidents and incidents by flight, make and model. It has further given details about the circumstances around each incident:-stage of flight, extent of damage, latitude and longitude,purpose of flight, fatalities and injuries,weather conditions, as well as characteristics of the aircraft:- make and model, number and type of engine amongst other details. There is also a flight report provided. One of the main weakness in this data set are missing or inconclusive values in some critical columns such as the report status which details if the accident was caused by pilot error or by technical factors. However, because this is a fairly large database, a sample of the data is still big enough to give reasobale conclusions of the relative safety between various makes and models and the relationship between safety with other factors such as type and number of engines.

In my analysis, I will use the CRISP-DM methodology and employ various Python libraries like Pandas, Numpy, Matplotlib and Seaborn for data analysis, data cleaning and visualization. I will further make use of Tableau to present the visualization in an interactive dashboard format and publish my work in a GitHub repository.

2.1 The Problem Statement

Use the above database to analyze different aircraft makes and models accident history in order to provide recommendations to my company on the best make/model (s) for our proposed airline business. Also identify gaps in the data that may limit this analysis and propose a way forward to address those gaps.

2.2 Metric of Success

Provide three solid recommendations to the Head of aviation to aid in the critical decision of which are the safest airplane makes/models to use in the proposed business and justify my recomendations using data and visualizations.

3. Understanding the Data

In [1]:
```
# import pandas, numpy, matplotlib
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
# import the AviationData.csv as a DataFrame and display the first 5 rows
df = pd.read_csv("AviationData.csv",encoding="latin-1",low_memory=False)
df.head()
```

Out[2]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country
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
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 [3]:
```
# displaying the last 5 rows
df.tail()
```

Out[3]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country
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
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 [4]:
```
#checking column names
df.columns
```

Out[4]:
```
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.Descript
ion',
       'Schedule', 'Purpose.of.flight', 'Air.carrier', 'Total.Fatal.Injur
ies',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjure
d',
       'Weather.Condition', 'Broad.phase.of.flight', 'Report.Status',
       'Publication.Date'],
      dtype='object')
```

In [5]:
```
#checking the shape of the Data (rows, columns)
df.shape
```

Out[5]:
```
(88889, 31)
```

4. Data Frame Summary

In [6]:

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

The data has significant missing values in the folowing columns: Latitude, Longitude, Airport.Name, Aircraft.Category,FAR.Description,Schedule, Air.Carrier. These columns do not have any significant impact to our safety analysis and can be dropped.

In [7]:
```
# Descriptive statistics of the numerical variables
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

The number.of.Engines column seems to have erroneous data, as it is not possible to have zero engines. I will use the outlier method to filter out that data.

In [8]:
```
# Getting statistical summary of the categorical columns
df.describe(include='O').T
```

Out[8]:

	count	unique	top	freq
Event.Id	88889	87951	20001214X45071	3
Investigation.Type	88889	2	Accident	85015
Accident.Number	88889	88863	CEN22FA424	2
Event.Date	88889	14782	1982-05-16	25
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
Publication.Date	75118	2924	25-09-2020	17019

The date column is critical in our analysis and will be converted to date format.

5. Data Cleaning

Now that we have understood the data structure, types we can now go ahead and clean the data so that we can perform Explorative Data Analysis.

In [9]:
```
# Making a copy of the DataFrame before we clean
df1 = df.copy(deep= True)
df1.head()
```

Out[9]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country
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
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

5.1 Validity Challenges

This procedure will drop irrelevant columns, clean up the column names and also certain values in the data

In [10]:
```
# Procedure 1: Dropping irrevant Data Observations.
# Data Cleaning Action: Dropping the following columns: Latitude, Longitude
#Registration.Number,FAR.Description,Schedule, Air.Carrier,Aircraft.Categor
# Explanation: Columns have too many missing values and are not necessary f

# dropping columns
df1.drop(['Latitude','Longitude','Airport.Code','Airport.Name','Aircraft.Ca
          'Registration.Number','FAR.Description','Schedule','Air.carrier',
df1.head()
```

Out[10]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country
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
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States

5 rows × 21 columns

In [11]:
```
df1.columns
```

Out[11]:
```
Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Date',
       'Location', 'Country', 'Injury.Severity', 'Aircraft.damage', 'Mak
e',
       'Model', 'Amateur.Built', 'Number.of.Engines', 'Engine.Type',
       'Purpose.of.flight', 'Total.Fatal.Injuries', 'Total.Serious.Injuri
es',
       'Total.Minor.Injuries', 'Total.Uninjured', 'Weather.Condition',
       'Broad.phase.of.flight', 'Report.Status'],
      dtype='object')
```

In [12]:
```
# Procedure 2 : Drop the "." from column names
df1.columns=df1.columns.str.replace(".","")
df1
```

Out[12]:

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

88889 rows × 21 columns

In [13]:
```
df1.columns
```

Out[13]:
```
Index(['EventId', 'InvestigationType', 'AccidentNumber', 'EventDate',
       'Location', 'Country', 'InjurySeverity', 'Aircraftdamage', 'Make',
       'Model', 'AmateurBuilt', 'NumberofEngines', 'EngineType',
       'Purposeofflight', 'TotalFatalInjuries', 'TotalSeriousInjuries',
       'TotalMinorInjuries', 'TotalUninjured', 'WeatherCondition',
       'Broadphaseofflight', 'ReportStatus'],
      dtype='object')
```

In [14]:
```
# Procedure 3: Replace the various 'Fatal()' to 'Fatal' in the 'InjurySever
# provided inside the brackets can be found in the 'TotalFatalInjuries' col
# Find the unique values
df1['InjurySeverity'].unique()
```

Out[14]:
```
array(['Fatal(2)', 'Fatal(4)', 'Fatal(3)', 'Fatal(1)', 'Non-Fatal',
       'Incident', 'Fatal(8)', 'Fatal(78)', 'Fatal(7)', 'Fatal(6)',
       'Fatal(5)', 'Fatal(153)', 'Fatal(12)', 'Fatal(14)', 'Fatal(23)',
       'Fatal(10)', 'Fatal(11)', 'Fatal(9)', 'Fatal(17)', 'Fatal(13)',
       'Fatal(29)', 'Fatal(70)', 'Unavailable', 'Fatal(135)', 'Fatal(3
1)',
       'Fatal(256)', 'Fatal(25)', 'Fatal(82)', 'Fatal(156)', 'Fatal(28)',
       'Fatal(18)', 'Fatal(43)', 'Fatal(15)', 'Fatal(270)', 'Fatal(144)',
       'Fatal(174)', 'Fatal(111)', 'Fatal(131)', 'Fatal(20)', 'Fatal(7
3)',
       'Fatal(27)', 'Fatal(34)', 'Fatal(87)', 'Fatal(30)', 'Fatal(16)',
       'Fatal(47)', 'Fatal(56)', 'Fatal(37)', 'Fatal(132)', 'Fatal(68)',
       'Fatal(54)', 'Fatal(52)', 'Fatal(65)', 'Fatal(72)', 'Fatal(160)',
       'Fatal(189)', 'Fatal(123)', 'Fatal(33)', 'Fatal(110)',
       'Fatal(230)', 'Fatal(97)', 'Fatal(349)', 'Fatal(125)', 'Fatal(3
5)',
       'Fatal(228)', 'Fatal(75)', 'Fatal(104)', 'Fatal(229)', 'Fatal(8
0)',
       'Fatal(217)', 'Fatal(169)', 'Fatal(88)', 'Fatal(19)', 'Fatal(60)',
       'Fatal(113)', 'Fatal(143)', 'Fatal(83)', 'Fatal(24)', 'Fatal(44)',
       'Fatal(64)', 'Fatal(92)', 'Fatal(118)', 'Fatal(265)', 'Fatal(26)',
       'Fatal(138)', 'Fatal(206)', 'Fatal(71)', 'Fatal(21)', 'Fatal(46)',
       'Fatal(102)', 'Fatal(115)', 'Fatal(141)', 'Fatal(55)',
       'Fatal(121)', 'Fatal(45)', 'Fatal(145)', 'Fatal(117)',
       'Fatal(107)', 'Fatal(124)', 'Fatal(49)', 'Fatal(154)', 'Fatal(9
6)',
       'Fatal(114)', 'Fatal(199)', 'Fatal(89)', 'Fatal(57)', 'Fatal', na
n,
       'Minor', 'Serious'], dtype=object)
```

In [15]:

```
# Replace 'Fatal()' to 'Fatal'
df1['InjurySeverity'].replace(['Fatal(2)', 'Fatal(4)', 'Fatal(3)','Fatal(1)
       'Fatal(8)', 'Fatal(78)', 'Fatal(7)', 'Fatal(6)',
       'Fatal(5)', 'Fatal(153)', 'Fatal(12)', 'Fatal(14)', 'Fatal(23)',
       'Fatal(10)', 'Fatal(11)', 'Fatal(9)', 'Fatal(17)', 'Fatal(13)',
       'Fatal(29)', 'Fatal(70)', 'Fatal(135)', 'Fatal(31)',
       'Fatal(256)', 'Fatal(25)', 'Fatal(82)', 'Fatal(156)', 'Fatal(28)',
       'Fatal(18)', 'Fatal(43)', 'Fatal(15)', 'Fatal(270)', 'Fatal(144)',
       'Fatal(174)', 'Fatal(111)', 'Fatal(131)', 'Fatal(20)', 'Fatal(73)',
       'Fatal(27)', 'Fatal(34)', 'Fatal(87)', 'Fatal(30)', 'Fatal(16)',
       'Fatal(47)', 'Fatal(56)', 'Fatal(37)', 'Fatal(132)', 'Fatal(68)',
       'Fatal(54)', 'Fatal(52)', 'Fatal(65)', 'Fatal(72)', 'Fatal(160)',
       'Fatal(189)', 'Fatal(123)', 'Fatal(33)', 'Fatal(110)',
       'Fatal(230)', 'Fatal(97)', 'Fatal(349)', 'Fatal(125)', 'Fatal(35)',
       'Fatal(228)', 'Fatal(75)', 'Fatal(104)', 'Fatal(229)', 'Fatal(80)',
       'Fatal(217)', 'Fatal(169)', 'Fatal(88)', 'Fatal(19)', 'Fatal(60)',
       'Fatal(113)', 'Fatal(143)', 'Fatal(83)', 'Fatal(24)', 'Fatal(44)',
       'Fatal(64)', 'Fatal(92)', 'Fatal(118)', 'Fatal(265)', 'Fatal(26)',
       'Fatal(138)', 'Fatal(206)', 'Fatal(71)', 'Fatal(21)', 'Fatal(46)',
       'Fatal(102)', 'Fatal(115)', 'Fatal(141)', 'Fatal(55)',
       'Fatal(121)', 'Fatal(45)', 'Fatal(145)', 'Fatal(117)',
       'Fatal(107)', 'Fatal(124)', 'Fatal(49)', 'Fatal(154)', 'Fatal(96)',
       'Fatal(114)', 'Fatal(199)', 'Fatal(89)', 'Fatal(57)'], 'Fatal',inpla
```

In [16]:

```
df1['InjurySeverity'].value_counts()
```

Out[16]:

```
Non-Fatal      67357
Fatal          17826
Incident        2219
Minor            218
Serious          173
Unavailable       96
Name: InjurySeverity, dtype: int64
```

In [17]:

```
# Procedure 4: Replace 'Incident',Minor'and 'Serious'to 'Non-Fatal', since
df1['InjurySeverity'].replace(['Incident','Minor','Serious'],'Non-Fatal',in
```

In [18]:

```
df1['InjurySeverity'].value_counts()
```

Out[18]:

```
Non-Fatal      69967
Fatal          17826
Unavailable       96
Name: InjurySeverity, dtype: int64
```

In [19]:
```
df1.sample(5)
```

Out[19]:

	EventId	InvestigationType	AccidentNumber	EventDate	Location	Countr
56806	20040707X00913	Accident	ATL04CA127	2004-06-06	DECATUR, AL	Unite State
24141	20001213X29468	Accident	NYC89DFA02	1989-09-28	MARCY, NY	Unite State
42647	20001208X08829	Accident	FTW97FA340	1997-09-07	MONTROSE, CO	Unite State
83000	20190331X20824	Accident	WPR19FA103	2019-03-31	Farmington, NM	Unite State
80506	20170824X14615	Accident	GAA17CA507	2017-08-24	Hillsboro, OR	Unite State

5 rows × 21 columns

In [20]:
```
df1['Make'].value_counts().nlargest(20)
```

Out[20]:
```
Cessna             22227
Piper              12029
CESSNA              4922
Beech               4330
PIPER               2841
Bell                2134
Boeing              1594
BOEING              1151
Grumman             1094
Mooney              1092
BEECH               1042
Robinson             946
Bellanca             886
Hughes               795
Schweizer            629
Air Tractor          595
BELL                 588
Mcdonnell Douglas    526
Aeronca              487
Maule                445
Name: Make, dtype: int64
```

In [21]:
```
# Procedure 5
# Replace CESSNA with Cessna, PIPER with Piper and BEECH with Beech and BEL

df1['Make'].replace({'CESSNA':'Cessna','PIPER':'Piper','BEECH':'Beech','BEL
 'ROBINSON HELICOPTER':'Robinson','ROBINSON HELICOPTER COMPANY' :'Robinson
'AIR TRACTOR INC':'Air Tractor','HUGHES':'Hughes','AERONCA':'Aeronca','EURO
'STINSON':'Stinson','LUSCOMBE':'Luscombe','DEHAVILLAND':'De Havilland','CHA
 'AERO COMMANDER':'Aero Commander','BELLANCA':'Bellanca','NORTH AMERICAN':
 'ROBINSON':'Robinson','CIRRUS DESIGN CORP':'Cirrus','TAYLORCRAFT':'Taylor
  'GRUMMAN ACFT ENG COR-SCHWEIZER':'Grumman-schweizer','Cirrus Design Corp.
    'DIAMOND AIRCRAFT IND INC':'Diamond'}, inplace=True)
df1['Make'].value_counts()
```

Out[21]:
```
Cessna               27149
Piper                14870
Beech                 5372
Boeing                2745
Bell                  2722
                     ...
Jasper                   1
MILLER RAYMOND A         1
MATHIS MELVIN R          1
Aeronca/bubeck           1
FETTERMAN LANNY R        1
Name: Make, Length: 8206, dtype: int64
```

5.2 Completeness Challenges

In [22]:
```
# Procedure 1: Checking for missing values
df1.isnull().sum()
```

Out[22]:
```
EventId                    0
InvestigationType          0
AccidentNumber             0
EventDate                  0
Location                  52
Country                  226
InjurySeverity          1000
Aircraftdamage          3194
Make                      63
Model                     92
AmateurBuilt             102
NumberofEngines         6084
EngineType              7077
Purposeofflight         6192
TotalFatalInjuries     11401
TotalSeriousInjuries   12510
TotalMinorInjuries     11933
TotalUninjured          5912
WeatherCondition        4492
Broadphaseofflight     27165
ReportStatus            6381
dtype: int64
```

In [23]:
```
#The data has  missing values in almost all columns.
# Procedure 2: For columns where missing values are less than 1000 I will d
df1.dropna(subset=['Location','Country','Make','Model','AmateurBuilt','Inju
```

In [24]:
```
df1.isnull().sum()
```

Out[24]:
```
EventId                  0
InvestigationType        0
AccidentNumber           0
EventDate                0
Location                 0
Country                  0
InjurySeverity           0
Aircraftdamage        2639
Make                     0
Model                    0
AmateurBuilt             0
NumberofEngines       5212
EngineType            6136
Purposeofflight       5132
TotalFatalInjuries   11299
TotalSeriousInjuries 12378
TotalMinorInjuries   11797
TotalUninjured        5813
WeatherCondition      3480
Broadphaseofflight   25991
ReportStatus          5442
dtype: int64
```

In [25]:
```
# Procedure 3: for categorical columns  I will replace the NaN Values with
#(include='O').T> ;for numerical columns I will replace the NaN Values with

df1.fillna({'Aircraftdamage':'Substantial','EngineType':'Reciprocating','Pu
               'Broadphaseofflight':'Landing','ReportStatus':'Probable Caus
        'TotalSeriousInjuries':0,'TotalMinorInjuries':0,'TotalUninjured':1

df1.isnull().sum()
```

Out[25]:
```
EventId                 0
InvestigationType       0
AccidentNumber          0
EventDate               0
Location                0
Country                 0
InjurySeverity          0
Aircraftdamage          0
Make                    0
Model                   0
AmateurBuilt            0
NumberofEngines         0
EngineType              0
Purposeofflight         0
TotalFatalInjuries      0
TotalSeriousInjuries    0
TotalMinorInjuries      0
TotalUninjured          0
WeatherCondition        0
Broadphaseofflight      0
ReportStatus            0
dtype: int64
```

5.3 Uniformity Challenges

In [26]:

```
# Procedure 1: Convert all columns to Camel Case for uniformity

df1.rename(columns={'Aircraftdamage':'AircraftDamage','NumberofEngines':'Nu
                    'Purposeofflight':'PurposeOfFlight','Broadphaseofflight
df1.head()
```

Out[26]:

	EventId	InvestigationType	AccidentNumber	EventDate	Location	Country
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
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States

5 rows × 21 columns

5.4 Checking for Duplicates

In [27]:

```
# Checking for duplicates
df1.duplicated().sum()
```

Out[27]: 1

In [28]:

```
#drop the duplicates
df1.drop_duplicates(inplace=True)

#check
df1.duplicated().sum()
```

Out[28]: 0

5.5 Checking for outliers

In [29]:

```
# Checking the statistics of the numerical columns
df1.describe().T

# It makes sense to have the min and max values indicated below for fatal c
# However having 0 engines does not make sense;
```

Out[29]:

	count	mean	std	min	25%	50%	75%	max
NumberOfEngines	87426.0	1.134422	0.429726	0.0	1.0	1.0	1.0	8.0
TotalFatalInjuries	87426.0	0.564409	5.118530	0.0	0.0	0.0	0.0	349.0
TotalSeriousInjuries	87426.0	0.242376	1.437184	0.0	0.0	0.0	0.0	161.0
TotalMinorInjuries	87426.0	0.312253	2.098541	0.0	0.0	0.0	0.0	380.0
TotalUninjured	87426.0	5.068149	27.059143	0.0	0.0	1.0	2.0	699.0

In [30]:

```
# Checking for outlier
sns.boxplot(data=df1, y='NumberOfEngines')
```

Out[30]: <AxesSubplot:ylabel='NumberOfEngines'>

In [31]:

```
# Remove the outlier using the min quantile
min_eng = df1['NumberOfEngines'].quantile(.0005)
min_eng
```

Out[31]: 0.0

In [32]:
```
df1[df1['NumberOfEngines']<= min_eng]
```

Out[32]:

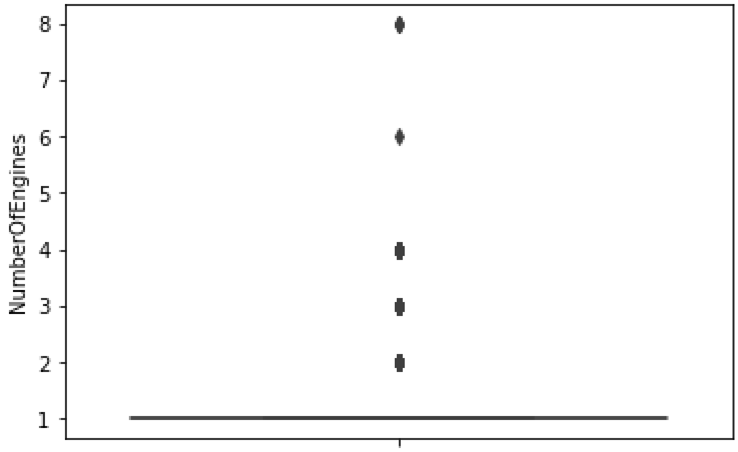
	EventId	InvestigationType	AccidentNumber	EventDate	Location	Countr
62	20020917X02247	Accident	LAX82DVG13	1982-01-09	CALISTOGA, CA	Unite State
247	20020917X02190	Accident	LAX82DA098	1982-02-06	GLENDALE, AZ	Unite State
353	20020917X02298	Accident	LAX82FUJ28	1982-02-19	PHOENIX, AZ	Unite State
433	20020917X01824	Accident	CHI82DA076	1982-02-27	CINCINNATI, OH	Unite State
436	20020917X02181	Accident	LAX82DA089	1982-02-28	NAPA, CA	Unite State
...	...	...	...	...	...	.
88322	20220808105678	Accident	CEN22LA363	2022-08-07	Waller, TX	Unite State
88462	20220912105904	Accident	ERA22LA407	2022-09-03	Mount Bethel, PA	Unite State
88476	20221004106058	Accident	WPR22LA368	2022-09-04	Las Cruces, NM	Unite State
88596	20221003106045	Accident	WPR22LA364	2022-09-29	Hood River, OR	Unite State
88646	20221010106089	Accident	ERA23LA013	2022-10-08	Woodstock, VA	Unite State

1220 rows × 21 columns

In [33]:
```
# Remove the outliers
df1= df1[df1['NumberOfEngines']> min_eng]
```

In [34]:
```
# Confirm removal of outliers
sns.boxplot(data=df1, y='NumberOfEngines')
```

Out[34]: <AxesSubplot:ylabel='NumberOfEngines'>



5.6 Feature Engineering

For better analysis of the data I will create additional columns and filter out certain rows as explained below:

ReportStatus: This column contains string type data explaining the reason for the accident; going through the data, one realizes that most accidents are due to pilot error and not technical issues. There are also significant number of accidents that are reportyed as 'probable cause'.This means that that data has not been filled in. I will create a new column where if a string contains the name 'Pilot' this will be classified as 'Pilot Error'. If string contains 'Probable Cause' classify as 'Undetermined' else classify as 'Technical Failure'.

Location : Create a new column 'State' by filtering out the last two elements (state codes)

SurvivalRate: Create a new Column whosae value is TotalUninjured +TotalSeriousInjuries+TotalMinorInjuries divided by TotalUninjured +TotalSeriousInjuries+TotalMinorInjuries+TotalFatalInjuries

EventDate: The column is currently in str format; convert column to date format for time bassed analysis

Investigation Type Remove rows that contain 'incident'. These are immaterial and I want my analysis to focus on accidents only; i.e. apples for apples

Countries Remove countries that are non-US, because they are immaterial and the contain incomplete data.

In [35]:
```
df1['ReportStatus'].unique()
```

Out[35]:
```
array(['Probable Cause', 'Factual', 'Foreign', ...,
       'The pilot did not ensure adequate clearance from construction veh
icles during taxi.',
       'The pilot\x92s failure to secure the magneto switch before attemp
ting to hand rotate the engine which resulted in an inadvertent engine st
art, a runaway airplane, and subsequent impact with parked airplanes. Con
tributing to the accident was the failure to properly secure the airplane
with chocks.',
       'The pilot\x92s loss of control due to a wind gust during landin
g.'],
      dtype=object)
```

In [36]:
```
# create a copy of the dataframe before subsetting
df2 = df1.copy()
```

In [37]:
```
# Create a new column summarizing the ReportStatus column

m1 = df2['ReportStatus'].str.contains('pilot')
m2 = df2['ReportStatus'].str.contains('Probable Cause')
m3 = df2['ReportStatus'].str.contains('Factual')
m4 = df2['ReportStatus'].str.contains('Foreign')

df2['AccidentCause'] = np.select(condlist=[m1,m2,m3,m4],choicelist=['Pilot
df2['AccidentCause'].value_counts()
```

Out[37]:
```
Unknown        67969
Pilot Error    13209
0               5028
Name: AccidentCause, dtype: int64
```

In [38]:
```
# In the new column created replace '0' with 'Technical Failure'

df2['AccidentCause'].replace('0','Technical Failure', inplace=True)
df2['AccidentCause'].value_counts()
```

Out[38]:
```
Unknown              67969
Pilot Error          13209
Technical Failure     5028
Name: AccidentCause, dtype: int64
```

In [39]:
```
# Combine Make and Model columns into a new column MakeModel
# df1['MakeModel'] = df1[['Make','Model']].agg(' '.join, axis=1)
```

In [40]:
```
#df1['MakeModel'].value_counts()
```

In [41]:
```
# Create a new column called State by extracting the last 2 string values t
df2['State'] = df2['Location'].str[-2:]
```

In [42]:
```
df2['State'].replace({'ID':'Idaho', 'CA':'California', 'VA':'Virginia', 'OH
         'WA':'Washington', 'NJ':'New Jersey', 'FL':'Florida', 'NM':'New Mex
         'TX':'Texas', 'OK':'Oklahoma', 'AR':'Arkansas', 'UT':'Utah', 'AK':
         'GA':'Georgia', 'NC':'North Carolina', 'NY':'New York', 'MT':'Monta
         'AZ':'Arizona', 'MO':'Missouri', 'WY':'Wyoming', 'IL':'Illinois',
        'CO':'Colorado', 'WV':'West Virginia', 'MS':'Mississippi', 'DC':'Was
         'NH':'New Hampshire', 'IA':'Iowa', 'WI':'Wisconsin', 'KY':'Kentucky
         'AN':'Non US', 'SD':'South Dakota', 'NE':'Nebraska', 'RI':'Rhode Is
         '89':'Non US', 'BO':'Non US', 'DE':'Delaware','as':'Non US', 'FT':
         'la':'Non US', 'PR':'Puerto Rico', 'Of':'Non US', 'EN':'Non US', '9
        'da':'Non US', 'ia':'Non US', 'co':'Non US', 'NG':'Non US', 'es':'No
         'EA':'Non US', 'ES':'Non US', 'DA':'Non US', 'GU':'Guam', 'ny':'Non
         'ca':'Non US', 'ue':'Non US', 'an':'Non US', 'oa':'Non US', 'na':'N
         'al':'Non US',  'ic':'Non US', 'me':'Non US', '74':'Non US', 'O6':
         'ZE':'Non US', 'ce':'Non US', 'ti':'Non US', 'ea':'Non US', 'en':'N
         'us':'Non US', 'ya':'Non US', 'or':'Non US', 'BA':'Non US','ba':'No
         'RK':'Non US', 'OM':'Non US', '34':'Non US','in':'Non US', 'ey':'No
          'on':'Non US', 'ru':'Non US', 'UE':'Non US', 'GM':'Gulf of mexico'
         'rk':'Non US', 'US':'Non US', 'um':'Non US', 'AY':'Non US', 'li':'N
         'LY':'Non US', 'ua':'Non US', 're':'Non US', 'we':'Non US', 'EY':'N
         '16':'Non US','ST':'Non US', 'pe':'Non US', 'AO':'Atlantic Ocean',
         'VI':'Virgin Islands', 'el':'Non US', 'IS':'Non US', 'ne':'Non US',
         'ar':'Non US', 'PE':'Non US', 'wi':'Non US', 'wn':'Non US', 'f)':'N
         'el':'Non US', 'IS':'Non US', 'ne':'Non US', 'ry':'Non US', 'SH':'N
         'PE':'Non US', 'wi':'Non US', 'wn':'Non US', 'f)':'Non US', 'n,':'N
         '9,':'Non US', 'e)':'Non US',  ',':'Non US', 'ao':'Non US', 'my':'N
        'd,':'Non US', 'A,':'Non US', 'x,':'Non US', 'rg':'Non US', 'g,':'No
         'pa':'Non US', 'a,':'Non US', 'ka':'Non US', 'sh':'Non US', 'ad':'N
         'of':'Non US', 'ng':'Non US', '7,':'Non US', 'h)':'Non US', 'O,':'N
```

In [43]:
```
df2['State'].unique()
```

Out[43]:
```
array(['Idaho', 'California', 'Virginia', 'Ohio', 'Massachusetts',
       'Minnesota', 'Washington', 'New Jersey', 'Florida', 'New Mexico',
       'Alabama', 'Louisiana', 'Texas', 'Oklahoma', 'Arkansas', 'Utah',
       'Alaska', 'Pennsylvania', 'Michigan', 'Georgia', 'North Carolina',
       'New York', 'Montana', 'Oregon', 'Nevada', 'Indiana', 'Arizona',
       'Missouri', 'Wyoming', 'Illinois', 'South Carolina', 'Maryland',
       'Hawaii', 'Colorado', 'West Virginia', 'Mississippi',
       'Washington DC', 'Vermont', 'Kansas', 'New Hampshire', 'Iowa',
       'Wisconsin', 'Kentucky', 'Connecticut', 'Tennessee', 'Maine',
       'Non US', 'South Dakota', 'Nebraska', 'Rhode Island',
       'North Dakota', 'Delaware', 'American Samoa', 'Puerto Rico',
       'Guam', 'Pacific Ocean', 'Gulf of mexico', 'Atlantic Ocean',
       'Virgin Islands', ', '], dtype=object)
```

In [44]:
```
df2.sample(3)
```

Out[44]:

	EventId	InvestigationType	AccidentNumber	EventDate	Location	Count
78845	20160906X03328	Accident	ERA16WA310	2016-08-25	Eleuthera, Bahamas	Baham
48614	20001212X21327	Incident	SEA00IA108	2000-06-17	SEATTLE, WA	Unit Stat
6616	20001214X44755	Accident	ATL84LA027	1983-10-21	ARLINGTON, TN	Unit Stat

3 rows × 23 columns

In [45]:
```
# Create SurvivalRate column
survivors= df2[['TotalSeriousInjuries','TotalMinorInjuries','TotalUninjured
Passengers = df2[['TotalFatalInjuries','TotalSeriousInjuries','TotalMinorIr
df2['SurvivalRate'] = (survivors.div(Passengers))
df2.head()
```

Out[45]:

	EventId	InvestigationType	AccidentNumber	EventDate	Location	Country
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
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States

5 rows × 24 columns

In [46]:
```
df2.isna().sum()
```

Out[46]:
```
EventId                  0
InvestigationType        0
AccidentNumber           0
EventDate                0
Location                 0
Country                  0
InjurySeverity           0
AircraftDamage           0
Make                     0
Model                    0
AmateurBuilt             0
NumberOfEngines          0
EngineType               0
PurposeOfFlight          0
TotalFatalInjuries       0
TotalSeriousInjuries     0
TotalMinorInjuries       0
TotalUninjured           0
WeatherCondition         0
BroadPhaseOfFlight       0
ReportStatus             0
AccidentCause            0
State                    0
SurvivalRate            74
dtype: int64
```

In [47]:
```
df2=df2.dropna()
df2.isna().sum()
```

Out[47]:
```
EventId                  0
InvestigationType        0
AccidentNumber           0
EventDate                0
Location                 0
Country                  0
InjurySeverity           0
AircraftDamage           0
Make                     0
Model                    0
AmateurBuilt             0
NumberOfEngines          0
EngineType               0
PurposeOfFlight          0
TotalFatalInjuries       0
TotalSeriousInjuries     0
TotalMinorInjuries       0
TotalUninjured           0
WeatherCondition         0
BroadPhaseOfFlight       0
ReportStatus             0
AccidentCause            0
State                    0
SurvivalRate             0
dtype: int64
```

In [48]:
```
# delete rows where investigation type is incident
df2['InvestigationType'].value_counts()
```

Out[48]:
```
Accident    83080
Incident     3052
Name: InvestigationType, dtype: int64
```

In [49]:
```
# Create a Boolean mask for the rows to remove
mask = df2['InvestigationType']=='Incident'
# select all rows except the ones that contain 'Incident'
df2=df2[~mask]
df2['InvestigationType'].value_counts()
```

Out[49]:
```
Accident    83080
Name: InvestigationType, dtype: int64
```

In [50]:
```
# delete rows where country is not USA;
df2['Country'].value_counts()
```

Out[50]:
```
United States    78670
Brazil             317
Canada             294
Mexico             266
Australia          191
                 ...
Cote D'ivoire        1
Corsica              1
Eritrea              1
Macao                1
Obyan                1
Name: Country, Length: 199, dtype: int64
```

In [51]:
```
# Create a Boolean mask for the rows to remove
mask = df2['Country']=='United States'
# select all rows except the ones that contain 'Incident'
df2=df2[mask]
df2['Country'].value_counts()
```

Out[51]:
```
United States    78670
Name: Country, dtype: int64
```

In [52]:
```
# drop EventId ReportStatus, Location, AccidentNumber Columns

df2.drop(['EventId','InvestigationType','AccidentNumber','Location','Report
df2.head(3)
```

Out[52]:

	EventDate	Country	InjurySeverity	AircraftDamage	Make	Model	AmateurBuilt	Numbe
0	1948-10-24	United States	Fatal	Destroyed	Stinson	108-3	No	
1	1962-07-19	United States	Fatal	Destroyed	Piper	PA24-180	No	
2	1974-08-30	United States	Fatal	Destroyed	Cessna	172M	No	

In [53]:
```
# Check date format
df2['EventDate'].dtypes
```

Out[53]:
```
dtype('O')
```

In [54]:
```
#Convert date format
df2['EventDate'] = pd.to_datetime(df2['EventDate'])
df2['EventDate'].head()
```

Out[54]:
```
0   1948-10-24
1   1962-07-19
2   1974-08-30
3   1977-06-19
4   1979-08-02
Name: EventDate, dtype: datetime64[ns]
```

In [55]:
```
# create a year column
df2['EventYear']= df2['EventDate'].dt.year
df2['EventYear'].dtypes
```

Out[55]:
```
dtype('int64')
```

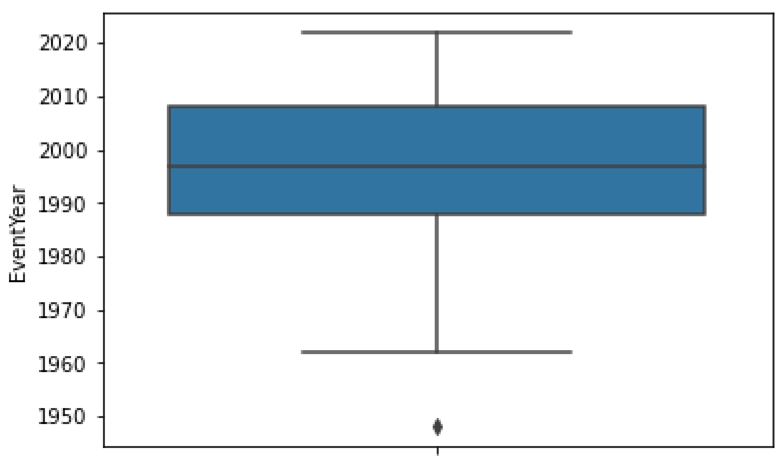
In [56]:
```
df2.head(3)
```

Out[56]:

	EventDate	Country	InjurySeverity	AircraftDamage	Make	Model	AmateurBuilt	Numbe
0	1948-10-24	United States	Fatal	Destroyed	Stinson	108-3	No	
1	1962-07-19	United States	Fatal	Destroyed	Piper	PA24-180	No	
2	1974-08-30	United States	Fatal	Destroyed	Cessna	172M	No	

In [57]:
```
# Checking for outlier in EventYear col
sns.boxplot(data=df2, y='EventYear')
```

Out[57]:
```
<AxesSubplot:ylabel='EventYear'>
```



In [58]:
```
# Remove the outliers using quantile
min_year = df2['EventYear'].quantile(.005)
min_year
```

Out[58]: 1982.0

In [59]:
```
# display the outlier records
df2[df2['EventYear']< min_year]

# There were only 7 records betwwen 1948 and 1981
```

Out[59]:

	EventDate	Country	InjurySeverity	AircraftDamage	Make	Model	AmateurBuilt	Num
0	1948-10-24	United States	Fatal	Destroyed	Stinson	108-3	No	
1	1962-07-19	United States	Fatal	Destroyed	Piper	PA24-180	No	
2	1974-08-30	United States	Fatal	Destroyed	Cessna	172M	No	
3	1977-06-19	United States	Fatal	Destroyed	Rockwell	112	No	
4	1979-08-02	United States	Fatal	Destroyed	Cessna	501	No	
5	1979-09-17	United States	Non-Fatal	Substantial	Mcdonnell Douglas	DC9	No	
6	1981-08-01	United States	Fatal	Destroyed	Cessna	180	No	

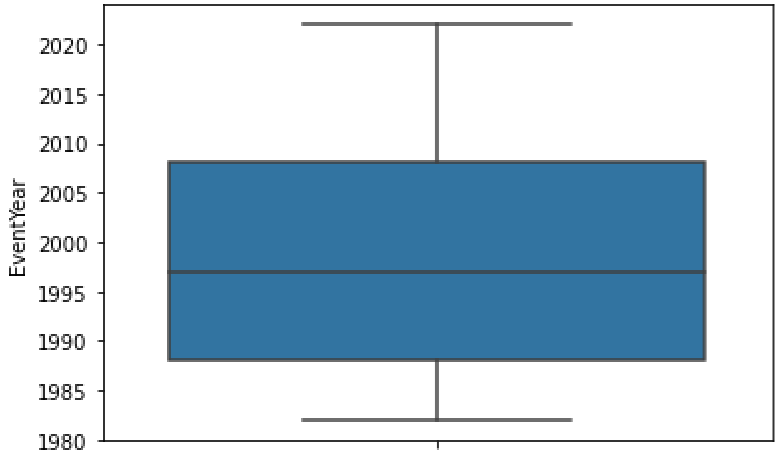
In [60]:
```
# Remove the outliers
df2= df2[df2['EventYear']>= min_year]
df2.sample(5)
```

Out[60]:

	EventDate	Country	InjurySeverity	AircraftDamage	Make	Model	AmateurBui
81181	2018-02-13	United States	Non-Fatal	Substantial	Grumman-schweizer	269D	N
88451	2022-09-01	United States	Non-Fatal	Substantial	Boeing	737-824	N
74799	2014-03-08	United States	Fatal	Substantial	ROGERS GEORGE T	LANCAIR IVP	Ye
57777	2004-11-04	United States	Fatal	Destroyed	Socata	TB 20	N
72768	2012-10-13	United States	Non-Fatal	Substantial	Piper	PA-38-112	N

In [61]:
```
# Confirm removal of outliers
sns.boxplot(data=df2, y='EventYear')
```

Out[61]: <AxesSubplot:ylabel='EventYear'>



5.7 Saving the clean dataset

In [62]:
```
#save the new dataframe in cvs format
df2.to_csv('AviationData_Clean.csv',index=False)
```

In [63]:
```
df2 =df2.copy(deep=True)
```

The 10 top accident makes comprise of 67% of the data. Statistically, it is safeto assume that these are also the top akes in use in the industry. I will focus my analysis by subsetting a new data frame with the information on these 10 makes only.

6 Explorative Data Analysis

I will now proceed to perform univariate, bivariate and multivariate data analysis using summary statistics and visualizations to determine the safest airplane make and model,in the United States. One of the key success factors in the airline business is the reduction of the cost of maintenance. Buying the most commonly used makes and models in the market is just as important as chosing the safest make and model. This will ensure that the company enjoys reduced maintenance costs, due to economies of scale, availability of technical staff to handle the aircraft, cheaper training costs and better re-sale values when upgrading. For that reason I will focus my analysis on the **Top 10 Makes** because they represent **66%** of the data

1. What are the various statistical measures by type (mean,median,max, min). Because the data set contains a lot of models, I will use a sample of the top 20 frequencies by make and assess those for various safety parameters.

2. Analyze the filtered types of airplanes accident history over time

3. Analyze the chosen airplane types by survival rate, aircraft damage, injury severity and accident cause.

4. Analyze the Correlation between number of accidents and engine size

5. Analyze the geographical distribution of accidents by state

This analysis will be done both on this notebook and in Tableau

In [64]:
```
# Load the clean dataset and create a new dataframe

data = pd.read_csv('AviationData_Clean.csv')
data
```

Out[64]:

	EventDate	Country	InjurySeverity	AircraftDamage	Make	Model	AmateurBu
0	1982-01-01	United States	Non-Fatal	Substantial	Cessna	140	N
1	1982-01-01	United States	Non-Fatal	Substantial	Cessna	401B	N
2	1982-01-01	United States	Non-Fatal	Substantial	North American	NAVION L-17B	N
3	1982-01-01	United States	Non-Fatal	Substantial	Piper	PA-28-161	N
4	1982-01-01	United States	Non-Fatal	Substantial	Beech	V35B	N
...	...	...	...	...	...	...	
78658	2022-12-21	United States	Non-Fatal	Substantial	Cessna	172F	N
78659	2022-12-21	United States	Non-Fatal	Substantial	GRUMMAN AMERICAN AVN. CORP.	AA-5B	N
78660	2022-12-26	United States	Non-Fatal	Substantial	Piper	PA-28-151	N
78661	2022-12-26	United States	Non-Fatal	Substantial	AMERICAN CHAMPION AIRCRAFT	8GCBC	N
78662	2022-12-29	United States	Non-Fatal	Substantial	Piper	PA-24-260	N

78663 rows × 20 columns

In [65]:
```
top_10_makes = data['Make'].value_counts().nlargest(10).sum()
top_10_makes
```

Out[65]: 53064

In [66]:
```
#checking for missing values
data.isna().sum().any()
```

Out[66]:
```
False
```

6.1 Univariate Analysis

I will use various univariate analysis techniques such as count, plots, histogram and boxplot to analyze a number of key variables that have a firect relationship with safety.

1. Frequency of accidents by Make and MakeModel

2. Frequencyof accidents by year

3, Frequency of Fatal and non-Fatal Accidents

4. Frequency of accidents based on number of Engines

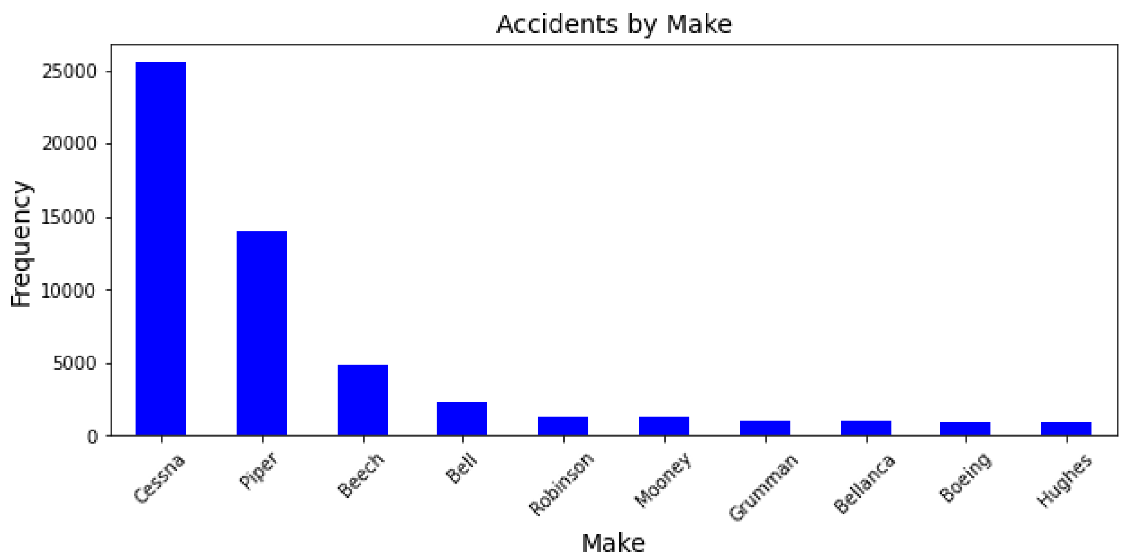
5. Frequency of accidents based on Engine Types

6. Main cause of accident

7. Level of damage

In [67]:

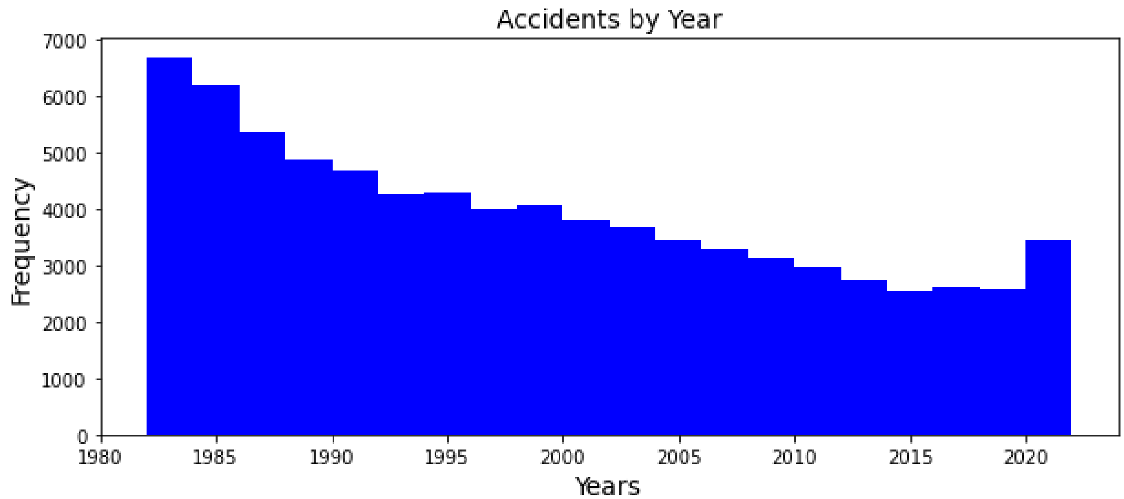
```
# Top 10 Makes # Frequency of accidents by make
plt.figure(figsize=(10,4))

top_10_makes = data['Make'].value_counts().nlargest(10)

top_10_makes.plot(kind='bar',color='b')

plt.title('Accidents by Make',fontsize=14)
plt.xlabel('Make',fontsize=14)
plt.ylabel('Frequency',fontsize=14)
plt.xticks(rotation=45)
plt.show()
```



The top 3 makes with the most accidents are Cessna, Piper and Beech. Grumman, Bellanca Boeing and Hughes have the least number of accidents

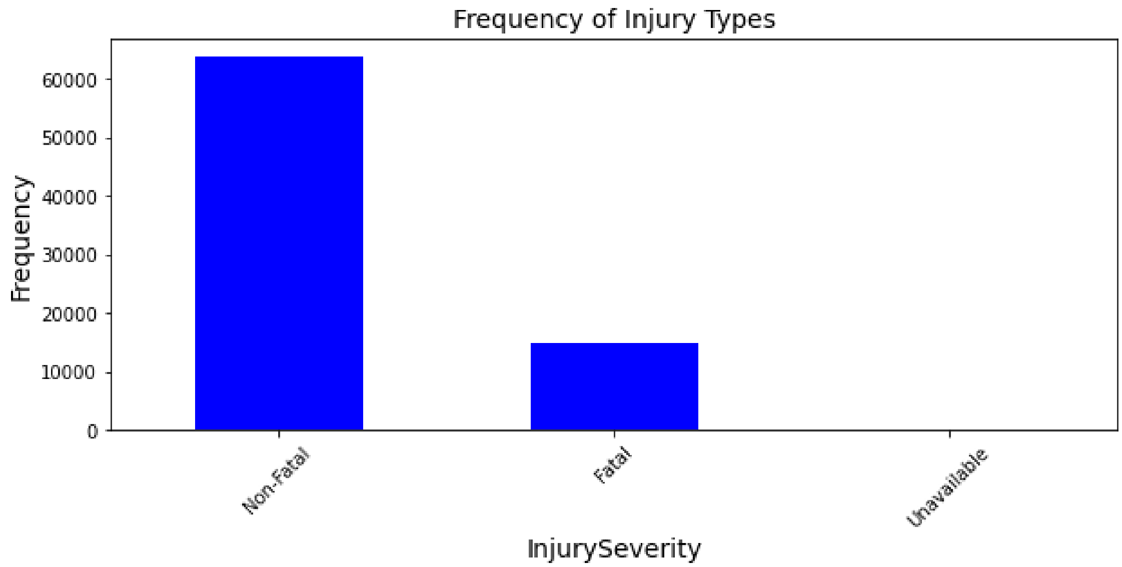
In [68]:

```
# Frequency of accidents over time
plt.figure(figsize=(10,4))
plt.hist(data['EventYear'],bins=20,color='b')

plt.title('Accidents by Year',fontsize=14)
plt.xlabel('Years',fontsize=14)
plt.ylabel('Frequency',fontsize=14)
plt.show()
```



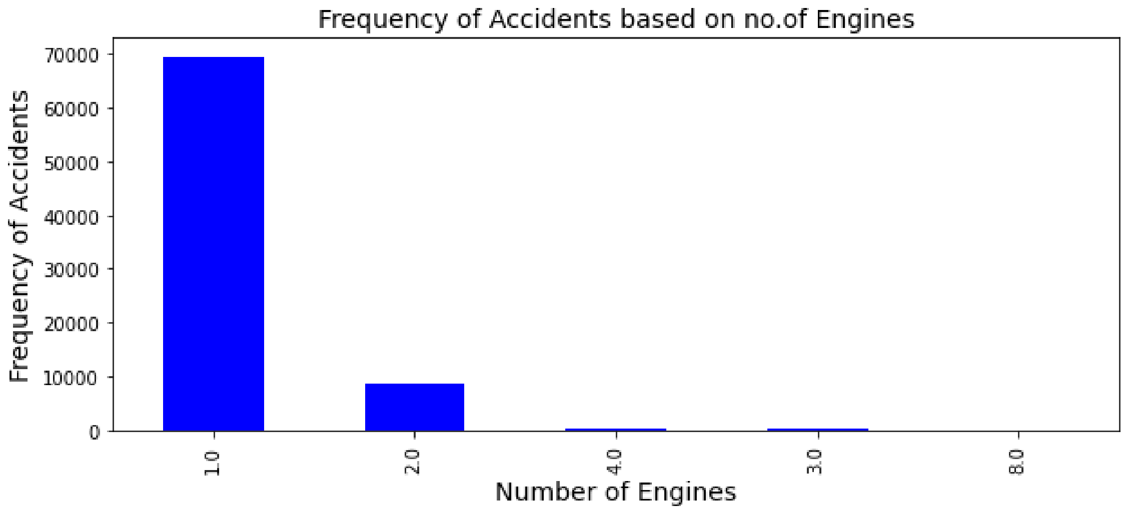
The data shows that accidents progressively decreased in frequency with a surprising peak between 2020 and 2023

In [69]:
```
# Frequency of fatal vs non-fatal accidents
Injury_Counts = data['InjurySeverity'].value_counts()

plt.figure(figsize=(10,4))
plt.xlabel('InjurySeverity',fontsize=14)
plt.ylabel('Frequency',fontsize=14)
plt.title('Frequency of Injury Types',fontsize=14)
Injury_Counts.plot(kind='bar',color='b');
plt.xticks(rotation=45)
plt.show()
```



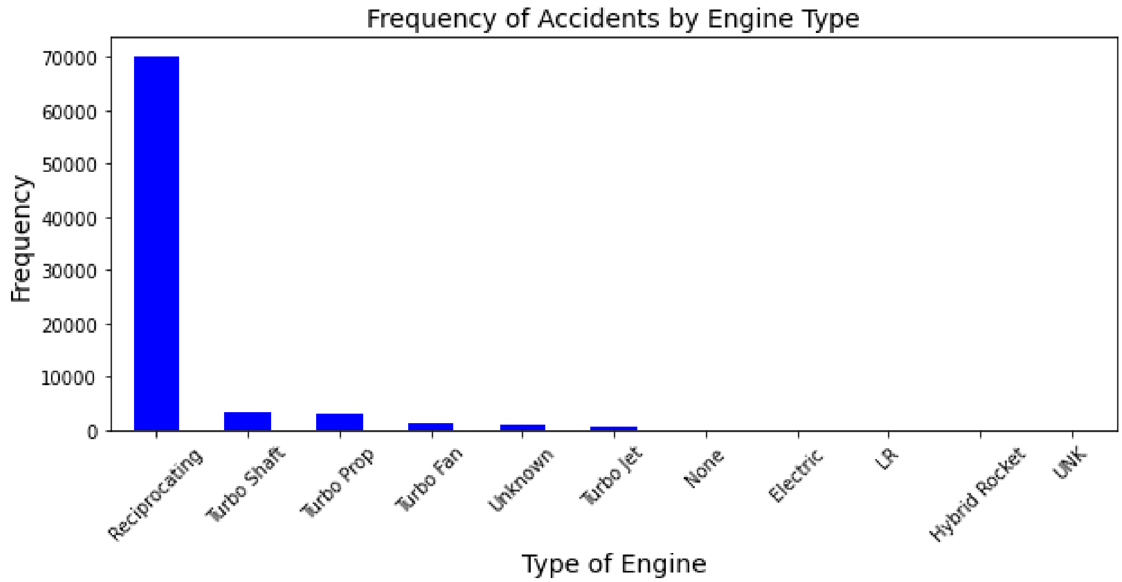
The data shows that a vast majority of accidents resulted in non-fatal casualties

In [70]:
```
# No.of Engines
No_Engines = data['NumberOfEngines'].value_counts()


plt.figure(figsize=(10, 4))
No_Engines.plot(kind='bar',color='b');
plt.xlabel('Number of Engines',fontsize=14)
plt.ylabel('Frequency of Accidents',fontsize=14)
plt.title('Frequency of Accidents based on no.of Engines',fontsize=14 )
plt.show()
```



The data shows that the less the number of engines an aircraft has, the higher the likelihood of an accident. Aircraft with over 3 engines are relatively safe.

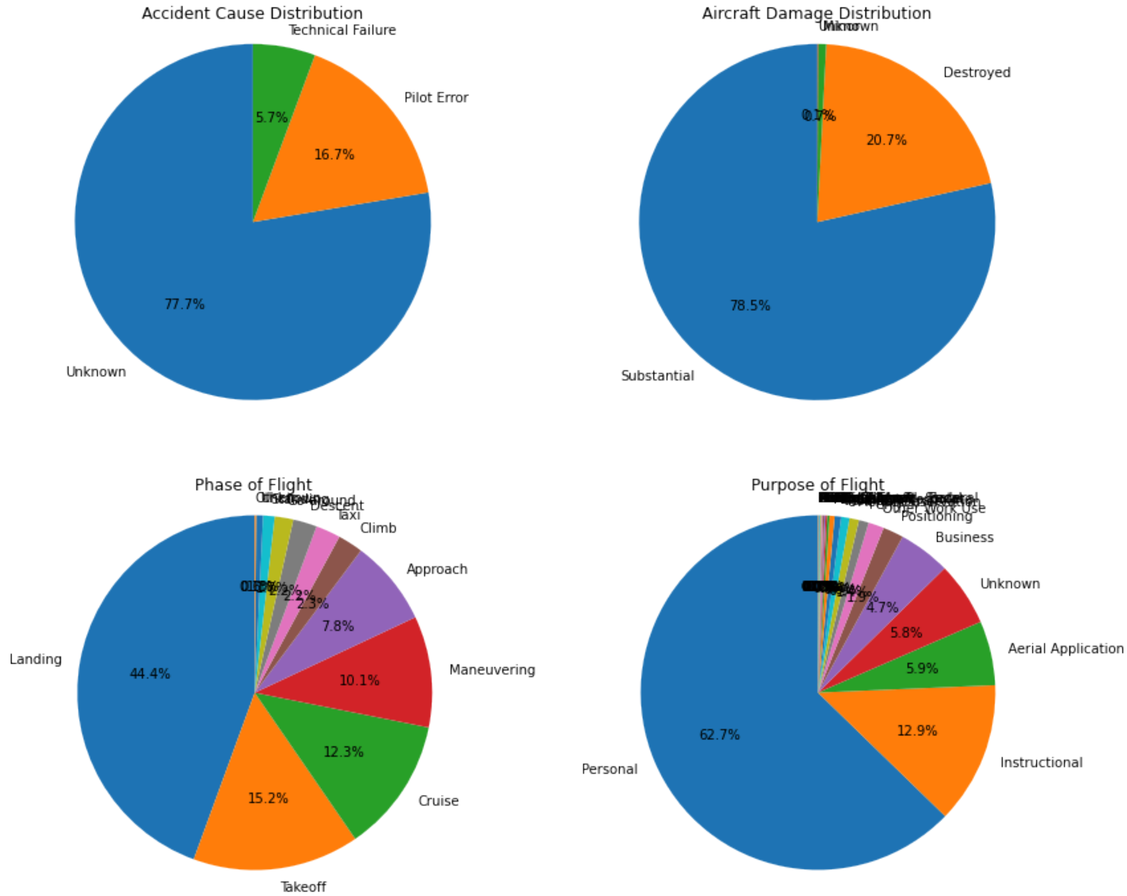
In [71]:
```
# Engine Types
Engine_Types = data['EngineType'].value_counts()

plt.figure(figsize=(10, 4))
Engine_Types.plot(kind='bar',color='b');
plt.xlabel('Type of Engine',fontsize=14)
plt.ylabel('Frequency',fontsize=14)
plt.title('Frequency of Accidents by Engine Type',fontsize=14)
plt.xticks(rotation=45)
plt.show()
```



Almost all accidents were by aircraft with reciprocating engines. These operate on the same principals as engines found in most automobiles. The company should not use any aircraft with reciprocating engines.

In [72]:

```
# Accident cause, extent of damage,phase of flight and purpose
import matplotlib.pyplot as plt

Accident_Cause = data['AccidentCause'].value_counts()
Damage = data['AircraftDamage'].value_counts()
PhaseofFlight = data['BroadPhaseOfFlight'].value_counts()
Purposeofflight = data['PurposeOfFlight'].value_counts()

fig, axes = plt.subplots(2, 2, figsize=(14, 12))
ax1, ax2, ax3, ax4 = axes.flatten()


ax1.pie(Accident_Cause, labels=Accident_Cause.index, autopct='%.1f%%', star
ax1.set_title('Accident Cause Distribution')
ax1.axis('equal')

ax2.pie(Damage, labels=Damage.index, autopct='%.1f%%', startangle=90)
ax2.set_title('Aircraft Damage Distribution')
ax2.axis('equal')

ax3.pie(PhaseofFlight, labels=PhaseofFlight.index, autopct='%.1f%%', starta
ax3.set_title('Phase of Flight')
ax3.axis('equal')

ax4.pie(Purposeofflight, labels=Purposeofflight.index, autopct='%.1f%%', st
ax4.set_title('Purpose of Flight')
ax4.axis('equal')


plt.show()
```



The data indicate that the cause of most accidents has not been indicate(Probable Cause). For those that were analyzed and summarized in the report status, a majority were caused by pilot error and not technical faults. This is not surprising. "In 2020, the National Transportation Safety Board found that “69.1% of all general aviation accidents in 2020 were caused by pilot error.”

In nearly all the accidents the aircraft suffered substantial damage or was completely destroyed.

Most accidents happened during Landing, followed by Take off. Peronal purpose flights were the leading cuse of accidents

6.2 Bivariate Data Analysis

In order to sharpen the analysis, I will use a new data set that only includes the top 10 makes. In this analysis, I will observe the relation between make of the aircraft and:-

Fatal and Serious Injuries

Survival Rates

In [73]:
```
# Get the top 10 makes based on frequency
top_10_makes = data['Make'].value_counts().nlargest(10).index

# Filter the dataframe to only include rows with the top 10 makes and creat
data2 = data[data['Make'].isin(top_10_makes)]
data2
```

Out[73]:

	EventDate	Country	InjurySeverity	AircraftDamage	Make	Model	AmateurBuilt	N
0	1982-01-01	United States	Non-Fatal	Substantial	Cessna	140	No	
1	1982-01-01	United States	Non-Fatal	Substantial	Cessna	401B	No	
3	1982-01-01	United States	Non-Fatal	Substantial	Piper	PA-28-161	No	
4	1982-01-01	United States	Non-Fatal	Substantial	Beech	V35B	No	
5	1982-01-02	United States	Non-Fatal	Destroyed	Bellanca	17-30A	No	
...	...	...	...	...	...	...	...	
78655	2022-12-16	United States	Non-Fatal	Substantial	Cessna	R172K	No	
78657	2022-12-18	United States	Non-Fatal	Substantial	Piper	PA28	No	
78658	2022-12-21	United States	Non-Fatal	Substantial	Cessna	172F	No	
78660	2022-12-26	United States	Non-Fatal	Substantial	Piper	PA-28-151	No	
78662	2022-12-29	United States	Non-Fatal	Substantial	Piper	PA-24-260	No	

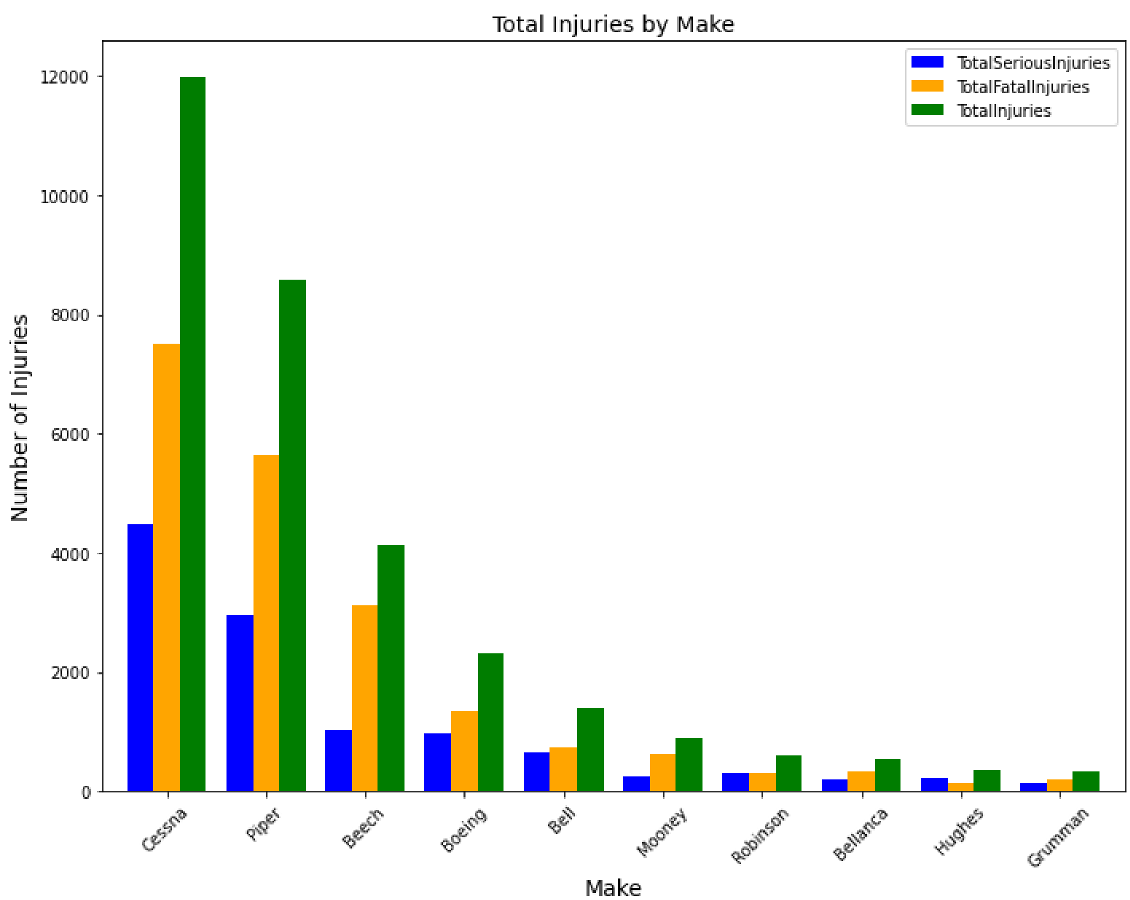
53064 rows × 20 columns

In [74]:
```
data2.columns
```

Out[74]:
```
Index(['EventDate', 'Country', 'InjurySeverity', 'AircraftDamage', 'Mak
e',
       'Model', 'AmateurBuilt', 'NumberOfEngines', 'EngineType',
       'PurposeOfFlight', 'TotalFatalInjuries', 'TotalSeriousInjuries',
       'TotalMinorInjuries', 'TotalUninjured', 'WeatherCondition',
       'BroadPhaseOfFlight', 'AccidentCause', 'State', 'SurvivalRate',
       'EventYear'],
      dtype='object')
```

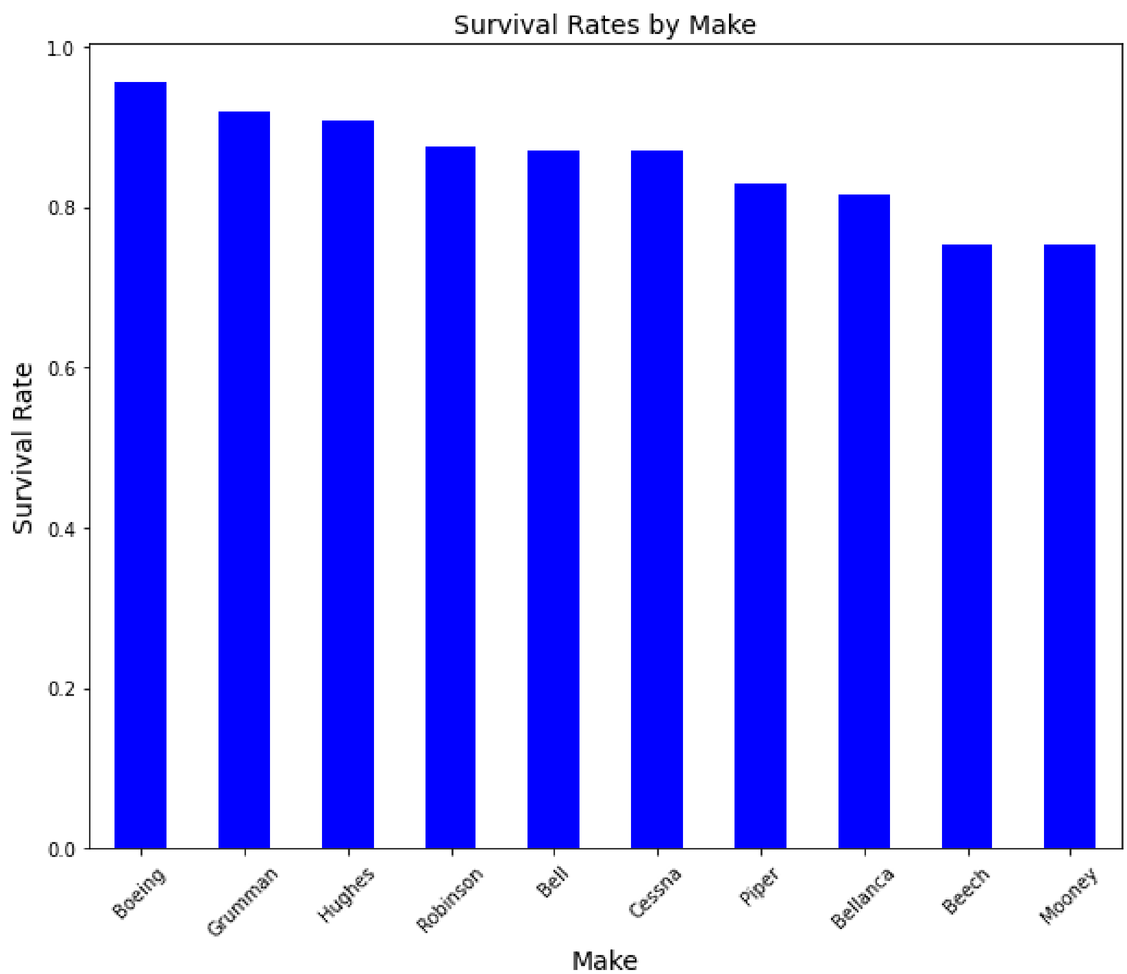
In [75]:
```
# Relationship between Make and the number of serious injuries and Fataliti

# Group by 'Make' and sum the total injuries
grp2 = data2.groupby('Make')[['TotalSeriousInjuries', 'TotalFatalInjuries']

# Calculate total injuries by adding serious and fatal injuries
grp2['TotalInjuries'] = grp2['TotalSeriousInjuries'] + grp2['TotalFatalInju

# Sort by total injuries and keep the top ten makes
grp2 = grp2.sort_values('TotalInjuries', ascending=False).head(10)

# Plotting
plt.figure(figsize=(10, 8))

grp2[['TotalSeriousInjuries', 'TotalFatalInjuries', 'TotalInjuries']].plot(
    kind='bar',  width=0.8,   color=['blue', 'orange', 'green'],  figsize=(

plt.title('Total Injuries by Make',fontsize=14)
plt.xlabel('Make', fontsize=14)
plt.ylabel('Number of Injuries', fontsize=14)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show();
```

```
<Figure size 720x576 with 0 Axes>
```



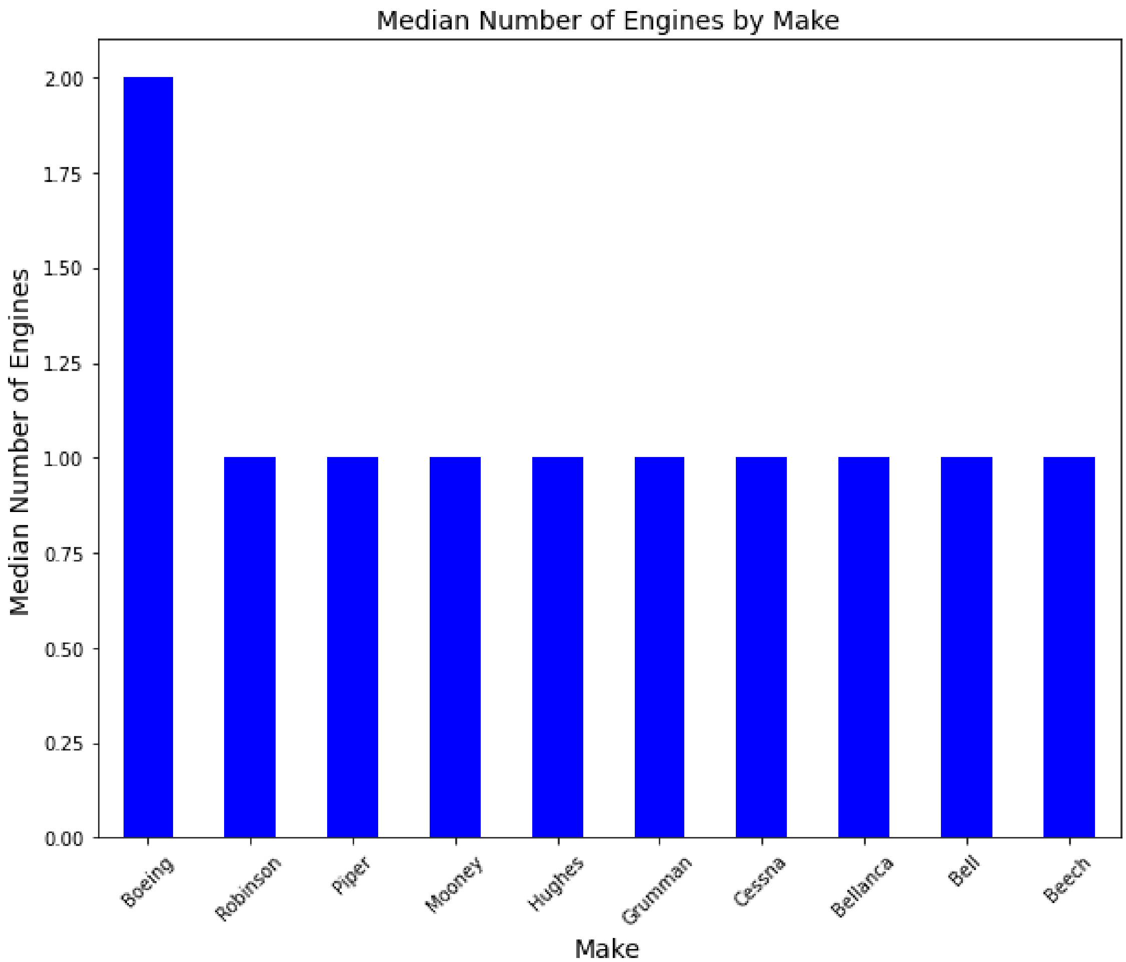
Cessna, Piper and Beech are leading in the number of injuries. As we have seen above, they also have the most accidents recorded.

In [76]:
```
grp3 = data2.groupby('Make')['SurvivalRate'].mean().sort_values(ascending=F

plt.figure(figsize=(10, 8))

grp3.plot(kind='bar',color=['blue']);
plt.title('Survival Rates by Make',fontsize=14);
plt.xlabel('Make',fontsize=14)
plt.ylabel('Survival Rate',fontsize=14)
plt.xticks(rotation=45)
plt.show();
```



The survival rate reduces the bias from the number of accidents and the no, of passengers that an aircraft can hold. From this analysis, the survival rate is highest for Boeing.

In [77]:
```
grp4 = data2.groupby('Make')['NumberOfEngines'].median().sort_values(ascend

plt.figure(figsize=(10, 8))

grp4.plot(kind='bar',color=['blue']);

plt.title('Median Number of Engines by Make',fontsize=14)
plt.xlabel('Make',fontsize=14)
plt.ylabel('Median Number of Engines',fontsize=14)
plt.xticks(rotation=45)
plt.show();
```



6.3 Multivariate Analysis

In this analysis, I will look into the relationship between multiple factors using the correlation of all numerical columns. This helps to see at a glance how different factors relate with each other.

In [78]:
```
# show the correlation of numeric columns with each other
data_num = data.select_dtypes(['int','float'])
data_num.head()
```

Out[78]:

	NumberOfEngines	TotalFatalInjuries	TotalSeriousInjuries	TotalMinorInjuries	TotalUninjure
0	1.0	0.0	0.0	0.0	2.
1	2.0	0.0	0.0	0.0	2.
2	1.0	0.0	0.0	3.0	0.
3	1.0	0.0	0.0	0.0	1.
4	1.0	0.0	0.0	0.0	1.

In [79]:
```

# subset the numeical columns
data_int = data[['NumberOfEngines','TotalFatalInjuries','TotalSeriousInjur
                 'TotalUninjured','SurvivalRate']]
```

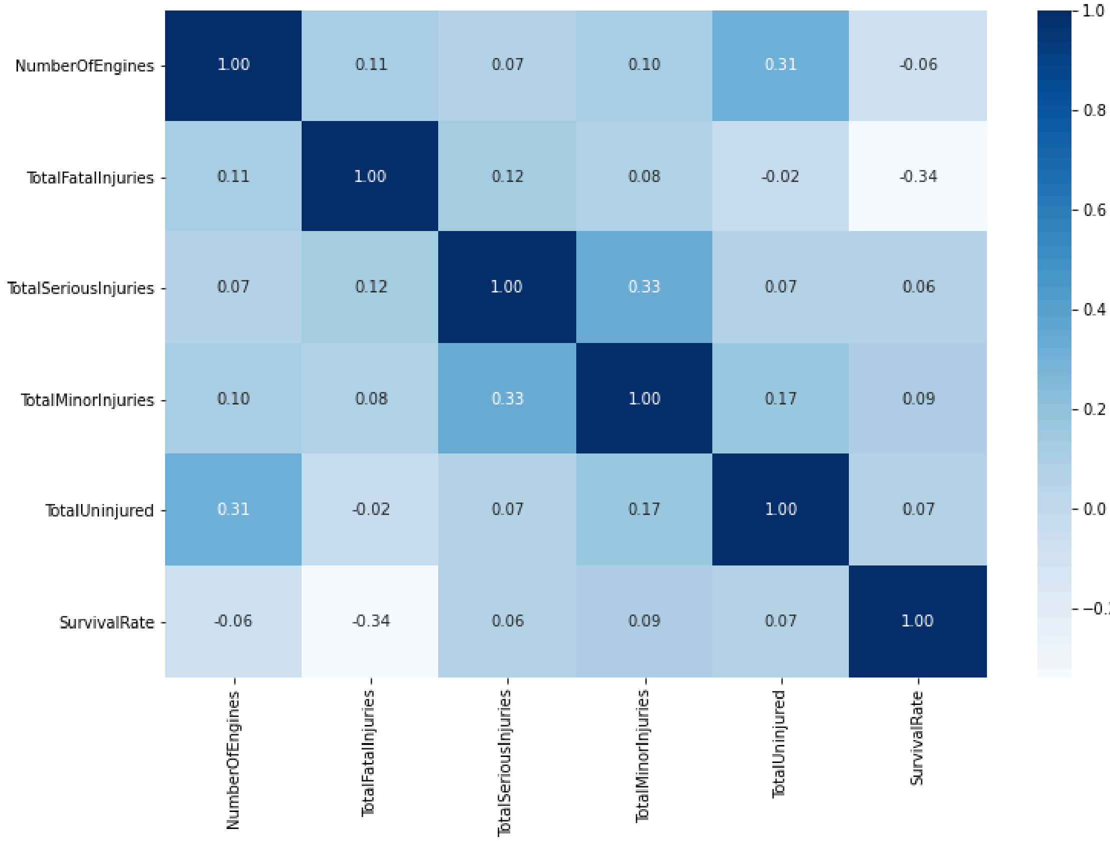
In [80]:
```
corr = data_num.corr()
corr
```

Out[80]:

	NumberOfEngines	TotalFatalInjuries	TotalSeriousInjuries	TotalMinorInju
NumberOfEngines	1.000000	0.107323	0.065406	0.102
TotalFatalInjuries	0.107323	1.000000	0.123219	0.080
TotalSeriousInjuries	0.065406	0.123219	1.000000	0.326
TotalMinorInjuries	0.102283	0.080170	0.326473	1.000
TotalUninjured	0.313050	-0.019069	0.066378	0.168
SurvivalRate	-0.064897	-0.338598	0.061041	0.090

In [81]:
```
plt.figure(figsize=(12,8))
sns.heatmap(corr, annot=True, fmt='.2f',cmap="Blues")
```

Out[81]: <AxesSubplot:>



Total Fata Injuries have the strongest impact on reducing survival rates

Number of Engines is positively correlated with the number of uninjured individuals, meaning more engines might contribute to lower injury counts, but does not significantly impacy survival rates

Total Serious and Minor Injuries are correlated showing accidents especially in terms of survival

7.0 Determining the Safest Make and Model

In [82]:

```
# Of the top 10 makes, Cessna, Piper and Beech have by far the worst safety
# being the safest
# I will create a new data frame that includes the 4 types of safest aircra
Safest_Makes =data2['Make'].value_counts().nsmallest(4).index

# Filter the dataframe to only include rows with the safest 3 makes
data3 = data2[data2['Make'].isin(Safest_Makes)]
data3.head()
```

Out[82]:

	EventDate	Country	InjurySeverity	AircraftDamage	Make	Model	AmateurBuilt	Nu
5	1982-01-02	United States	Non-Fatal	Destroyed	Bellanca	17-30A	No	
16	1982-01-03	United States	Fatal	Destroyed	Grumman	AA-5B	No	
21	1982-01-03	United States	Non-Fatal	Substantial	Bellanca	7GCBC	No	
40	1982-01-06	United States	Non-Fatal	Substantial	Boeing	A75	No	
70	1982-01-13	United States	Non-Fatal	Destroyed	Grumman	AA5B	No	

In [83]:

```
data3['Make'].value_counts()
```

Out[83]:

```
Grumman     1063
Bellanca    1034
Boeing       915
Hughes       864
Name: Make, dtype: int64
```

In [84]:

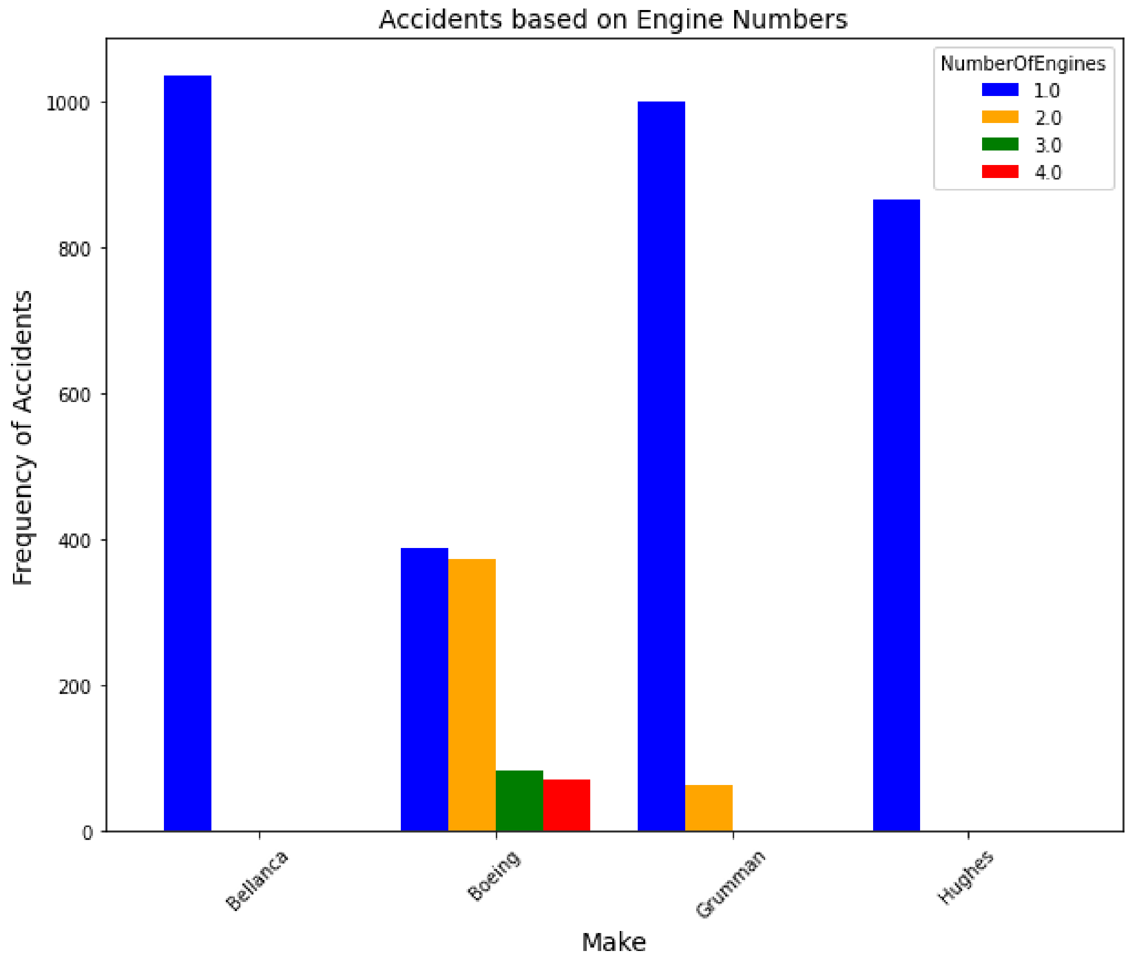
```
#Create a cross tab with Make against Engines
engine_No = pd.crosstab(data3['Make'],data3['NumberOfEngines'])
engine_No
```

Out[84]:

NumberOfEngines	1.0	2.0	3.0	4.0
Make				
Bellanca	1034	0	0	0
Boeing	388	372	84	71
Grumman	999	64	0	0
Hughes	864	0	0	0

In [85]:

```
# Plotting
engine_No.plot(kind='bar',width=0.8,   color=['blue', 'orange', 'green','re

plt.title('Accidents based on Engine Numbers',fontsize=14)
plt.xlabel('Make',fontsize=14)
plt.ylabel('Frequency of Accidents',fontsize=14)
plt.xticks(rotation=45)
plt.show();
```



Of the 4 makes with the least accidents Boeing is the only make that has 3 engines and above; The frequency of accidents for 3 and more engines is the lowest. I can conclude that the safest make is Boeing for the models that 3 or more engines. We will therefore now analyze the models of Boeing that meet this criteria.

In [86]:

```
# Create a new dataframe with just Boeing values so that we can filter out

Boeing =data3['Make'].value_counts().index[2]
Boeing
```

Out[86]:

```
'Boeing'
```

In [87]:

```
# Filter the dataframe to only include rows with Boeing
data4 = data3[data3['Make'] == 'Boeing']
data4
```

Out[87]:

	EventDate	Country	InjurySeverity	AircraftDamage	Make	Model	AmateurBu
40	1982-01-06	United States	Non-Fatal	Substantial	Boeing	A75	N
71	1982-01-13	United States	Fatal	Destroyed	Boeing	737-222	N
223	1982-02-06	United States	Non-Fatal	Minor	Boeing	A75N1	N
319	1982-02-17	United States	Non-Fatal	Substantial	Boeing	727-235	N
509	1982-03-13	United States	Fatal	Destroyed	Boeing	KC-135A	N
...	...	...	...	...	...	...	
78507	2022-10-15	United States	Non-Fatal	Substantial	Boeing	A75N1(PT17)	N
78539	2022-10-26	United States	Non-Fatal	Substantial	Boeing	A75N1(PT17)	N
78574	2022-11-10	United States	Non-Fatal	Substantial	Boeing	737-8	N
78579	2022-11-12	United States	Fatal	Destroyed	Boeing	B17	N
78638	2022-12-08	United States	Non-Fatal	Substantial	Boeing	767-322	N

915 rows × 20 columns

In [88]:
```
# Filter out models with greater than 3 engines - We have determined these
data5 = data4.loc[data4['NumberOfEngines']>=3]
data5
```

Out[88]:

	EventDate	Country	InjurySeverity	AircraftDamage	Make	Model	AmateurBuilt	Nu
319	1982-02-17	United States	Non-Fatal	Substantial	Boeing	727-235	No	
509	1982-03-13	United States	Fatal	Destroyed	Boeing	KC-135A	No	
613	1982-03-24	United States	Non-Fatal	Substantial	Boeing	707-123B	No	
827	1982-04-18	United States	Non-Fatal	Substantial	Boeing	727-200	No	
1741	1982-07-09	United States	Fatal	Destroyed	Boeing	727-235	No	
...	...	...	...	...	...	...	...	
65254	2012-05-30	United States	Non-Fatal	Minor	Boeing	747	No	
74003	2019-01-29	United States	Non-Fatal	Substantial	Boeing	727 200	No	
74964	2019-10-02	United States	Fatal	Destroyed	Boeing	B17	No	
77436	2021-11-29	United States	Non-Fatal	Substantial	Boeing	747-4B5F	No	
78579	2022-11-12	United States	Fatal	Destroyed	Boeing	B17	No	

155 rows × 20 columns

In [89]:
```
data5['Model'].value_counts().index
```

Out[89]:
```
Index(['727-200', '727', '747-400', '727-232', '727-224', '727-223', '747
-422',
       '707-323C', '747-122', '747-136', '727-225', '727-222', '727-264',
       '727-100', '747', '727-235', '707-321B', '727-227', 'B-17G', 'B1
7',
       '727-214', '747-200', '747-121', '727-31', '727-251', '727-233',
       '747-300', '727-281', '747-131', '747-228F', 'S-307', '727-247',
       '747-243B', '747SP', '747-269B', '727-23', '727-225A', '747-287B',
       'MD-11', '747-128', '747-SP', '747-368', '727-243', '747 SP-09',
       '747-236B', '727-225B', '727 200', '747-200B', 'HP-B-377', 'DC-1
0',
       '727-222A', '747-238', '747-212B', '747-256', '747-4B5F', '707-123
B',
       '747-259B', '747SP-21', '747-238B', '727-2M7', '747-230', '727-29
5',
       '727-51C', 'MD-10-10F', '727-212', '747-200F', '747-236', 'B747-43
3BCF',
       '707-351C', '707-324C', '727-230', '747-4F6B', '707-300', '727-2S2
F',
       '727-100QC', 'KC-135A'],
      dtype='object')
```

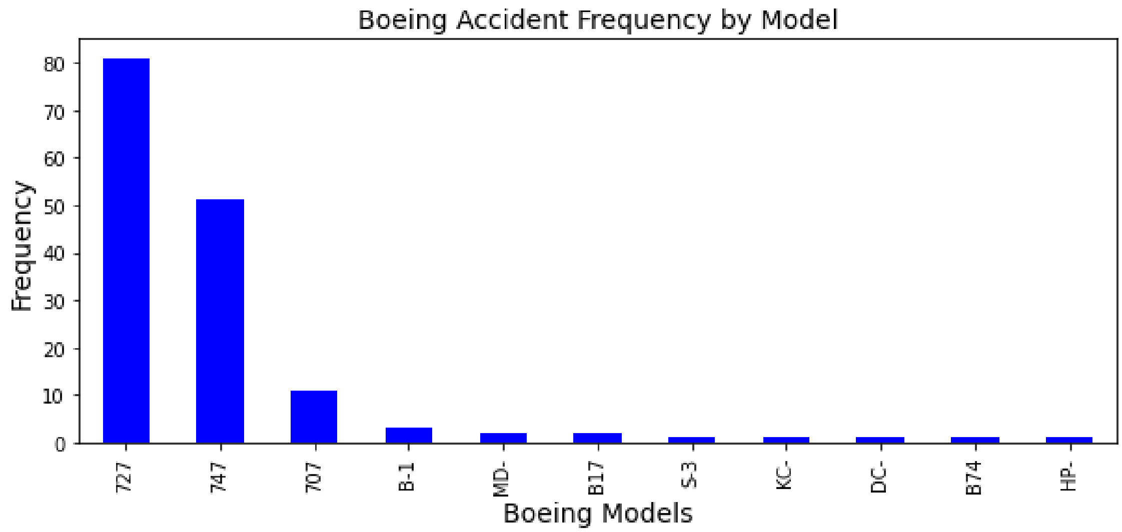
In [90]:
```
# create a copy of the dataframe before subsetting
data6 = data5.copy()
```

In [91]:
```
data6['Model1']=data5['Model'].str[:3]
```

In [92]:
```
Boeing_Accidents = data6['Model1'].value_counts()
Boeing_Accidents
```

Out[92]:
```
727    81
747    51
707    11
B-1     3
MD-     2
B17     2
S-3     1
KC-     1
DC-     1
B74     1
HP-     1
Name: Model1, dtype: int64
```

In [93]:
```
Boeing_Accidents = data6['Model1'].value_counts()

plt.figure(figsize=(10,4))
plt.xlabel('Boeing Models',fontsize=14)
plt.ylabel('Frequency',fontsize=14)
plt.title('Boeing Accident Frequency by Model',fontsize=14)
plt.xticks(rotation=45)
Boeing_Accidents.plot(kind='bar',color='b');
plt.show()
```

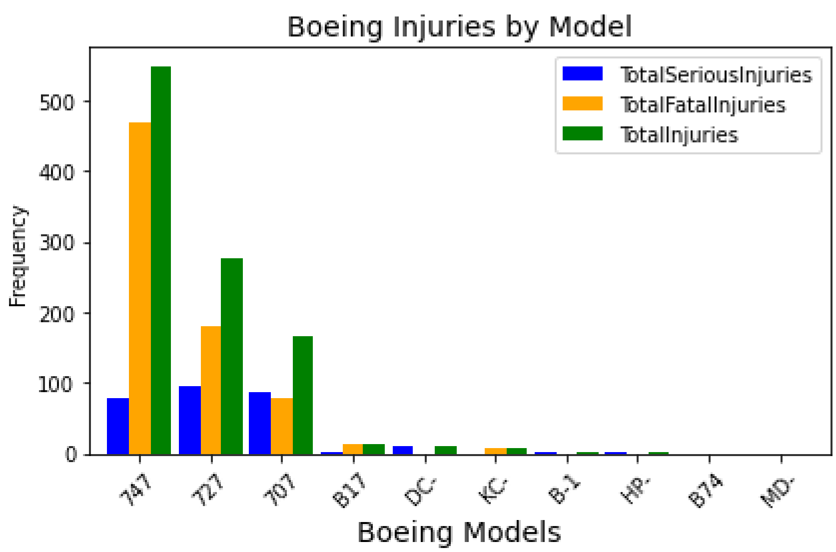


Boeing has 3 main models with greater than 3 engines; the other models seem to be outliers. Of the 3 main models the Boeing 707 has the least occurence of accidents.

In [94]:

```
grp4 = data6.groupby('Model1')[['TotalSeriousInjuries', 'TotalFatalInjuries
grp4['TotalInjuries'] = grp4['TotalSeriousInjuries'] + grp4['TotalFatalInju
grp4 = grp4.sort_values('TotalInjuries', ascending=False).head(10)

plt.figure(figsize=(10, 8))
grp4[['TotalSeriousInjuries', 'TotalFatalInjuries','TotalInjuries']].plot(k
color=['blue', 'orange','green'])
plt.title('Boeing Injuries by Model',fontsize=14);
plt.xlabel('Boeing Models',fontsize=14)
plt.ylabel('Frequency')

plt.xticks(rotation=45)
plt.tight_layout()

plt.show();
```

```
<Figure size 720x576 with 0 Axes>
```



The main Boeing Models are the 747, 727, and the 707. The other models are outliers. From the analysis, the Boeing 707 resulted in the least injuries.

However, comparing the number Boeing's accidents for models with 3 engines and above(155) with the total accidents in the AviationData_Clean (over 78K), it is correct to say that Boeing Models are overall saf and the company should consider Boeing as the make and chose the above models based on the level of usage e.g. no. of passengers, distance covered, maintenance costs etc.

In [95]:

```
Boeing_Accidents = data6['Model1'].value_counts().sum()
Boeing_Accidents
```

Out[95]: 155