Final Project Submission

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- Self Pace/Flex

Data Introduction Summmary

Introduce Data before presenting it in code below

First step is to import pandas and matplot lib in order to run the code needed to analyze the data.

Importing Pandas and Opening Datafile to Inspect and analyze elements

In [2]:

```
# Import Pandas and Matplotlib
import pandas as pd
import matplotlib.pyplot as plt
```

In [3]:

```
planes_df = pd.read_csv('Aviation_Data.csv')
planes_df.sort_values(by=('Total.Fatal.Injuries'), ascending=False)
```

```
C:\Users\neali\AppData\Local\Temp\ipykernel_9152\1510018960.py:1: DtypeWarning: Columns (
6,7,28) have mixed types. Specify dtype option on import or set low_memory=False.
  planes_df = pd.read_csv('Aviation_Data.csv')
```

Out[3]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport
40881	20020124X00116	Accident	DCA97WA007B	1996-11-12	New Delhi, India	India	NaN	NaN	
40882	20020124X00116	Accident	DCA97WA007A	1996-11-12	New Delhi, India	India	NaN	NaN	
75734	20140718X92314	Accident	DCA14RA127	2014-07-17	Hrabove, Ukraine	Ukraine	NaN	NaN	
22082	20001213X27403	Accident	DCA89RA014	1988-12-21	LOCKERBIE, United Kingdom	United Kingdom	NaN	NaN	
51769	20011130X02321	Accident	DCA02MA001	2001-11-12	Belle Harbor, NY	United States	NaN	NaN	
...	...	...	...	...	...	...	...	...	
90004	NaN	15-12-2022	NaN	NaN	NaN	NaN	NaN	NaN	
90010	NaN	15-12-2022	NaN	NaN	NaN	NaN	NaN	NaN	
90031	NaN	15-12-2022	NaN	NaN	NaN	NaN	NaN	NaN	
90090	NaN	20-12-2022	NaN	NaN	NaN	NaN	NaN	NaN	
90097	NaN	20-12-2022	NaN	NaN	NaN	NaN	NaN	NaN	

90348 rows × 31 columns

After viewing the layout of the data, it is time to further filter and identify the different columns and datatypes of the file.

In [4]:

```
planes_df.info
planes_df.dtypes
planes_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.Description',
       'Schedule', 'Purpose.of.flight', 'Air.carrier', 'Total.Fatal.Injuries',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured',
       'Weather.Condition', 'Broad.phase.of.flight', 'Report.Status',
       'Publication.Date'],
      dtype='object')
```

In [5]:

```
planes_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                88889 non-null  object
 1   Investigation.Type      90348 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        73659 non-null  object
dtypes: float64(5), object(26)
memory usage: 21.4+ MB
```

As we can see, most columns are objects, with a few float64 (integer) columns. Now, I will create an adittional column titled "Total Injuries" that acts as a weighted measure of total fatal injuries, total serious injuries, and total minor injuries.

fatal injuries, total serious injuries, and total minor injuries.

In [6]:

```
#create new column documenting total injuries, fatal + major + minor

planes_df['Total.Fatal.Injuries'].fillna(0, inplace=True)
planes_df['Total.Serious.Injuries'].fillna(0,inplace=True)
planes_df['Total.Minor.Injuries'].fillna(0,inplace=True)
planes_df['Total Injuries'] = planes_df['Total.Fatal.Injuries'] * 0.6 + planes_df['Total
.Serious.Injuries'] * 0.4 + planes_df['Total.Minor.Injuries'] * 0.2
planes_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 32 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                88889 non-null  object 
 1   Investigation.Type      90348 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    90348 non-null  float64
 24  Total.Serious.Injuries  90348 non-null  float64
 25  Total.Minor.Injuries    90348 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        73659 non-null  object 
 31  Total Injuries          90348 non-null  float64
dtypes: float64(6), object(26)
memory usage: 22.1+ MB
```

Data Analysis

At this step in the process, we will begin compartmentalizing data and taking detailed looks at each aspect we want to investigate further in order to discover appropriate stakeholder solutions.

First step- analyze number of total injuries per Number of Engines.

In [20]:

```
num_eng = planes_df.groupby('Number.of.Engines')['Total Injuries'].sum().reset_index()
num_eng_sorted = num_eng.sort_values(by='Total Injuries', ascending=False)
num_eng_sorted
```

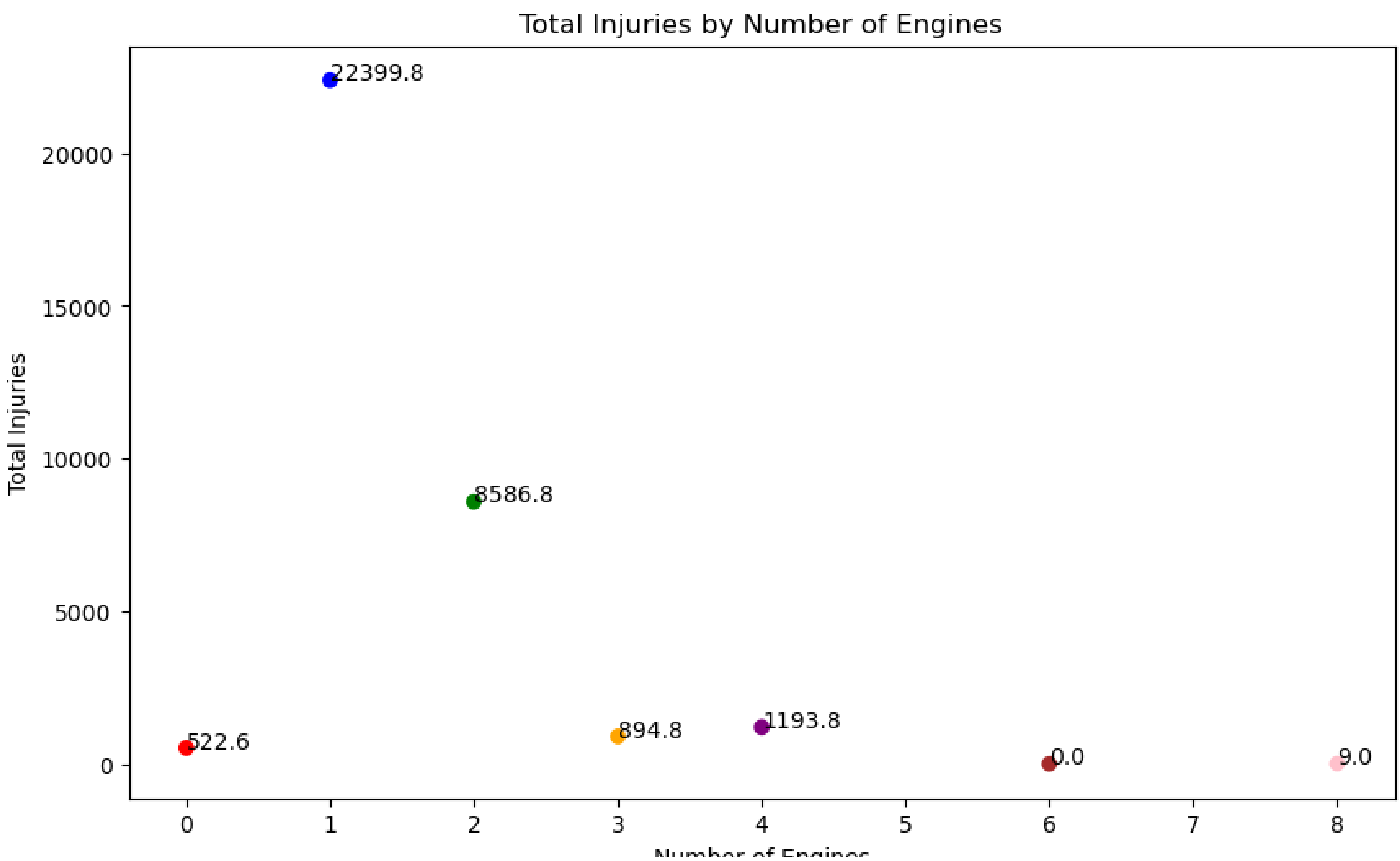
Out[20]:

	Number.of.Engines	Total Injuries
1	1.0	22399.8
2	2.0	8586.8
4	4.0	1193.8
3	3.0	894.8
0	0.0	522.6
6	8.0	9.0
5	6.0	0.0

Create Visualization highlighting above analysis

In [26]:

```
# Define a list of colors, one for each bar
colors = ['red', 'blue', 'green', 'orange', 'purple', 'brown', 'pink']

# Plotting
plt.figure(figsize=(10, 6))
plt.scatter(num_eng_sorted['Number.of.Engines'], num_eng_sorted['Total Injuries'], color=
colors)  # Create a scatter plot

# Adding title and labels
plt.title('Total Injuries by Number of Engines')
plt.xlabel('Number of Engines')
plt.ylabel('Total Injuries')

# Set x-axis ticks to show each integer interval
plt.xticks(range(int(num_eng_sorted['Number.of.Engines'].min()), int(num_eng_sorted['Numb
er.of.Engines'].max()) + 1))

# Optional: Add text labels next to each point for clarity
for i, txt in enumerate(num_eng_sorted['Total Injuries']):
    plt.annotate(f"{txt:.1f}", (num_eng_sorted['Number.of.Engines'].iat[i], num_eng_sorte
d['Total Injuries'].iat[i]))

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



Number of Engines

Analyzing Safest and Most Injury Producing Commercial and Military Aircrafts

Next step is to filter further and investigate the most dangerous Commercial and Military Aircrafts. The assumption being made is that most aircrafts with over 2 engines are commercial and military, also based on the Make (Airbus and Boeing are commercial, Lockheed is military)

In [8]:

```
# Group by "Make" and "Model" columns

grouped_data = planes_df[planes_df['Number.of.Engines'] >= 2].groupby(['Number.of.Engine
s','Make']).agg({
    'Total Injuries': ['sum', 'count']
}).reset_index()

# Flatten the multi-level column index
grouped_data.columns = [' '.join(col).strip() for col in grouped_data.columns.values]

# Calculate Injury Percentage
grouped_data['Injury Percentage'] = grouped_data['Total Injuries sum'] / grouped_data['T
otal Injuries count']

grouped_data = grouped_data[grouped_data[('Injury Percentage')] > 2]
grouped_data.sort_values(by=('Injury Percentage'), ascending=False)
```

Out[8]:

	Number.of.Engines	Make	Total Injuries sum	Total Injuries count	Injury Percentage
444	3.0	TUPOLEV	53.4	1	53.400000
369	2.0	SUKHOI	26.4	1	26.400000
40	2.0	Aviocar CASA	10.8	1	10.800000
422	3.0	BOEING	50.8	6	8.466667
299	2.0	Mil	7.8	1	7.800000
423	3.0	BRITTEN NORMAN	7.2	1	7.200000
163	2.0	Embraer Aircraft	6.0	1	6.000000
349	2.0	Robertson	11.4	2	5.700000
480	8.0	Lindstrand	5.6	1	5.600000
272	2.0	M7Aero	5.0	1	5.000000
246	2.0	Jetstream	14.4	3	4.800000
471	4.0	Mcdonnell Douglas	109.2	24	4.550000
11	2.0	AIRBUS INDUSTRIE	95.2	21	4.533333
56	2.0	BOEING-VERTOL	4.2	1	4.200000
454	4.0	Boeing	723.8	175	4.136000
37	2.0	Atr	46.4	13	3.569231
478	8.0	Cameron	3.4	1	3.400000
62	2.0	BRITISH AEROSPACE	10.2	3	3.400000
436	3.0	Lockheed	132.2	40	3.305000
23	2.0	Aerostar, S.a	3.0	1	3.000000
401	2.0	Textron Aviation	6.0	2	3.000000
243	2.0	Indonesian Aerospace	3.0	1	3.000000
463	4.0	Douglas	200.6	67	2.994030
448	4.0	Airbus Industrie	11.4	4	2.850000
9	2.0	AIRBUS	383.8	135	2.842963

	Number.of.Engines	Make	Total Injuries sum	Total Injuries count	Injury Percentage
28	2.0	Airbus Industrie	238.8	94	2.540426
26	2.0	Airbus	79.8	32	2.493750
63	2.0	BRITTEN NORMAN	7.4	3	2.466667
331	2.0	Pilatus Britten-norman	2.4	1	2.400000
289	2.0	Martin Company	4.8	2	2.400000
51	2.0	BHI H60 HELICOPTERS LLC	2.4	1	2.400000
322	2.0	PIPER AIRCRAFT INC	2.4	1	2.400000
470	4.0	Lockheed	69.2	31	2.232258
313	2.0	PARTENAVIA	4.4	2	2.200000
440	3.0	Mcdonnell Douglas	236.2	113	2.090265
473	4.0	Piasecki Acft. Corp.	2.0	1	2.000000

Replace all duplicate values

In [9]:

```
grouped_data["Make"] = grouped_data["Make"].replace("Boeing", "BOEING")
grouped_data["Make"] = grouped_data["Make"].replace("BOEING-VERTOL", "BOEING")
grouped_data["Make"] = grouped_data["Make"].replace("Airbus Industrie", "AIRBUS")
grouped_data["Make"] = grouped_data["Make"].replace("AIRBUS INDUSTRIE", "AIRBUS")
grouped_data["Make"] = grouped_data["Make"].replace("Airbus", "AIRBUS")



grouped_data['Make'] = grouped_data['Make'].str.strip()
grouped_data.sort_values(by=('Total Injuries sum'), ascending=False)
```

Out[9]:

	Number.of.Engines	Make	Total Injuries sum	Total Injuries count	Injury Percentage
454	4.0	BOEING	723.8	175	4.136000
9	2.0	AIRBUS	383.8	135	2.842963
28	2.0	AIRBUS	238.8	94	2.540426
440	3.0	Mcdonnell Douglas	236.2	113	2.090265
463	4.0	Douglas	200.6	67	2.994030
436	3.0	Lockheed	132.2	40	3.305000
471	4.0	Mcdonnell Douglas	109.2	24	4.550000
11	2.0	AIRBUS	95.2	21	4.533333
26	2.0	AIRBUS	79.8	32	2.493750
470	4.0	Lockheed	69.2	31	2.232258
444	3.0	TUPOLEV	53.4	1	53.400000
422	3.0	BOEING	50.8	6	8.466667
37	2.0	Atr	46.4	13	3.569231
369	2.0	SUKHOI	26.4	1	26.400000
246	2.0	Jetstream	14.4	3	4.800000
448	4.0	AIRBUS	11.4	4	2.850000
349	2.0	Robertson	11.4	2	5.700000
40	2.0	Aviocar CASA	10.8	1	10.800000
62	2.0	BRITISH AEROSPACE	10.2	3	3.400000
299	2.0	Mil	7.8	1	7.800000
63	2.0	BRITTEN NORMAN	7.4	3	2.466667

	Number.of.Engines	Make	Total Injuries sum	Total Injuries count	Injury Percentage
423	3.0	BRITTEN NORMAN	7.2	1	7.200000
163	2.0	Embraer Aircraft	6.0	1	6.000000
401	2.0	Textron Aviation	6.0	2	3.000000
480	8.0	Lindstrand	5.6	1	5.600000
272	2.0	M7Aero	5.0	1	5.000000
289	2.0	Martin Company	4.8	2	2.400000
313	2.0	PARTENAVIA	4.4	2	2.200000
56	2.0	BOEING	4.2	1	4.200000
478	8.0	Cameron	3.4	1	3.400000
243	2.0	Indonesian Aerospace	3.0	1	3.000000
23	2.0	Aerostar, S.a	3.0	1	3.000000
331	2.0	Pilatus Britten-norman	2.4	1	2.400000
51	2.0	BHI H60 HELICOPTERS LLC	2.4	1	2.400000
322	2.0	PIPER AIRCRAFT INC	2.4	1	2.400000
473	4.0	Piasecki Acft. Corp.	2.0	1	2.000000

In [10]:

```python
consolidated_data = grouped_data.groupby(['Make', 'Number.of.Engines']).agg({
    'Total Injuries sum': 'sum',
    'Total Injuries count': 'sum'
}).reset_index()

# Calculate Injury Percentage
consolidated_data['Injury Percentage'] = consolidated_data['Total Injuries sum'] / conso
lidated_data['Total Injuries count']
consolidated_data.sort_values(by=('Injury Percentage'), ascending=False)
```

Out[10]:

	Make	Number.of.Engines	Total Injuries sum	Total Injuries count	Injury Percentage
31	TUPOLEV	3.0	53.4	1	53.400000
30	SUKHOI	2.0	26.4	1	26.400000
4	Aviocar CASA	2.0	10.8	1	10.800000
7	BOEING	3.0	50.8	6	8.466667
24	Mil	2.0	7.8	1	7.800000
11	BRITTEN NORMAN	3.0	7.2	1	7.200000
14	Embraer Aircraft	2.0	6.0	1	6.000000
29	Robertson	2.0	11.4	2	5.700000
17	Lindstrand	8.0	5.6	1	5.600000
20	M7Aero	2.0	5.0	1	5.000000
16	Jetstream	2.0	14.4	3	4.800000
23	Mcdonnell Douglas	4.0	109.2	24	4.550000
6	BOEING	2.0	4.2	1	4.200000
8	BOEING	4.0	723.8	175	4.136000
3	Atr	2.0	46.4	13	3.569231
12	Cameron	8.0	3.4	1	3.400000
9	BRITISH AEROSPACE	2.0	10.2	3	3.400000
18	Lockheed	3.0	132.2	40	3.305000
32	Textron Aviation	2.0	6.0	2	3.000000

	Make	Number.of.Engines	Total Injuries sum	Total Injuries count	Injury Percentage
15	Indonesian Aerospace	2.0	3.0	1	3.000000
2	Aerostar, S.a	2.0	3.0	1	3.000000
13	Douglas	4.0	200.6	67	2.994030
1	AIRBUS	4.0	11.4	4	2.850000
0	AIRBUS	2.0	797.6	282	2.828369
10	BRITTEN NORMAN	2.0	7.4	3	2.466667
21	Martin Company	2.0	4.8	2	2.400000
26	PIPER AIRCRAFT INC	2.0	2.4	1	2.400000
28	Pilatus Britten-norman	2.0	2.4	1	2.400000
5	BHI H60 HELICOPTERS LLC	2.0	2.4	1	2.400000
19	Lockheed	4.0	69.2	31	2.232258
25	PARTENAVIA	2.0	4.4	2	2.200000
22	Mcdonnell Douglas	3.0	236.2	113	2.090265
27	Piasecki Acft. Corp.	4.0	2.0	1	2.000000

FIlter out Outliers (any Makes with only 1 incident)

In [11]:

```
Consolidated_filter = consolidated_data[consolidated_data['Total Injuries count'] >= 4]
Consolidated_filter.sort_values(by=('Injury Percentage'), ascending=False)
```

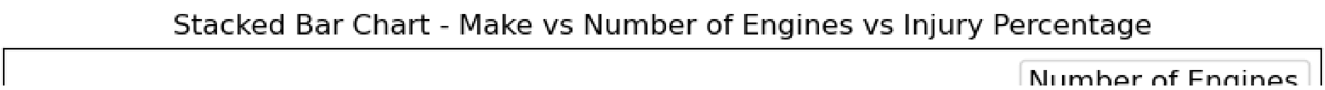
Out[11]:

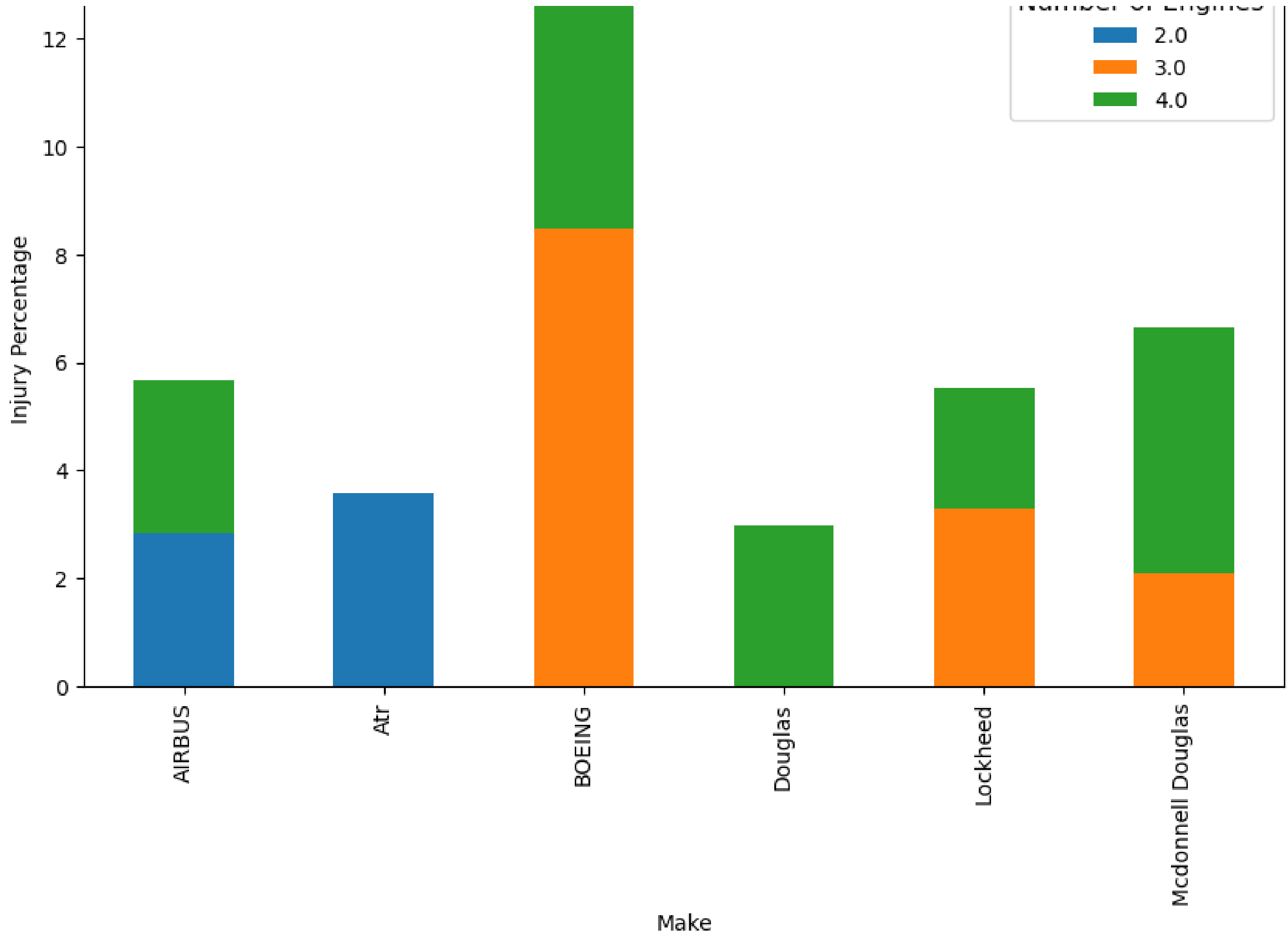
	Make	Number.of.Engines	Total Injuries sum	Total Injuries count	Injury Percentage
7	BOEING	3.0	50.8	6	8.466667
23	Mcdonnell Douglas	4.0	109.2	24	4.550000
8	BOEING	4.0	723.8	175	4.136000
3	Atr	2.0	46.4	13	3.569231
18	Lockheed	3.0	132.2	40	3.305000
13	Douglas	4.0	200.6	67	2.994030
1	AIRBUS	4.0	11.4	4	2.850000
0	AIRBUS	2.0	797.6	282	2.828369
19	Lockheed	4.0	69.2	31	2.232258
22	Mcdonnell Douglas	3.0	236.2	113	2.090265

Construct Graph visualizing above findings on Commercial and Military Aircrafts with highest Injury Percentage with at least 4 total incidents

In [12]:

```
pivot_df = Consolidated_filter.pivot_table(index='Make', columns='Number.of.Engines', val
ues='Injury Percentage', aggfunc='sum', fill_value=0)

# Plot the stacked bar chart
ax = pivot_df.plot(kind='bar', stacked=True, figsize=(10, 6))
plt.title('Stacked Bar Chart - Make vs Number of Engines vs Injury Percentage')
plt.xlabel('Make')
plt.ylabel('Injury Percentage')
plt.legend(title='Number of Engines', title_fontsize='12')
plt.show()
```





The above graph shows that Boeing aircrafts have the highest injury percentage per crash with both 3 and 4 engine planes. Mcdonnell Douglas also has a high injury percentage with their 4 engine aircrafts. A business takeaway from this display could be to go with AIRBUS for commercial and Lockheed for Military, respectively.

The next task is to filter the data to display highest injury rates per non commercial and military aircrafts.

In [13]:

```
import pandas as pd

# Group by specified columns and aggregate Total Injuries
outcome = planes_df.groupby(['Number.of.Engines', 'Purpose.of.flight', 'Make'])['Total I
njuries'].agg(['sum', 'count']).reset_index()

# Rename columns
outcome.columns = ['Number.of.Engines', 'Purpose.of.flight', 'Make', 'Total Injuries', '
Total Incidents']

# Calculate Injury Percentage
outcome['Injury Percentage'] = outcome['Total Injuries'] / outcome['Total Incidents']


# Sort the DataFrame by 'Injury Percentage' in descending order
outcome = outcome[(outcome['Total Incidents'] > 10) & (outcome['Number.of.Engines'] <= 2
)]

outcome = outcome.sort_values(by='Total Injuries', ascending=False)

outcome["Make"] = outcome["Make"].replace("CESSNA", "Cessna")
outcome['Make'] = outcome['Make'].str.strip()

outcome["Make"] = outcome["Make"].replace("PIPER", "Piper")
outcome['Make'] = outcome['Make'].str.strip()
```

```python
outcome["Make"] = outcome["Make"].replace("BEECH", "Beech")
outcome['Make'] = outcome['Make'].str.strip()

# Display the result
outcome
```

Out[13]:

	Number.of.Engines	Purpose.of.flight	Make	Total Injuries	Total Incidents	Injury Percentage
3279	1.0	Personal	Cessna	3660.4	12044	0.303919
6687	1.0	Personal	Piper	2776.2	6942	0.399914
2782	1.0	Personal	Beech	957.6	1942	0.493100
3089	1.0	Personal	Cessna	708.8	2541	0.278945
1561	1.0	Instructional	Cessna	592.6	4169	0.142144
...	...	...	...	...	...	...
2214	1.0	Personal	AMERICAN LEGEND AIRCRAFT CO	0.8	11	0.072727
6921	1.0	Personal	ROCKWELL INTERNATIONAL	0.6	12	0.050000
8716	1.0	Positioning	De Havilland	0.6	13	0.046154
3913	1.0	Personal	EVEKTOR-AEROTECHNIK AS	0.4	15	0.026667
10177	2.0	Unknown	Dornier	0.0	11	0.000000

474 rows × 6 columns

Display Count of each Make with 2 or less Engines based on Total Injuries and Total Incidents and filter out any makes with incident count less than 500.

In [14]:

```python
sum_outcome = outcome.groupby(['Make', 'Number.of.Engines'])[['Total Injuries', 'Total I
ncidents', 'Injury Percentage']].sum().reset_index()
sum_outcome = sum_outcome[sum_outcome['Total Incidents'] > 500]
sum_outcome['Injury Percentage'] = sum_outcome['Total Injuries'] / sum_outcome['Total In
cidents']
sum_outcome.sort_values(by='Injury Percentage', ascending=False)
```

Out[14]:

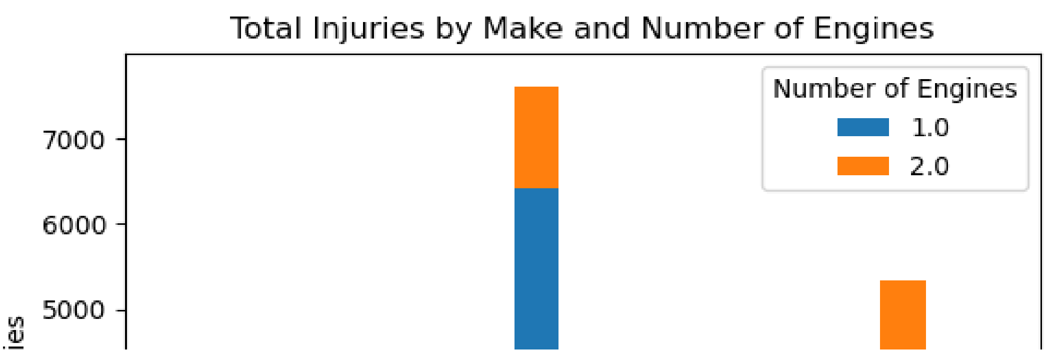
	Make	Number.of.Engines	Total Injuries	Total Incidents	Injury Percentage
40	Beech	2.0	1028.8	1804	0.570288
69	Cessna	2.0	1189.2	2119	0.561208
165	Piper	2.0	1016.0	1969	0.515998
39	Beech	1.0	1426.2	3051	0.467453
155	Mooney	1.0	459.0	1064	0.431391
43	Bell	1.0	670.0	1738	0.385501
164	Piper	1.0	4310.2	12061	0.357367
45	Bellanca	1.0	284.8	850	0.335059
131	Hughes	1.0	207.4	734	0.282561
68	Cessna	1.0	6420.4	23435	0.273966
184	Robinson	1.0	225.8	838	0.269451
118	Grumman	1.0	150.0	978	0.153374
24	Air Tractor	1.0	82.0	547	0.149909

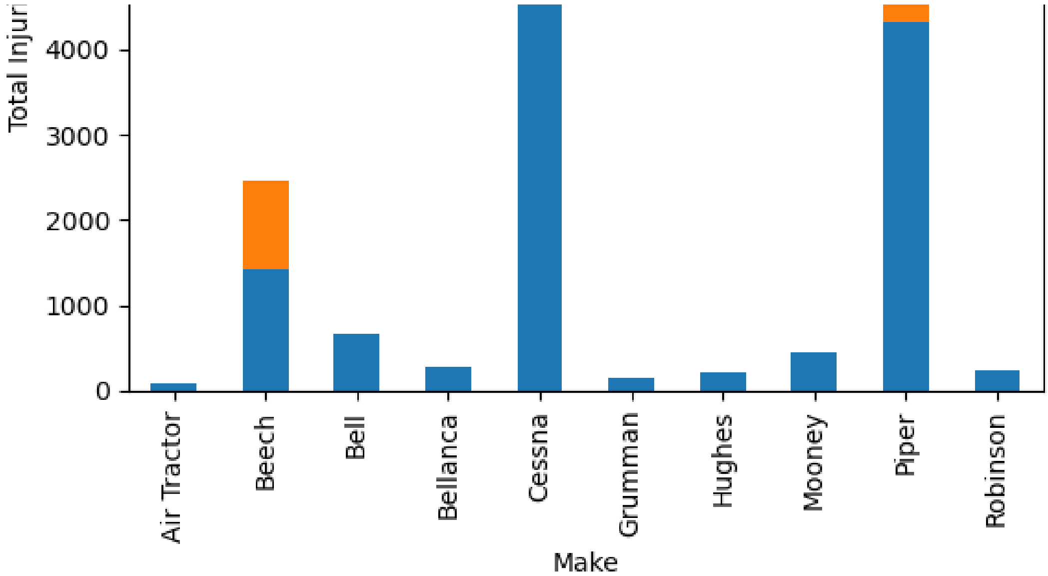
Visualize the above data in a graph best fitting

In [15]:

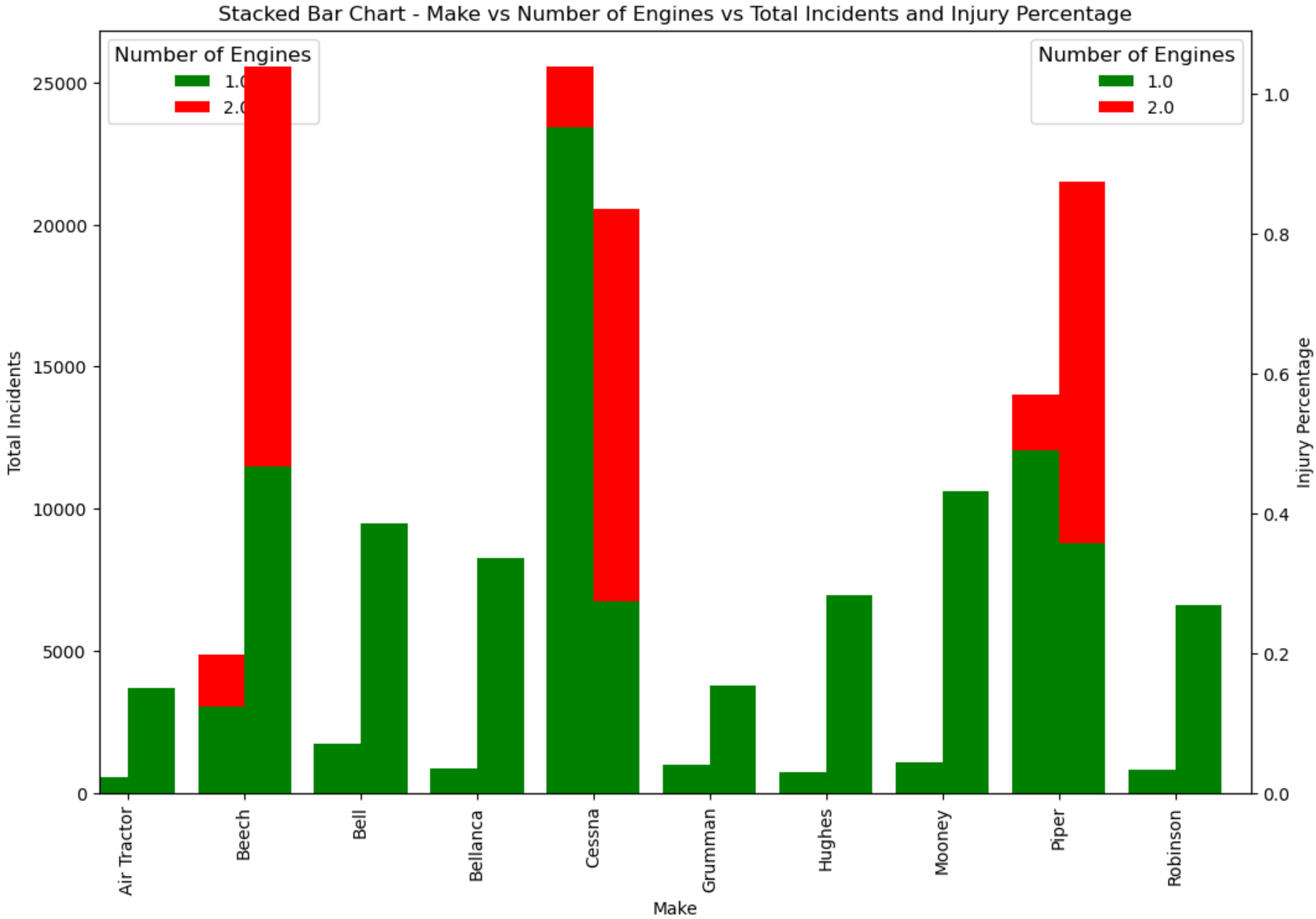
```
# Plot 1: Bar Plot for Total Injuries
plt.figure(figsize=(12, 8))
bar_plot = sum_outcome.groupby(['Make', 'Number.of.Engines'])['Total Injuries'].sum().un
stack().plot(kind='bar', stacked=True)
plt.title('Total Injuries by Make and Number of Engines')
plt.xlabel('Make')
plt.ylabel('Total Injuries')
plt.legend(title='Number of Engines')
plt.show()

# Plot 2: Bar Plot for Total Incidents and Injury Percentage
# Pivot the data for stacked bar chart
pivot_df2 = sum_outcome.pivot_table(index='Make', columns='Number.of.Engines', values=['
Total Incidents', 'Injury Percentage'], aggfunc='sum', fill_value=0)

# Plot the stacked bar chart with secondary y-axis for Injury Percentage
fig, ax1 = plt.subplots(figsize=(12, 8))

# Plot Total Incidents on primary y-axis
pivot_df2['Total Incidents'].plot(kind='bar', stacked=True, ax=ax1, color=['green', 'red
'], position=1, width=0.4)

# Create a secondary y-axis for Injury Percentage
ax2 = ax1.twinx()
pivot_df2['Injury Percentage'].plot(kind='bar', stacked=True, ax=ax2, color=['green', 'r
ed'], position=0, width=0.4)

# Set labels and title
ax1.set_title('Stacked Bar Chart - Make vs Number of Engines vs Total Incidents and Injur
y Percentage')
ax1.set_xlabel('Make')
ax1.set_ylabel('Total Incidents', color='black')
ax2.set_ylabel('Injury Percentage', color='black')

# Set legends
ax1.legend(title='Number of Engines', title_fontsize='12', loc='upper left')
ax2.legend(title='Number of Engines', title_fontsize='12', loc='upper right')

plt.show()

# Plot 3: Stacked Bar Graph for Injury Percentage
# Create a stacked bar graph
pivot_df3 = sum_outcome.pivot(index='Make', columns='Number.of.Engines', values='Injury
Percentage')
pivot_df3.plot(kind='bar', stacked=True, colormap='viridis')

# Add labels and title
plt.xlabel('Make')
plt.ylabel('Injury Percentage')
plt.title('Stacked Bar Graph of Make, Number of Engines, and Injury Percentage')

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

```
<Figure size 1200x800 with 0 Axes>
```

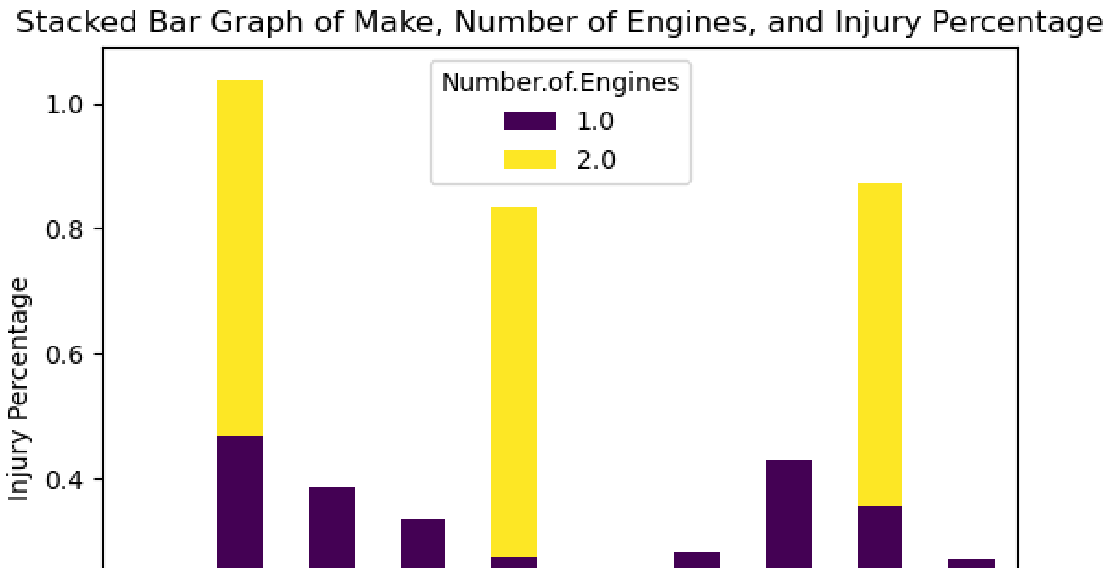




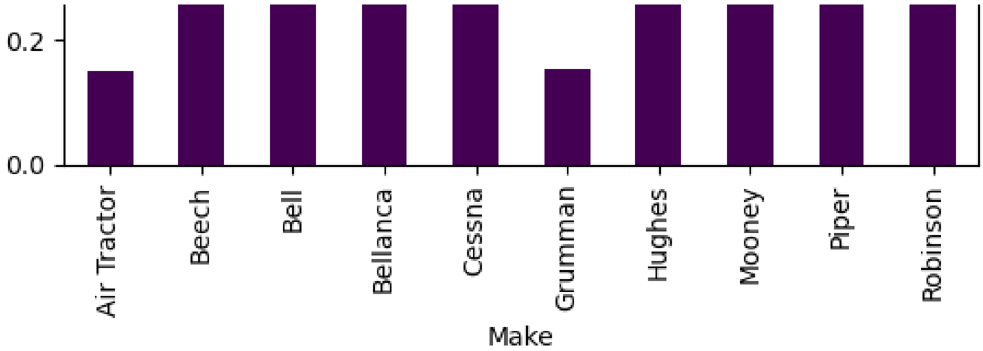
0
1000
2000
3000
4000
Air Tractor
Beech
Bell
Bellanca
Cessna
Grumman
Hughes
Mooney
Piper
Robinson
Make



Stacked Bar Chart - Make vs Number of Engines vs Total Incidents and Injury Percentage
Number of Engines
1.0
2.0
Total Incidents
Injury Percentage
0
5000
10000
15000
20000
25000
0.0
0.2
0.4
0.6
0.8
1.0
Air Tractor
Beech
Bell
Bellanca
Cessna
Grumman
Hughes
Mooney
Piper
Robinson
Make



Stacked Bar Graph of Make, Number of Engines, and Injury Percentage
Number.of.Engines
1.0
2.0
Injury Percentage
0.4
0.6
0.8
1.0



The Above cell shows that amongst personal aircrafts (2 engines or less), Cessnas have the most total injuries but also the most total incidents, meaning Cessna's are used much more frequently. The results also show that although Cessna's have the most total injuries, Cessna's overall injury perentage is much lower than the other Aircraft Make's with both 1 and 2 engines, including Cessna 2 Engine Planes. Thus, a conclusion could be made that Cessna 1 engine aircrafts are the safest to use.

Step 2- Analyze data to show highest rates of injuries among Phase of Flights

Next, we will analyze safest and most dangerous aircrafts based on Phases of flight (Cruise, Takeoff, Maneuvering, Landing, etc)

In [60]:

```
# Group by specified columns and aggregate Total Injuries
num_phase = planes_df.groupby(['Broad.phase.of.flight'])['Total Injuries'].agg(['sum', '
count']).reset_index()

# Rename columns
num_phase.columns = ['Broad.phase.of.flight', 'Total Injuries', 'Total Incidents']

# Calculate Injury Percentage
num_phase['Injury Percentage'] = num_phase['Total Injuries'] / num_phase['Total Incident
s']

num_phase.sort_values(by='Total Injuries', ascending=False)
```

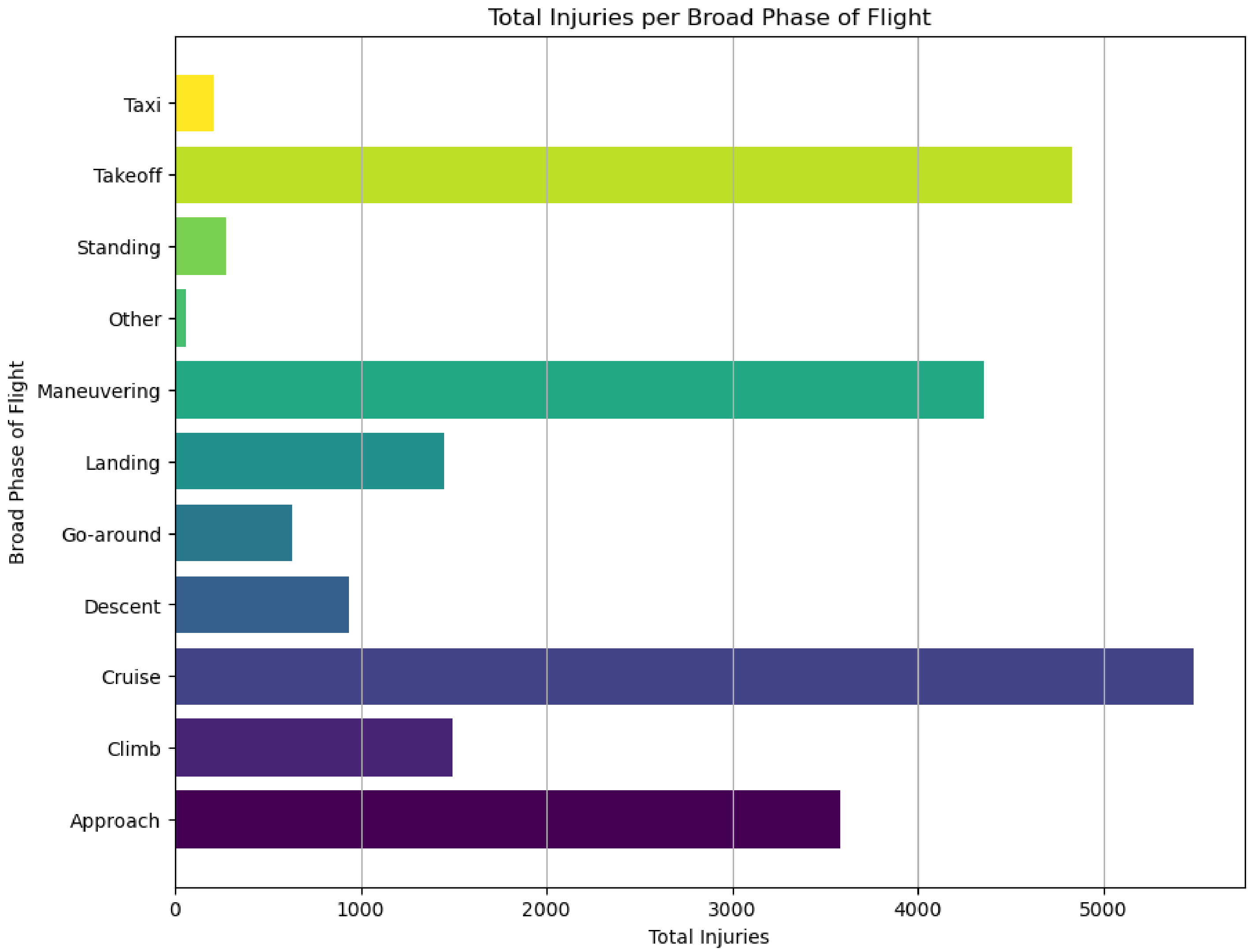
Out[60]:

	Broad.phase.of.flight	Total Injuries	Total Incidents	Injury Percentage
2	Cruise	5483.2	10269	0.533957
9	Takeoff	4828.6	12493	0.386504
6	Maneuvering	4354.6	8144	0.534700
0	Approach	3578.4	6546	0.546654
1	Climb	1492.0	2034	0.733530
5	Landing	1446.2	15428	0.093739
3	Descent	936.6	1887	0.496343
4	Go-around	631.8	1353	0.466962
11	Unknown	472.4	548	0.862044
8	Standing	272.4	945	0.288254
10	Taxi	205.8	1958	0.105107
7	Other	60.4	119	0.507563

Create Visualization of above Data on Broad Phase of Flights

In [62]:

```python
import numpy as np

filtered_num_phase = num_phase[num_phase['Broad.phase.of.flight'] != 'Unknown']

# Color
num_colors = len(filtered_num_phase['Broad.phase.of.flight'])
colors = plt.cm.viridis(np.linspace(0, 1, num_colors))

# Plotting
plt.figure(figsize=(10, 8))
bar = plt.barh(filtered_num_phase['Broad.phase.of.flight'], filtered_num_phase['Total Injuries'], color=colors)
plt.xlabel('Total Injuries')
plt.ylabel('Broad Phase of Flight')
plt.title('Total Injuries per Broad Phase of Flight')
plt.grid(axis='x')

# Show
plt.show()
```



Now that we have a general outline of Injury percentages based on phase of flight, we are going to delve deeper and filter the data by make and number of engines. The idea behind this is to understand which Aircrafts have the highest and lowest injury percentage per phase of flight in order to determine an appropriate resolution for stakeholders.

In [59]:

```python
# Group by specified columns and aggregate Total Injuries
phase_counts = planes_df.groupby(['Broad.phase.of.flight', 'Number.of.Engines', 'Make'])
['Total Injuries'].agg(['sum', 'count']).reset_index()

# Rename columns
phase_counts.columns = ['Broad.phase.of.flight', 'Number.of.Engines', 'Make', 'Total Injuries', 'Total Incidents']
```

```
# Calculate Injury Percentage
phase_counts['Injury Percentage'] = phase_counts['Total Injuries'] / phase_counts['Total Incidents']

# Sort the DataFrame by 'Injury Percentage' in descending order
phase_counts = phase_counts[(phase_counts['Total Incidents'] > 10) & (phase_counts['Number.of.Engines'] <= 8)]

phase_counts.sort_values(by='Total Injuries', ascending=False)
```

Out[59]:

	Broad.phase.of.flight	Number.of.Engines	Make	Total Injuries	Total Incidents	Injury Percentage
1419	Cruise	1.0	Cessna	1321.0	3170	0.416719
4114	Maneuvering	1.0	Cessna	1072.6	1750	0.612914
5439	Takeoff	1.0	Cessna	970.2	3540	0.274068
1893	Cruise	1.0	Piper	959.4	1732	0.553926
6211	Takeoff	1.0	Piper	753.8	2105	0.358100
...	...	...	...	...	...	...
2965	Landing	1.0	Christen Industries	0.0	14	0.000000
6947	Taxi	2.0	Douglas	0.0	11	0.000000
2850	Landing	1.0	American Champion (acac)	0.0	15	0.000000
3104	Landing	1.0	Fairchild	0.0	14	0.000000
2914	Landing	1.0	Boeing Stearman	0.0	22	0.000000

393 rows × 6 columns

Filter dataframe "phase counts" for Total Incidents over 1000 to remove outliers

In [43]:

```
#create filtered_phase to show injury percentage per phase of flight for incident counts over 1000
filtered_phase = phase_counts.groupby(['Broad.phase.of.flight', 'Number.of.Engines', 'Make'])[['Total Injuries', 'Total Incidents', 'Injury Percentage']].sum().reset_index()
filtered_phase = filtered_phase[filtered_phase['Total Incidents'] > 500]
filtered_phase['Injury Percentage'] = filtered_phase['Total Injuries'] / filtered_phase['Total Incidents']
filtered_phase.sort_values(by='Injury Percentage', ascending=False)
```

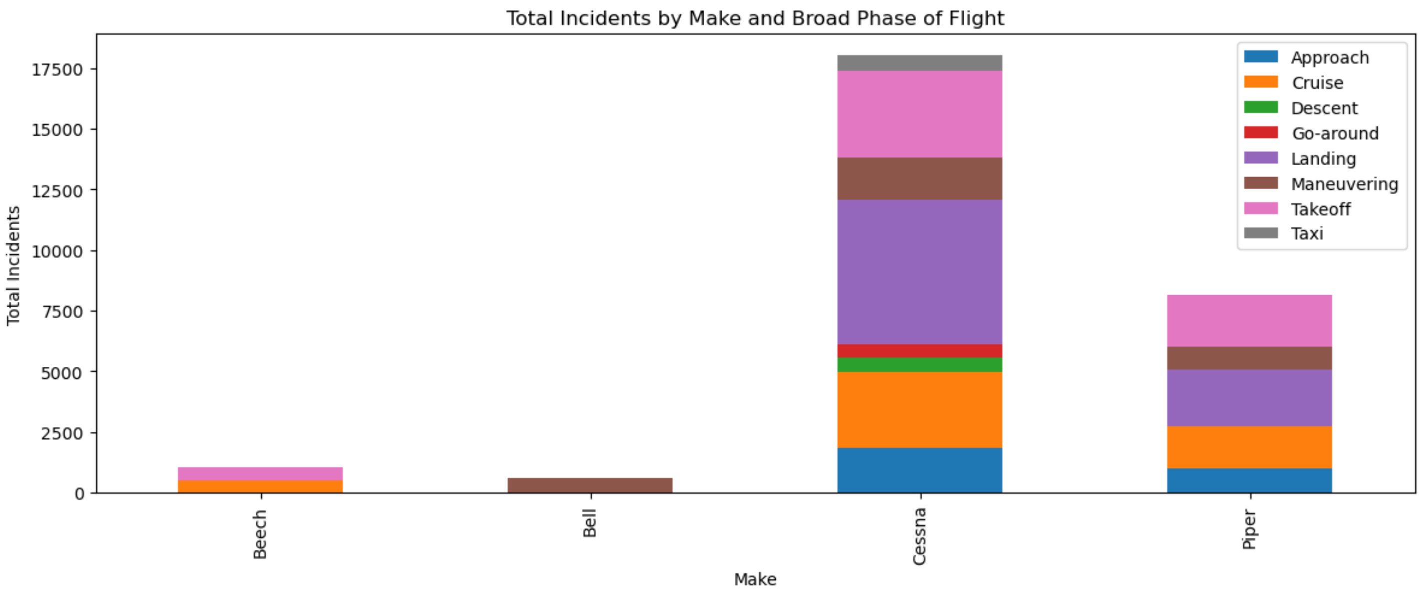
Out[43]:

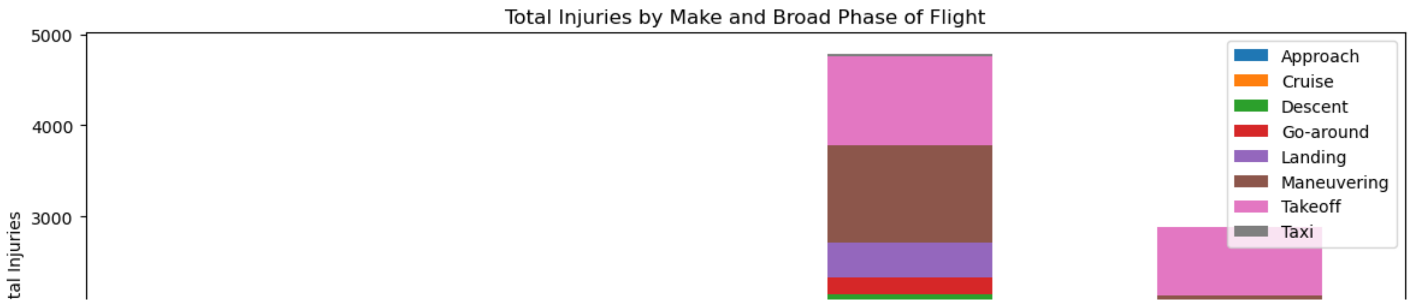
	Broad.phase.of.flight	Number.of.Engines	Make	Total Injuries	Total Incidents	Injury Percentage
47	Maneuvering	1.0	Cessna	1072.6	1750	0.612914
10	Cruise	1.0	Beech	302.6	513	0.589864
51	Maneuvering	1.0	Piper	578.4	991	0.583653
16	Cruise	1.0	Piper	959.4	1732	0.553926
56	Takeoff	1.0	Beech	262.4	538	0.487732
4	Approach	1.0	Piper	445.8	970	0.459588
13	Cruise	1.0	Cessna	1321.0	3170	0.416719
45	Maneuvering	1.0	Bell	246.4	600	0.410667
62	Takeoff	1.0	Piper	753.8	2105	0.358100
2	Approach	1.0	Cessna	629.4	1807	0.348312
21	Descent	1.0	Cessna	197.4	576	0.342708
23	Go-around	1.0	Cessna	188.4	564	0.334043

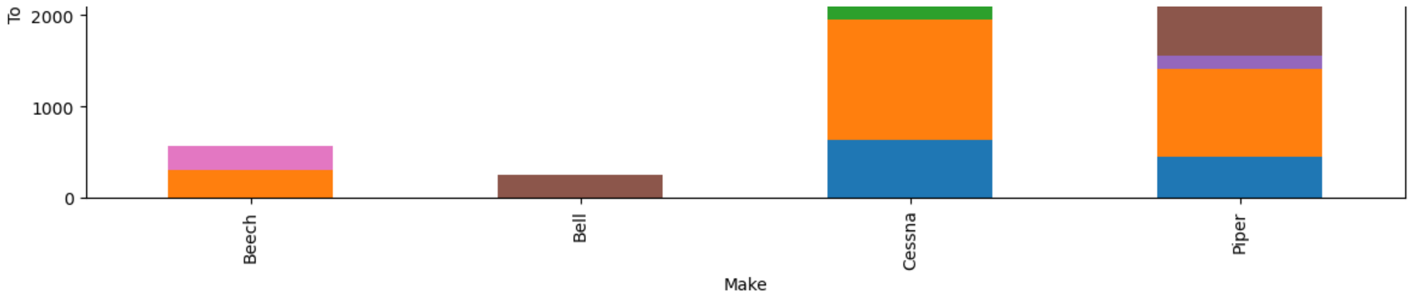
	Broad.phase.of.flight	Number.of.Engines	Make	Total Injuries	Total Incidents	Injury Percentage
59	Takeoff	1.0	Cessna	970.2	3540	0.274068
37	Landing	1.0	Piper	148.6	2333	0.063695
30	Landing	1.0	Cessna	376.2	5953	0.063195
66	Taxi	1.0	Cessna	23.2	640	0.036250

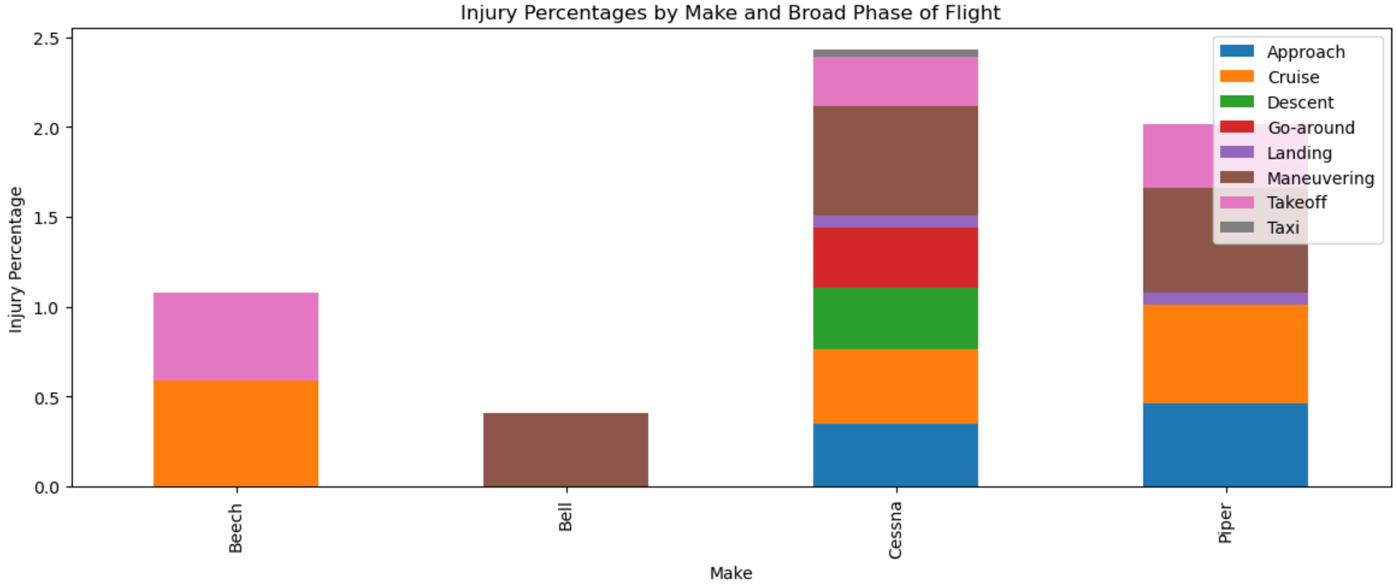
In [44]:

```
# Pivot data for 'Total Incidents' and 'Total Injuries'
pivot_incidents = filtered_phase.pivot_table(index='Make', columns='Broad.phase.of.fligh
t', values='Total Incidents', aggfunc='sum', fill_value=0)
pivot_injuries = filtered_phase.pivot_table(index='Make', columns='Broad.phase.of.flight'
, values='Total Injuries', aggfunc='sum', fill_value=0)
pivot_percentage = filtered_phase.pivot_table(index='Make', columns='Broad.phase.of.flig
ht', values='Injury Percentage', aggfunc='sum', fill_value=0)


# Creating subplots for three plots
fig, axes = plt.subplots(nrows=3, ncols=1, figsize=(12, 15))

# Plotting Total Incidents
pivot_incidents.plot(kind='bar', stacked=True, ax=axes[0], title='Total Incidents by Mak
e and Broad Phase of Flight')
axes[0].set_ylabel('Total Incidents')
axes[0].legend(loc='upper right')

# Plotting Total Injuries
pivot_injuries.plot(kind='bar', stacked=True, ax=axes[1], title='Total Injuries by Make
and Broad Phase of Flight')
axes[1].set_ylabel('Total Injuries')
axes[1].legend(loc='upper right')

# Plotting Injury Percentage
pivot_percentage.plot(kind='bar', stacked=True, ax=axes[2], title='Injury Percentages by
Make and Broad Phase of Flight')
axes[2].set_ylabel('Injury Percentage')
axes[2].legend(loc='upper right')

plt.tight_layout()
plt.show()
```





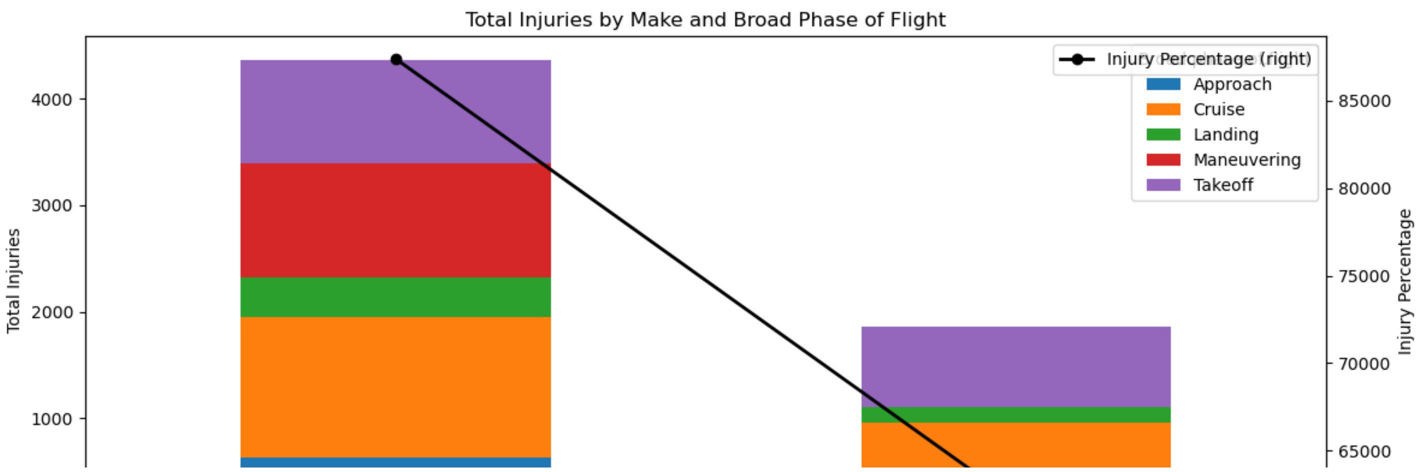


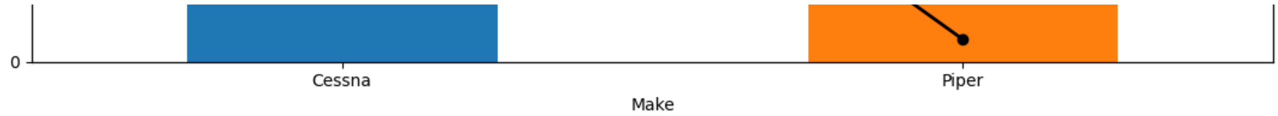


As the bar graph above shows, Cessna and Piper have both the most different phases of flight as well as the highest injury percentages. Thus, we are going to plot a visalization to display Total Injuries combined with average Injury Percentage for all phases of flights for both Cessna and Piper.

In [31]:

```
# Plotting
fig, ax = plt.subplots(nrows=1, ncols=1, figsize=(12, 5))

pivot_injuries.plot(kind='bar', stacked=True, ax=ax, title='Total Injuries by Make and Br
oad Phase of Flight')

# Overlay Injury Percentage on chart as a line plot
injury_percentage = filtered_phase.groupby('Make')['Total Injuries'].mean() * 100

injury_percentage.plot(ax=ax, secondary_y=True, color='black', marker='o', linewidth=2,
label='Injury Percentage')

# Labels and Legends
ax.set_ylabel('Total Injuries')
ax.right_ax.set_ylabel('Injury Percentage')
ax.right_ax.legend(loc='upper right')

plt.tight_layout()
plt.show()
```





Based on the above data and charts, Cessna has a higher overall injury percentage for the 5 most prevalent common phases of flight.

One may also deduce that, based on the findings, both Cessna and Piper are safest with their landing procedures, as both have the highest incident count and lowest injury totals for all "landing" phases of flight.

Contrastingly, Cessna's "Maneuvering" phase of flight has the highest injury percentage by far with the lowest amount of incidents.

Apart of "Maneuvering" resulting in many injuries, it appears that the "Cruise" phase of flight results in a large percentage of injuries for both Cessna and Piper, with Cessna's largest amount of injuries and second highest percentage all coming from flights in the "Cruise" phase of flight.

Next, an Analysis on Injuries based on Engine Type

In [45]:

```
# Group by 'Engine.Type' and aggregate 'Total Injuries'
engine_injure = planes_df.groupby('Engine.Type')['Total Injuries'].agg(['sum', 'count'])
.reset_index()

# Calculate Injury Percentage correctly
# 'sum' refers to the total injuries, and 'count' refers to the number of incidents
engine_injure['Injury Percentage'] = engine_injure['sum'] / engine_injure['count']

# Rename columns to make them more descriptive
engine_injure.columns = ['Engine.Type', 'Total Injuries', 'Total Incidents', 'Injury Per
centage']

engine_injure.sort_values(by='Total Injuries', ascending=False)
```

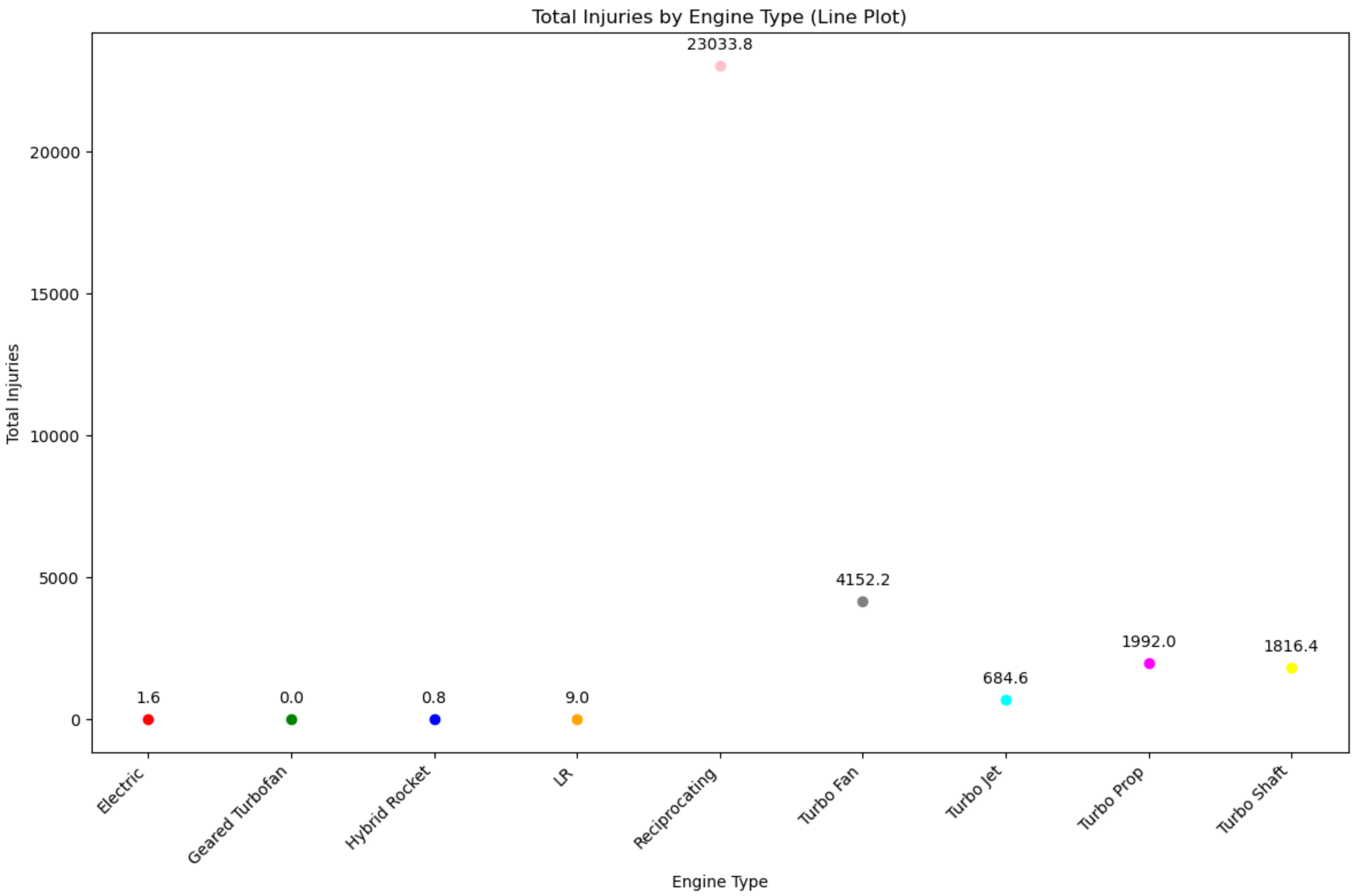
Out[45]:

	Engine.Type	Total Injuries	Total Incidents	Injury Percentage
6	Reciprocating	23033.8	69530	0.331279
7	Turbo Fan	4152.2	2481	1.673599
12	Unknown	3065.0	2051	1.494393
9	Turbo Prop	1992.0	3391	0.587437
10	Turbo Shaft	1816.4	3609	0.503297
8	Turbo Jet	684.6	703	0.973826
3	LR	9.0	2	4.500000
5	None	7.0	19	0.368421
0	Electric	1.6	10	0.160000
2	Hybrid Rocket	0.8	1	0.800000
11	UNK	0.4	1	0.400000
1	Geared Turbofan	0.0	12	0.000000
4	NONE	0.0	2	0.000000

Create Visualization to display above initial findings

In [58]:

```python
plt.figure(figsize=(12, 8))  # Adjust the size as needed

# Assuming Engine_filtered['Engine.Type'] is categorical and you want each category to have its own color
# First, ensure 'Engine.Type' is sorted if it isn't already, as you've done
Engine_filtered = engine_injure.sort_values(by='Engine.Type')

Engine_filtered = Engine_filtered[~Engine_filtered['Engine.Type'].str.lower().isin(['none', 'unk', 'unknown'])]


# Plot each point individually
for i, row in Engine_filtered.iterrows():
    plt.plot(row['Engine.Type'], row['Total Injuries'], marker='o', linestyle='', color=colors2[i % len(colors2)])

plt.xlabel('Engine Type')  # X-axis label
plt.ylabel('Total Injuries')  # Y-axis label
plt.title('Total Injuries by Engine Type (Line Plot)')  # Chart title

# Fix for the xticks error: manually set the ticks and labels
ticks = range(len(Engine_filtered['Engine.Type'].unique()))
labels = Engine_filtered['Engine.Type'].unique()
plt.xticks(ticks, labels, rotation=45, ha="right")

# Adding text labels for each marker
for i, txt in enumerate(Engine_filtered['Total Injuries']):
    # Adjusting the annotation to align with the corrected ticks
    plt.annotate(f"{txt:.1f}", (ticks[i % len(ticks)], txt), textcoords="offset points", xytext=(0,10), ha='center')

plt.tight_layout()  # Adjust layout to not cut off labels
plt.show()
```



Investigate further by analyzing total injuries, incidents, and injury percentage by engine type with make and number of engines

In [ ]:

```
#Group by specified columns and aggregate Total Injuries
engine_t_outcome = planes_df.groupby(['Number.of.Engines', 'Engine.Type', 'Make'])['Tota
l Injuries'].agg(['sum', 'count']).reset_index()

# Rename columns
engine_t_outcome.columns = ['Number.of.Engines', 'Engine.Type', 'Make', 'Total Injuries'
, 'Total Incidents']

# Calculate Injury Percentage
engine_t_outcome['Injury Percentage'] = engine_t_outcome['Total Injuries'] / engine_t_ou
tcome['Total Incidents']

engine_t_outcome = engine_t_outcome[(engine_t_outcome['Total Injuries'] > 200) & (engine
_t_outcome['Number.of.Engines'] >= 1)]


engine_t_outcome["Make"] = engine_t_outcome["Make"].replace("CESSNA", "Cessna")
engine_t_outcome['Make'] = engine_t_outcome['Make'].str.strip()

engine_t_outcome["Make"] = engine_t_outcome["Make"].replace("PIPER", "Piper")
engine_t_outcome['Make'] = engine_t_outcome['Make'].str.strip()

engine_t_outcome["Make"] = engine_t_outcome["Make"].replace("BEECH", "Beech")
engine_t_outcome['Make'] = engine_t_outcome['Make'].str.strip()

engine_t_outcome["Make"] = engine_t_outcome["Make"].replace("Boeing", "BOEING")
engine_t_outcome['Make'] = engine_t_outcome['Make'].str.strip()

engine_t_outcome.sort_values(by='Total Injuries', ascending=False)
```

Out[ ]:

	Number.of.Engines	Engine.Type	Make	Total Injuries	Total Incidents	Injury Percentage
1372	1.0	Reciprocating	Cessna	5373.2	19642	0.273557
4972	1.0	Reciprocating	Piper	3612.0	9893	0.365107
843	1.0	Reciprocating	Beech	1172.8	2522	0.465028
1170	1.0	Reciprocating	Cessna	931.6	3499	0.266247
7566	2.0	Reciprocating	Cessna	913.4	1680	0.543690
7654	2.0	Reciprocating	Piper	854.0	1704	0.501174
8122	4.0	Turbo Fan	BOEING	709.4	144	4.926389
7553	2.0	Reciprocating	Beech	634.6	1169	0.542857
7725	2.0	Turbo Fan	BOEING	618.8	421	1.469834
4814	1.0	Reciprocating	Piper	615.0	1972	0.311866
7366	1.0	Turbo Shaft	Bell	610.2	1217	0.501397
4475	1.0	Reciprocating	Mooney	465.8	1076	0.432900
8074	3.0	Turbo Fan	BOEING	353.6	178	1.986517
7892	2.0	Turbo Prop	Beech	308.0	459	0.671024
870	1.0	Reciprocating	Bellanca	293.2	875	0.335086
7792	2.0	Turbo Fan	Mcdonnell Douglas	281.8	145	1.943448
7715	2.0	Turbo Fan	BOEING	251.4	188	1.337234
7710	2.0	Turbo Fan	Airbus Industrie	238.2	86	2.769767
5428	1.0	Reciprocating	Robinson	230.6	858	0.268765
8085	3.0	Turbo Fan	Mcdonnell Douglas	230.6	101	2.283168
592	1.0	Reciprocating	Beech	213.2	481	0.443243

Filter overall results by best fitting cases which, in this instance, is Total Injuries over 200

In [ ]:

```
engine_t_filter_outcome = engine_t_outcome.groupby(['Number.of.Engines', 'Engine.Type', 'Make'])[['Total Injuries', 'Total Incidents', 'Injury Percentage']].sum().reset_index()
engine_t_filter_outcome = engine_t_filter_outcome[engine_t_filter_outcome['Total Injuries'] > 200]
engine_t_filter_outcome['Injury Percentage'] = engine_t_filter_outcome['Total Injuries'] / engine_t_filter_outcome['Total Incidents']
engine_t_filter_outcome.sort_values(by='Injury Percentage', ascending=False)
```

Out[ ]:

	Number.of.Engines	Engine.Type	Make	Total Injuries	Total Incidents	Injury Percentage
16	4.0	Turbo Fan	BOEING	709.4	144	4.926389
10	2.0	Turbo Fan	Airbus Industrie	238.2	86	2.769767
15	3.0	Turbo Fan	Mcdonnell Douglas	230.6	101	2.283168
14	3.0	Turbo Fan	BOEING	353.6	178	1.986517
12	2.0	Turbo Fan	Mcdonnell Douglas	281.8	145	1.943448
11	2.0	Turbo Fan	BOEING	870.2	609	1.428900
13	2.0	Turbo Prop	Beech	308.0	459	0.671024
8	2.0	Reciprocating	Cessna	913.4	1680	0.543690
7	2.0	Reciprocating	Beech	634.6	1169	0.542857
6	1.0	Turbo Shaft	Bell	610.2	1217	0.501397
9	2.0	Reciprocating	Piper	854.0	1704	0.501174
0	1.0	Reciprocating	Beech	1386.0	3003	0.461538
3	1.0	Reciprocating	Mooney	465.8	1076	0.432900
4	1.0	Reciprocating	Piper	4227.0	11865	0.356258
1	1.0	Reciprocating	Bellanca	293.2	875	0.335086
2	1.0	Reciprocating	Cessna	6304.8	23141	0.272451
5	1.0	Reciprocating	Robinson	230.6	858	0.268765

Filter by Total Injuries, High to low

In [ ]:

```
engine_t_filter_outcome = engine_t_outcome.groupby(['Number.of.Engines', 'Engine.Type', 'Make'])[['Total Injuries', 'Total Incidents', 'Injury Percentage']].sum().reset_index()
engine_t_filter_outcome = engine_t_filter_outcome[engine_t_filter_outcome['Total Incidents'] > 500]
engine_t_filter_outcome['Injury Percentage'] = engine_t_filter_outcome['Total Injuries'] / engine_t_filter_outcome['Total Incidents']
engine_t_filter_outcome.sort_values(by='Total Injuries', ascending=False)
```

Out[ ]:

	Number.of.Engines	Engine.Type	Make	Total Injuries	Total Incidents	Injury Percentage
2	1.0	Reciprocating	Cessna	6304.8	23141	0.272451
4	1.0	Reciprocating	Piper	4227.0	11865	0.356258
0	1.0	Reciprocating	Beech	1386.0	3003	0.461538
8	2.0	Reciprocating	Cessna	913.4	1680	0.543690
11	2.0	Turbo Fan	BOEING	870.2	609	1.428900
9	2.0	Reciprocating	Piper	854.0	1704	0.501174
7	2.0	Reciprocating	Beech	634.6	1169	0.542857

	Number.of.Engines	Engine.Type	Make	Total Injuries	Total Incidents	Injury Percentage
6	1.0	Turbo Shaft	Bell	610.2	1217	0.501397
3	1.0	Reciprocating	Mooney	465.8	1076	0.432900
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```
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Make'])[['Total Injuries', 'Total Incidents', 'Injury Percentage']].sum().reset_index()
engine_t_filter_outcome = engine_t_filter_outcome[engine_t_filter_outcome['Total Incident
s'] > 500]
engine_t_filter_outcome['Injury Percentage'] = engine_t_filter_outcome['Total Injuries']
/ engine_t_filter_outcome['Total Incidents']
engine_t_filter_outcome.sort_values(by='Injury Percentage', ascending=False)
```

Out[ ]:

	Number.of.Engines	Engine.Type	Make	Total Injuries	Total Incidents	Injury Percentage
11	2.0	Turbo Fan	BOEING	870.2	609	1.428900
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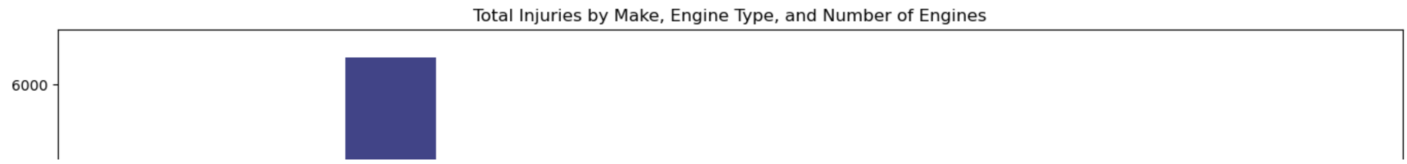
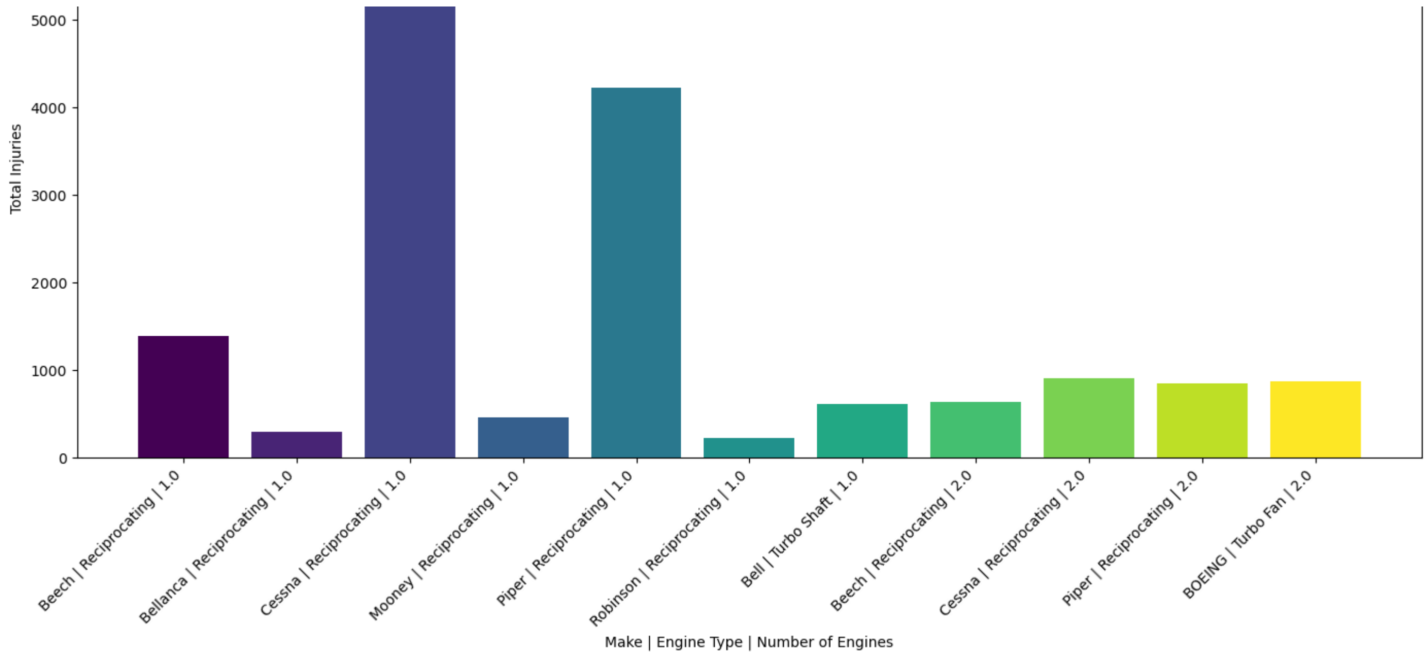
5	1.0	Reciprocating	Robinson	230.6	858	0.268765

Create visualization to represent

In [ ]:

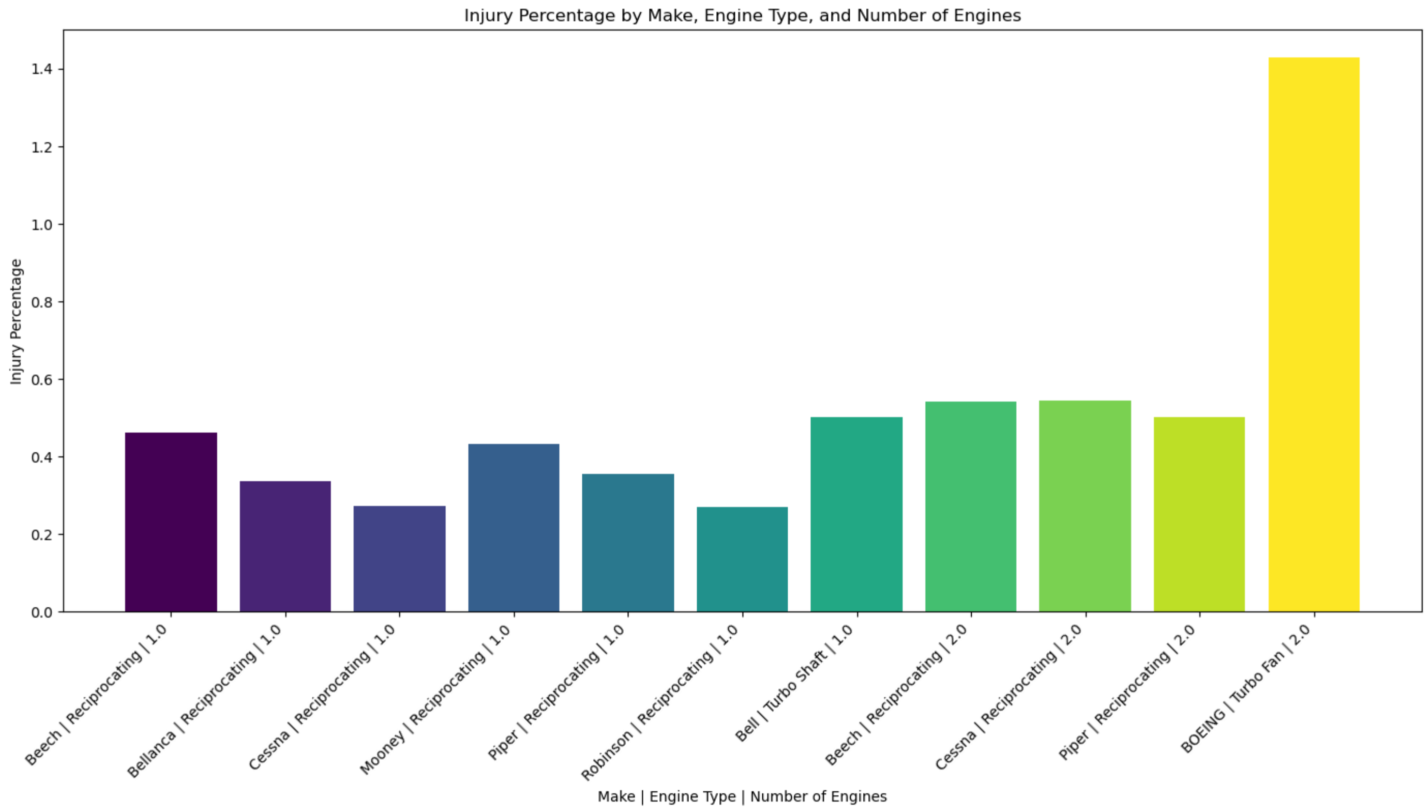
```
import numpy as np

# Creating a new column for the X-axis labels
engine_t_filter_outcome['Label'] = engine_t_filter_outcome['Make'] + ' | ' + engine_t_fi
lter_outcome['Engine.Type'] + ' | ' + engine_t_filter_outcome['Number.of.Engines'].astyp
e(str)

# Use a colormap to generate a list of colors based on the number of unique labels
colors = plt.cm.viridis(np.linspace(0, 1, len(engine_t_filter_outcome['Label'])))

# Plotting
plt.figure(figsize=(14, 8))  # Adjust the size as needed
plt.bar(engine_t_filter_outcome['Label'], engine_t_filter_outcome['Total Injuries'], colo
r=colors)  # Pass the list of colors here
plt.xlabel('Make | Engine Type | Number of Engines')
plt.ylabel('Total Injuries')
plt.xticks(rotation=45, ha="right")  # Rotate labels to avoid overlap
plt.title('Total Injuries by Make, Engine Type, and Number of Engines')
plt.tight_layout()  # Adjust layout to make room for the rotated x-axis labels

plt.show()
```





In [ ]:

```
# Creating a new column for the X-axis labels
engine_t_filter_outcome['Label'] = engine_t_filter_outcome['Make'] + ' | ' + engine_t_fi
lter_outcome['Engine.Type'] + ' | ' + engine_t_filter_outcome['Number.of.Engines'].astyp
e(str)

# Use a colormap to generate a list of colors based on the number of unique labels
colors = plt.cm.viridis(np.linspace(0, 1, len(engine_t_filter_outcome['Label'])))

# Plotting
plt.figure(figsize=(14, 8))  # Adjust the size as needed
plt.bar(engine_t_filter_outcome['Label'], engine_t_filter_outcome['Injury Percentage'], c
olor=colors)  # Pass the list of colors here
plt.xlabel('Make | Engine Type | Number of Engines')
plt.ylabel('Injury Percentage')
plt.xticks(rotation=45, ha="right")  # Rotate labels to avoid overlap
plt.title('Injury Percentage by Make, Engine Type, and Number of Engines')
plt.tight_layout()  # Adjust layout to make room for the rotated x-axis labels

plt.show()
```



Based on the above data on enginge types, although Cessna Reciprocating 1 engine planes have the most injuries, they appear to also be the safest to fly based on the amount of incidents and resulting low injury percentage (just under 30%)

Conclusion

The main takeaways one could assume based on the above data and visualizations are as follows:

-Airbus appears to be the safest choice for Commercial Airline travel and Lockheed for Military Travel/Transport, as Boeing and Mcdonnell Douglas both have high injury percentages for multiple engine type air carriers.

-Cessna 1 Engine and both Cessna and Piper 2 Engine appear to be the safest choices for personal aircraft travel, with Cessna 1 engine planes having a high injury total but the lowest injury percentage, and Cessna and Piper 2 engine planes having the lowest injury percentage amongst the respective group.

-When it comes to phase of flight, both Cessna and Piper are safest with their landing procedures, as both have the highest incident count and lowest injury totals for all "landing" phases of flight. Contrastingly, Cessna's "Maneuvering" phase of flight has the highest injury percentage by far with the lowest amount of incidents. Apart of "Maneuvering" resulting in many injuries, it appears that the "Cruise" phase of flight results in a large percentage of injuries for both Cessna and Piper, with Cessna's largest amount of injuries and second highest percentage all coming from flights in the "Cruise" phase of flight.

-One solution to this issue would be to implement more training programs for pilots pertaining to the "Maneuvering" phase of flight, as Cessna aircrafts have the highest injury percentage in this phase by far.

-Finally, regarding engine type, although Cessna Reciprocating 1 engine planes have the most injuries, they appear to also be the safest to fly based on the amount of incidents and resulting low injury percentage (just under 30%)