Pier & Co Services Ltd Aviation Analysis Project.

Objectives:

1) Evaluate the correlation between the features within the dataset. 2) Establish the current trends in fatal accidents between the period (2000 - 2022). 3) Determine which aircraft Pier & Co Services Ltd should invest in while they venture into the air transport business.

Summmary

Pier & Co Service Ltd is seeking to venture into the aviation industry, however, the company seeks insights that will inform their decisions about their new venture.

The following data analysis process will include the use of python libraries including pandas, numpy, matplotlib and seaborn, aiming to provide accurate information as to how specific factors contribute to aviation accidents. The factors to be analyzed are limited to the features provided in the AviationData.csv dataset.

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
df = pd.read_csv("AviationData.csv/AviationData.csv", encoding = "latin1", low_memory=Fal
se)

df.head()
```

Out[2]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.C
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	NaN	N
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	NaN	N
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.922223	-81.878056	N
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	NaN	N
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	NaN	N

5 rows × 31 columns

In [3]:

```
df.columns
```

Out[3]:

```
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 [4]:

```
df.info()
```

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

Definition of aviation term:

FAR.Description (Federal Aviation Regulations)- According to https://www.lawinsider.com/dictionary/federal-aviation-regulation-far , FAR is the body of rules prescribed by the Federal Aviation Authority(FAA) governing all aviation activities in the United States. Therefore, the applicable description(parts of the rules) is dependent on the type of aircraft.

Data cleaning and Analysis Process

First pick the columns to be featured and analyzed

In [5]:

```
select_df = df[["Event.Date","Location", "Country", "Weather.Condition","Aircraft.damage
", "Aircraft.Category", "Make", "Model", "Engine.Type", "Number.of.Engines", "Injury.Sev
erity", "Total.Fatal.Injuries", "Total.Serious.Injuries", "Total.Minor.Injuries", "Total
.Uninjured", "FAR.Description", "Broad.phase.of.flight", "Purpose.of.flight"]]
```

```
select_df.head()
```

Out[5]:

	Event.Date	Location	Country	Weather.Condition	Aircraft.damage	Aircraft.Category	Make	Model	Engine.Type
0	1948-10-24	MOOSE CREEK, ID	United States	UNK	Destroyed	NaN	Stinson	108-3	Reciprocating
1	1962-07-19	BRIDGEPORT, CA	United States	UNK	Destroyed	NaN	Piper	PA24-180	Reciprocating
2	1974-08-30	Saltville, VA	United States	IMC	Destroyed	NaN	Cessna	172M	Reciprocating
3	1977-06-19	EUREKA, CA	United States	IMC	Destroyed	NaN	Rockwell	112	Reciprocating
4	1979-08-02	Canton, OH	United States	VMC	Destroyed	NaN	Cessna	501	NaN

In [6]:

```
select_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Date              88889 non-null  object 
 1   Location                88837 non-null  object 
 2   Country                 88663 non-null  object 
 3   Weather.Condition       84397 non-null  object 
 4   Aircraft.damage         85695 non-null  object 
 5   Aircraft.Category       32287 non-null  object 
 6   Make                    88826 non-null  object 
 7   Model                   88797 non-null  object 
 8   Engine.Type             81793 non-null  object 
 9   Number.of.Engines       82805 non-null  float64
 10  Injury.Severity         87889 non-null  object 
 11  Total.Fatal.Injuries    77488 non-null  float64
 12  Total.Serious.Injuries  76379 non-null  float64
 13  Total.Minor.Injuries    76956 non-null  float64
 14  Total.Uninjured         82977 non-null  float64
 15  FAR.Description         32023 non-null  object 
 16  Broad.phase.of.flight   61724 non-null  object 
 17  Purpose.of.flight       82697 non-null  object 
dtypes: float64(5), object(13)
memory usage: 12.2+ MB
```

First Objective:

Demonstrate the correlation between the number of accidents and the following features; Aircraft.Damage, Injury.Severity, Engine.Type, Number of Engines, FAR.Description, Purpose.of.Flight, "Weather.Condition, Make , Broad.phase.of.flight and Aircraft.Category.

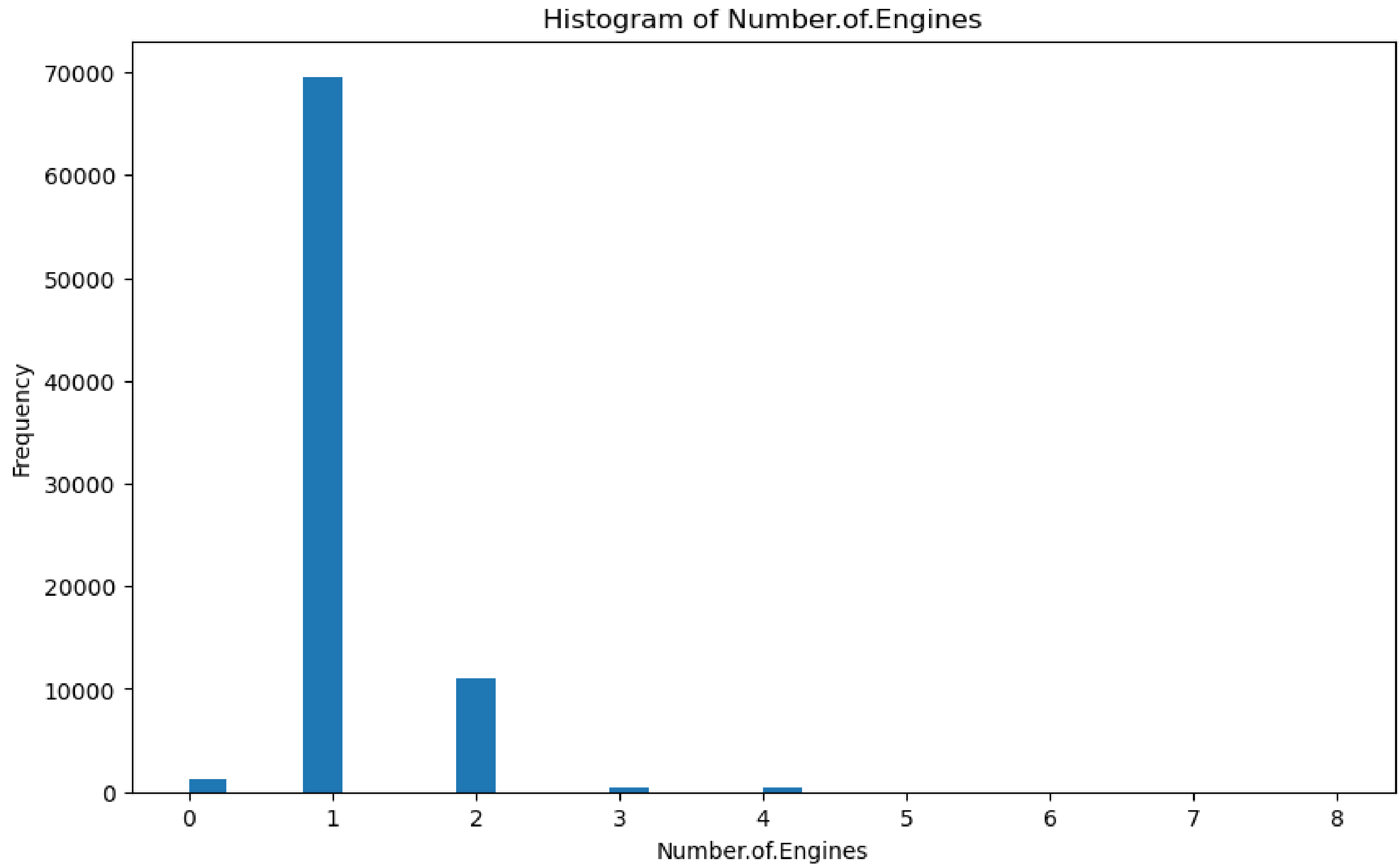
This is easily demonstrated by histogram charts.

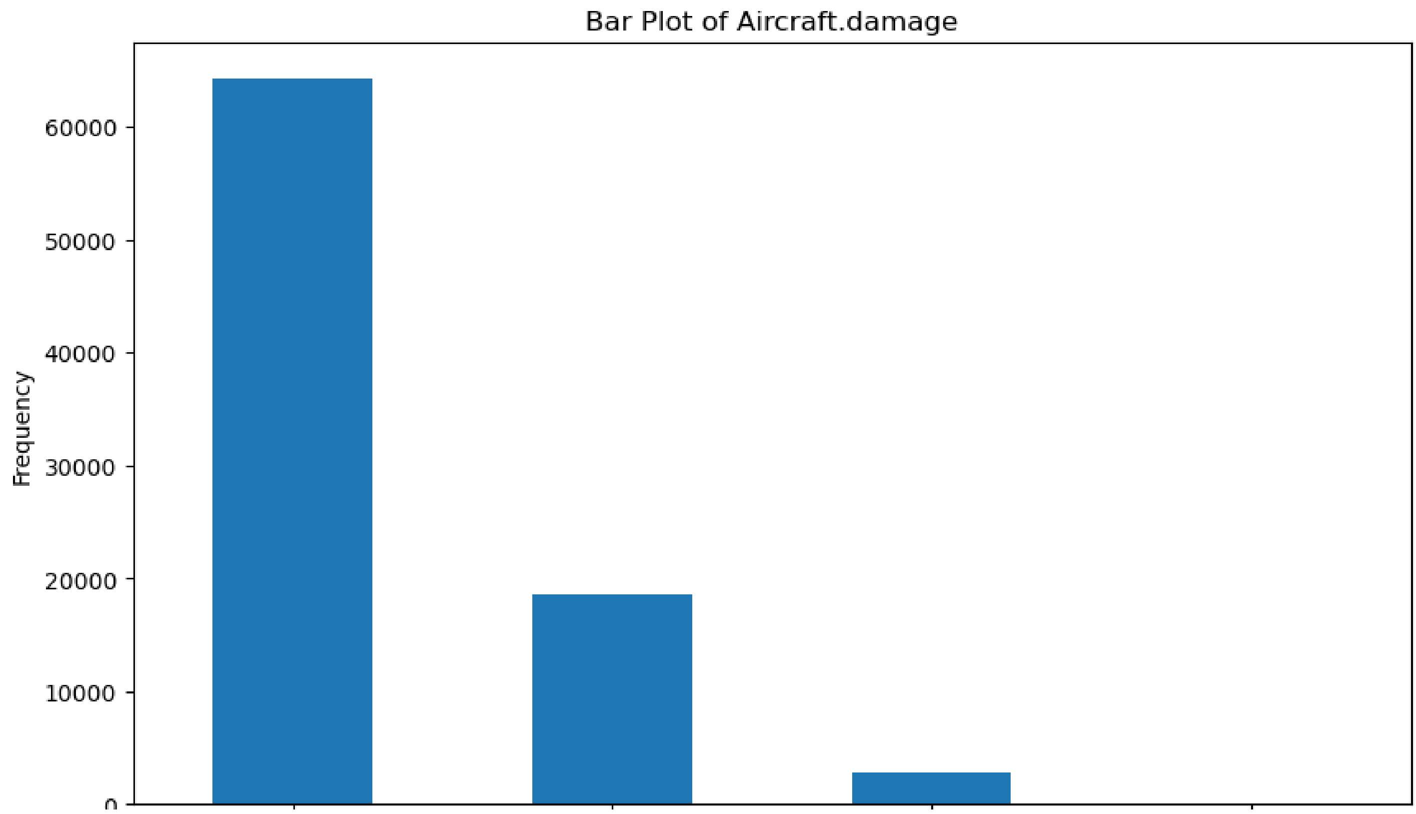
In [7]:

```
hist_features = ["Aircraft.damage", "Purpose.of.flight", "Engine.Type", "Number.of.Engine
s", "FAR.Description",
                 "Weather.Condition", "Broad.phase.of.flight", "Aircraft.Category"]

hist_obj =[x  for x in hist_features if select_df[x].dtypes == 'object']
hist_num =[x  for x in hist_features if select_df[x].dtypes != 'object']
```

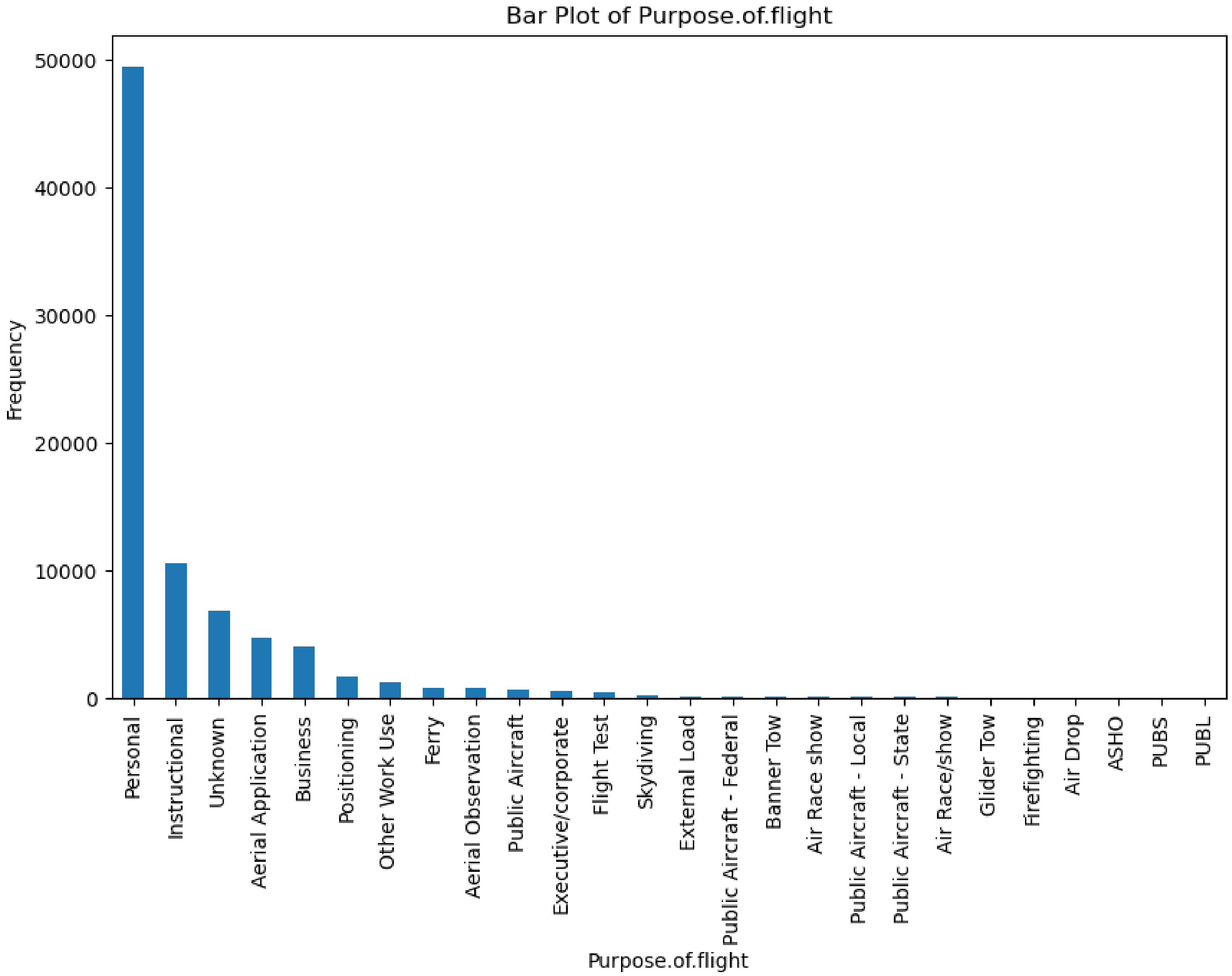
In [8]:

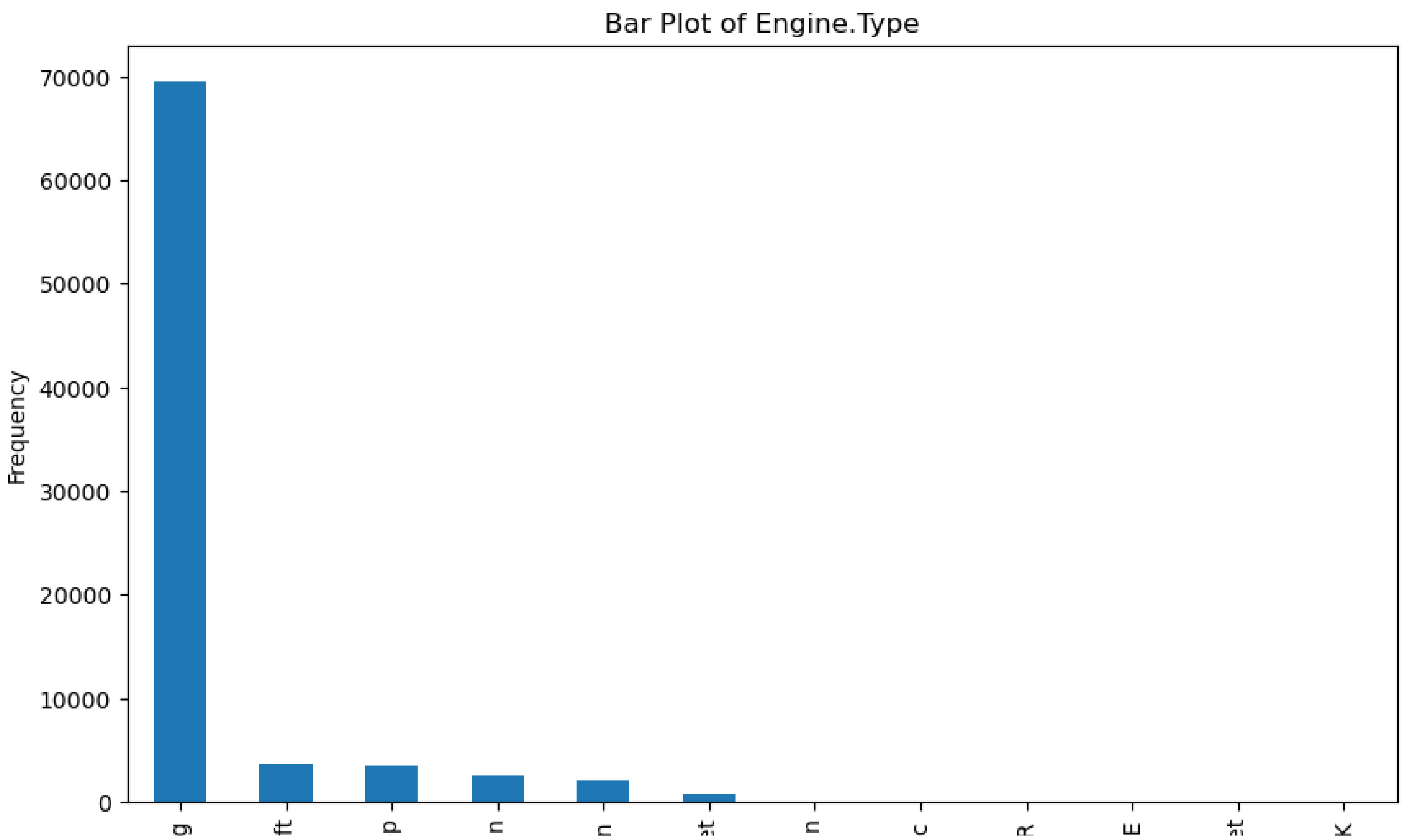
```python
#drawing the histograms
for feature in hist_num:
    plt.figure(figsize=(10, 6))
    select_df[feature].plot(kind='hist', bins=30, title=f'Histogram of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Frequency')
    plt.show()

# Plot bar plots for categorical features
for feature in hist_obj:
    plt.figure(figsize=(10, 6))
    select_df[feature].value_counts().plot(kind='bar', title=f'Bar Plot of {feature}')
    plt.xlabel(feature)
    plt.ylabel('Frequency')
    plt.show()
```

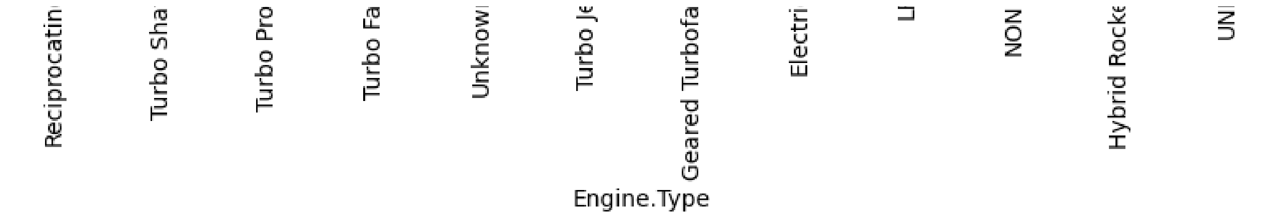


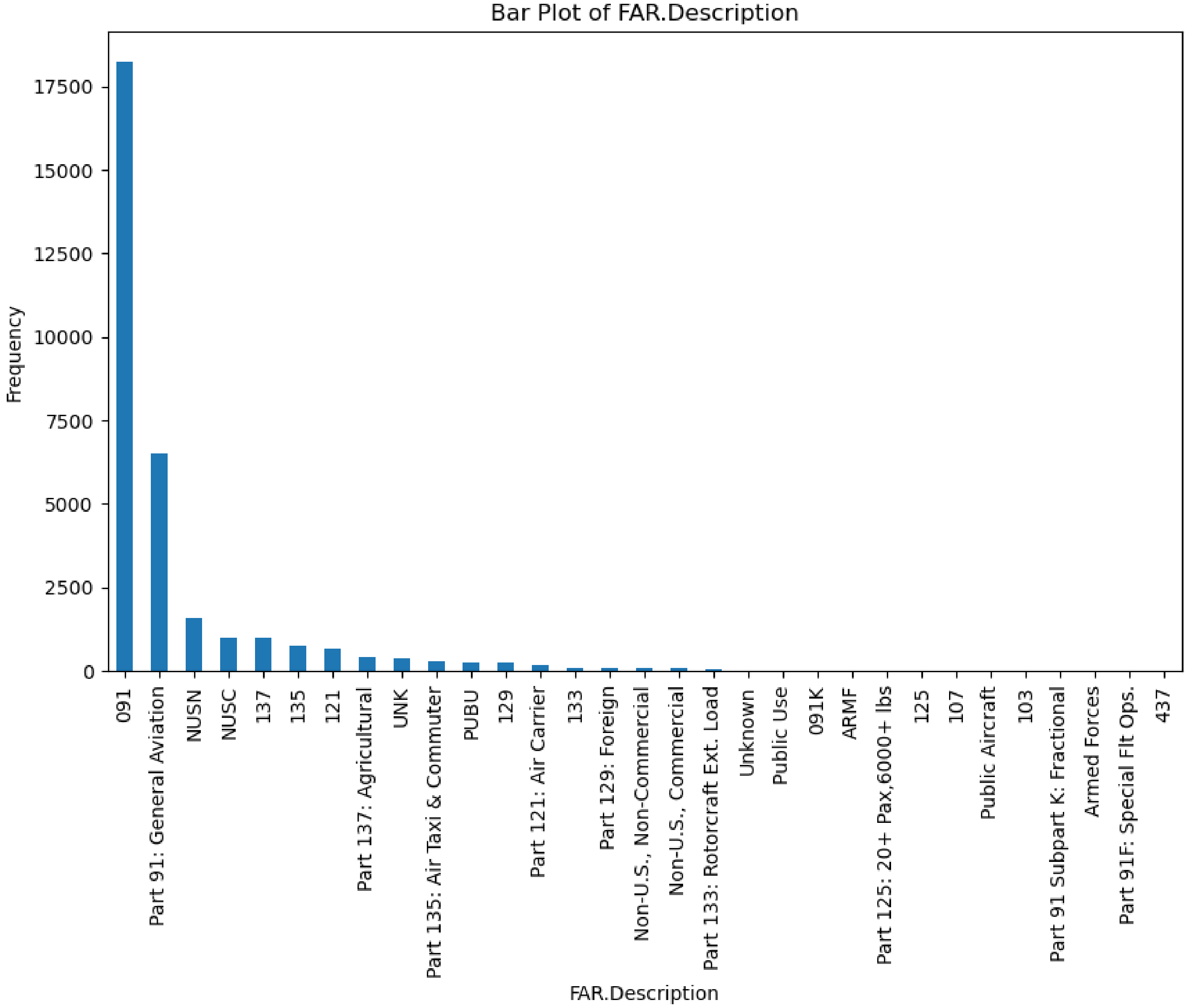


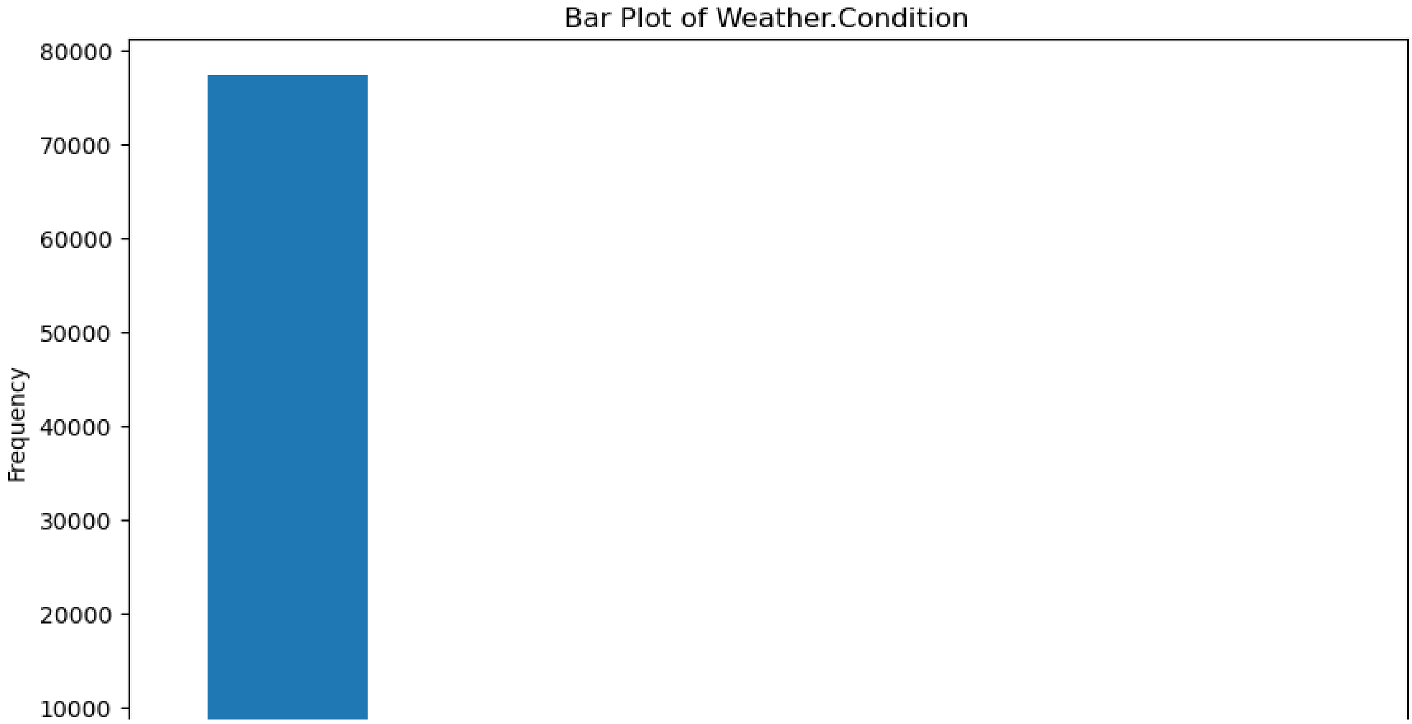

Substantial
Destroyed
Minor
Unknown
Aircraft.damage

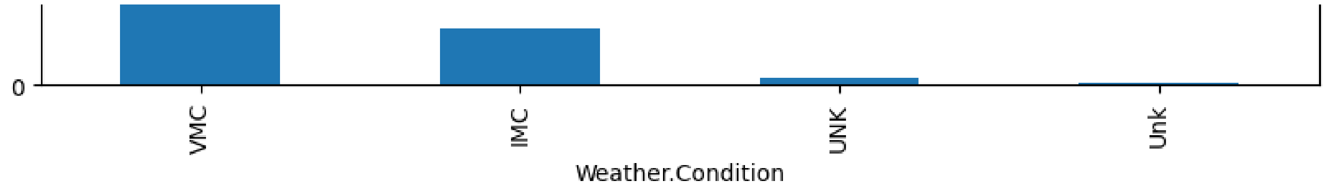

Bar Plot of Purpose.of.flight
Frequency
50000
40000
30000
20000
10000
0
Personal
Instructional
Unknown
Aerial Application
Business
Positioning
Other Work Use
Ferry
Aerial Observation
Public Aircraft
Executive/corporate
Flight Test
Skydiving
External Load
Public Aircraft - Federal
Banner Tow
Air Race show
Public Aircraft - Local
Public Aircraft - State
Air Race/show
Glider Tow
Firefighting
Air Drop
ASHO
PUBS
PUBL
Purpose.of.flight

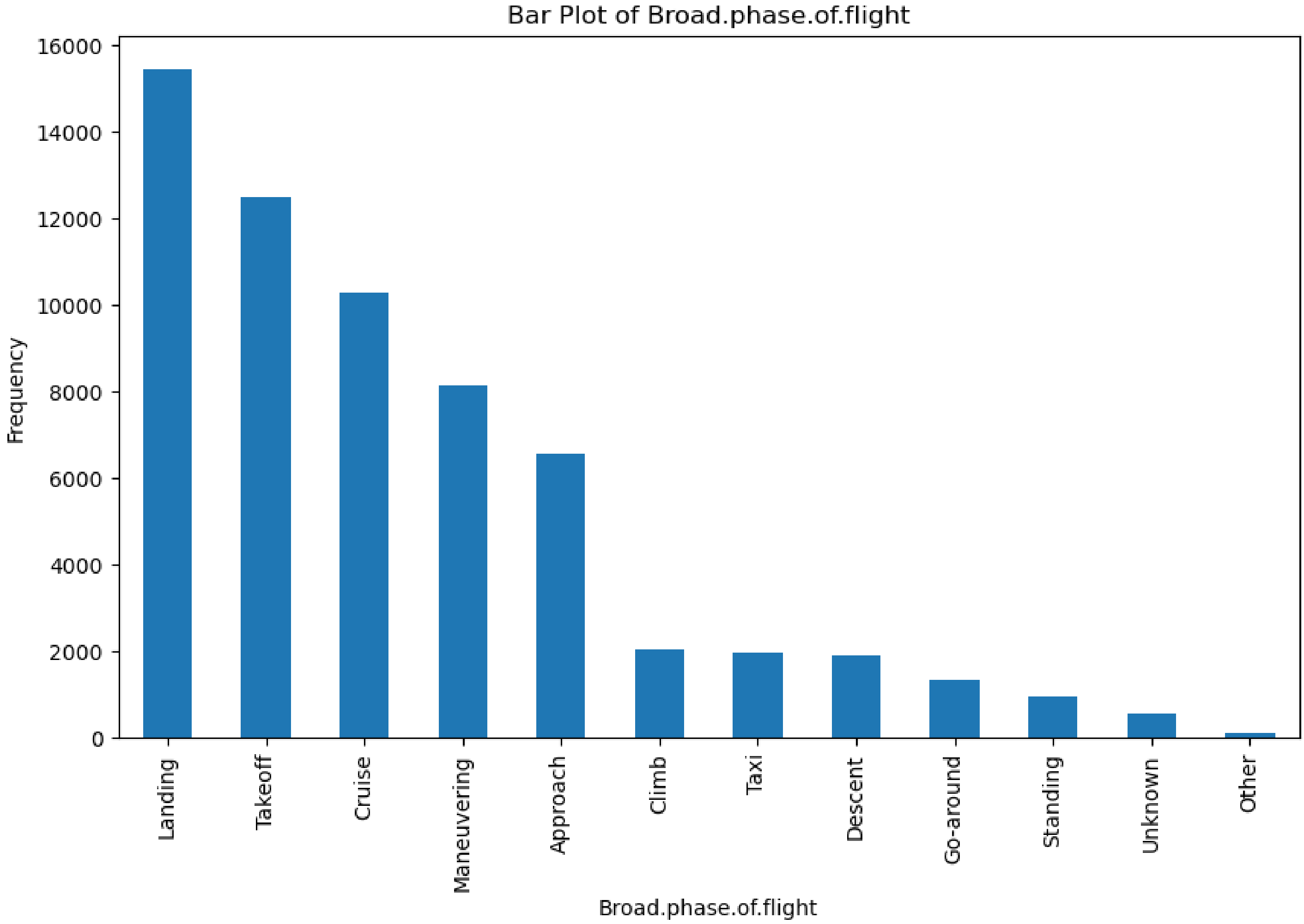

Bar Plot of Engine.Type
Frequency
70000
60000
50000
40000
30000
20000
10000
0

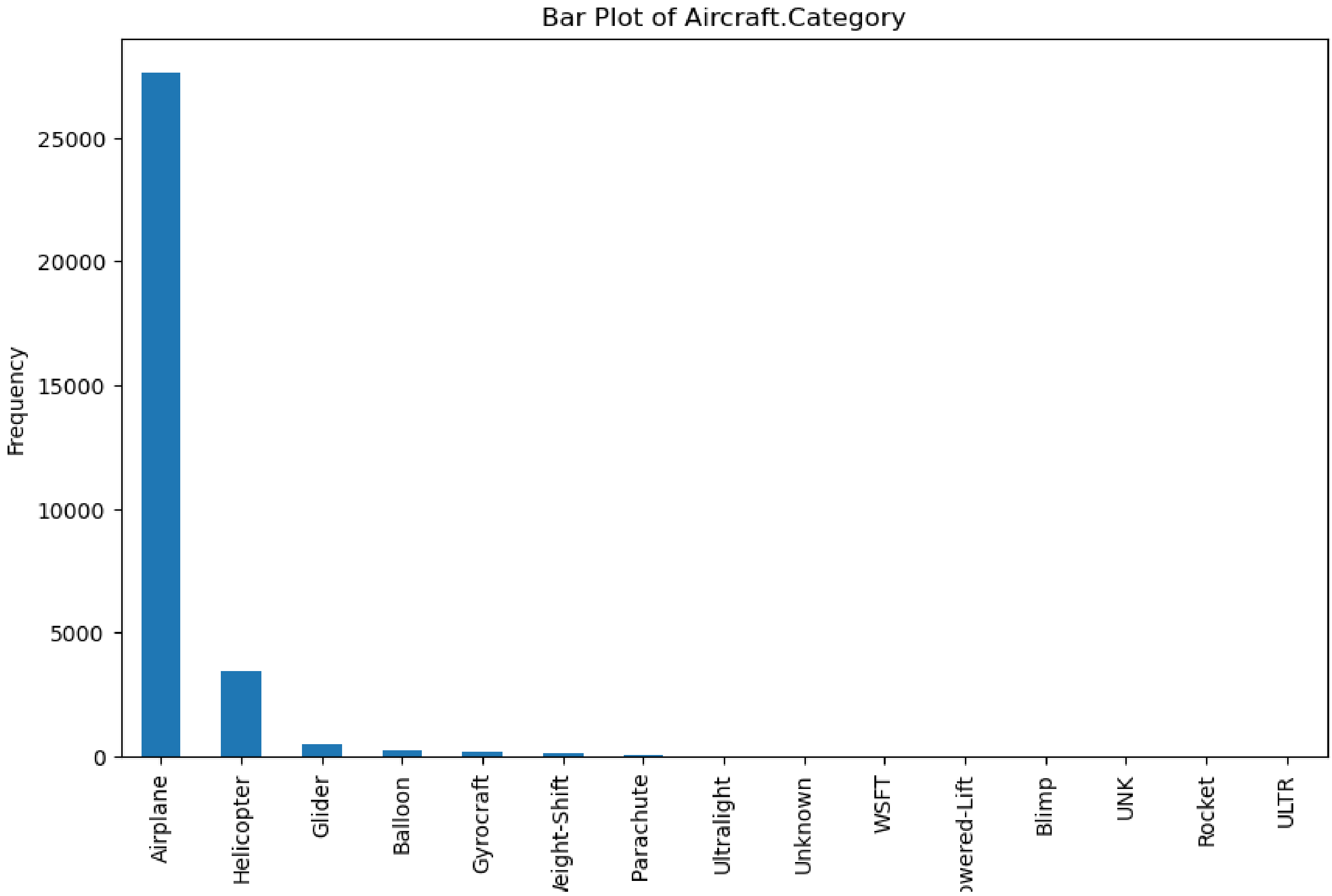

Reciprocatin
Turbo Sha
Turbo Pro
Turbo Fa
Unknow
Turbo Je
Geared Turbofa
Electri
NON
Hybrid Rock
UN
Engine.Type


Bar Plot of FAR.Description
Frequency
17500
15000
12500
10000
7500
5000
2500
0
091
Part 91: General Aviation
NUSN
NUSC
137
135
121
Part 137: Agricultural
UNK
Part 135: Air Taxi & Commuter
PUBU
129
Part 121: Air Carrier
133
Part 129: Foreign
Non-U.S., Non-Commercial
Non-U.S., Commercial
Part 133: Rotorcraft Ext. Load
Unknown
Public Use
091K
ARMF
Part 125: 20+ Pax,6000+ lbs
125
107
Public Aircraft
103
Part 91 Subpart K: Fractional
Armed Forces
Part 91F: Special Flt Ops.
437
FAR.Description


Bar Plot of Weather.Condition
Frequency
80000
70000
60000
50000
40000
30000
20000
10000


0
VMC
IMC
UNK
Unk
Weather.Condition


Bar Plot of Broad.phase.of.flight
16000
14000
12000
10000
8000
6000
4000
2000
0
Frequency
Landing
Takeoff
Cruise
Maneuvering
Approach
Climb
Taxi
Descent
Go-around
Standing
Unknown
Other
Broad.phase.of.flight


Bar Plot of Aircraft.Category
25000
20000
15000
10000
5000
0
Frequency
Airplane
Helicopter
Glider
Balloon
Gyrocraft
eight-Shift
Parachute
Ultralight
Unknown
WSFT
owered-Lift
Blimp
UNK
Rocket
ULTR

Observations

From the charts above comparing the frequency of accidents to each respective selected feature between 1948 - 2022, the following are the derived observations ; 1) Aircrafts with just 1 engine have higher numbers of accidents in comparison to those with 2,3 & 4 number of engines. 2) The frequency of accidents in relation to the purpose of flight, it can be observed that the personal and instructional bins have significant numbers in comparison to the others. 3) The FAR.Description chart, demonstrates that 91 & part 091 (civil aircrafts) are majorly affected when it comes to accidents. 4) Referencing the last 2 charts, it is observable that most of the accidents occur during landing and the highest category affected are airplanes followed by helicopters. 5) One outstanding observation is that many accidents occur during VMC which translates to good weather patterns in accordance with visual flight rules.

Second Objective:

To get a more current and accurate analysis, filtering the dataset to reflect recent data collected between the year 2000 - 2022

In [9]:

```
# Extract the year from the date format in the dataset
select_df["Event.Date"] = pd.to_datetime(select_df["Event.Date"])

select_df.loc[:, "year"] = select_df["Event.Date"].dt.year
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_10116\112988020.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  select_df["Event.Date"] = pd.to_datetime(select_df["Event.Date"])
C:\Users\User\AppData\Local\Temp\ipykernel_10116\112988020.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  select_df.loc[:, "year"] = select_df["Event.Date"].dt.year
```

In [10]:

```
# To avoid errors transform the year column to an integer format

select_df["year"] = select_df["year"].astype(int)

# Filter the dataframe to the years 2000 -2022

selected_df = select_df[(select_df["year"] >= 2000) & (select_df["year"]<= 2022)]

# Confirming the change has been effected

selected_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 41214 entries, 47675 to 88888
Data columns (total 19 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Date              41214 non-null  datetime64[ns]
 1   Location                41198 non-null  object
 2   Country                 41198 non-null  object
 3   Weather.Condition       36747 non-null  object
```

```
 4   Aircraft.damage        39146 non-null  object
 5   Aircraft.Category      28406 non-null  object
 6   Make                   41159 non-null  object
 7   Model                  41146 non-null  object
 8   Engine.Type            34135 non-null  object
 9   Number.of.Engines      36267 non-null  float64
 10  Injury.Severity        40214 non-null  object
 11  Total.Fatal.Injuries   30131 non-null  float64
 12  Total.Serious.Injuries 29120 non-null  float64
 13  Total.Minor.Injuries   29701 non-null  float64
 14  Total.Uninjured        35574 non-null  float64
 15  FAR.Description        28142 non-null  object
 16  Broad.phase.of.flight  14953 non-null  object
 17  Purpose.of.flight      35122 non-null  object
 18  year                   41214 non-null  int32
dtypes: datetime64[ns](1), float64(5), int32(1), object(12)
memory usage: 6.1+ MB
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_10116\2845049137.py:3: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  select_df["year"] = select_df["year"].astype(int)
```

Given the presence of missing values in the selected dataset, choosing to fill the null values with ("unknown") is a good strategy as it does not disrupt the dataset and avoid undue bias.

In [11]:

```python
# select the columns to be filled with "unknown"
columns_to_fill = [
    "Aircraft.Category", "Make", "Location", "Weather.Condition",
    "Country", "Broad.phase.of.flight", "Aircraft.damage",
    "FAR.Description", "Purpose.of.flight", "Model"
]

# Fill the selected columns
selected_df[columns_to_fill] = selected_df[columns_to_fill].fillna("unknown")

selected_df.head()
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_10116\680552497.py:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  selected_df[columns_to_fill] = selected_df[columns_to_fill].fillna("unknown")
```

Out[11]:

	Event.Date	Location	Country	Weather.Condition	Aircraft.damage	Aircraft.Category	Make	Model	Engine.T
47675	2000-01-01	HOMESTEAD, FL	United States	VMC	Substantial	unknown	Cessna	550	Turbo
47676	2000-01-01	MONTEAGLE, TN	United States	IMC	Destroyed	unknown	Bellanca	BL-17-30A	Reciproca
47677	2000-01-02	VICTORVILLE, CA	United States	VMC	Substantial	unknown	Cessna	172G	Reciproca
47678	2000-01-02	DOS PALOS, CA	United States	VMC	Substantial	unknown	Cessna	172A	Reciproca
47679	2000-01-02	CORNING, AR	United States	VMC	Substantial	unknown	Piper	PA-46-310P	Turbo F

In [12]:

```
selected_df.head()
```

Out[12]:

	Event.Date	Location	Country	Weather.Condition	Aircraft.damage	Aircraft.Category	Make	Model	Engine.T
47675	2000-01-01	HOMESTEAD, FL	United States	VMC	Substantial	unknown	Cessna	550	Turbo
47676	2000-01-01	MONTEAGLE, TN	United States	IMC	Destroyed	unknown	Bellanca	BL-17-30A	Reciproca
47677	2000-01-02	VICTORVILLE, CA	United States	VMC	Substantial	unknown	Cessna	172G	Reciproca
47678	2000-01-02	DOS PALOS, CA	United States	VMC	Substantial	unknown	Cessna	172A	Reciproca
47679	2000-01-02	CORNING, AR	United States	VMC	Substantial	unknown	Piper	PA-46-310P	Turbo F

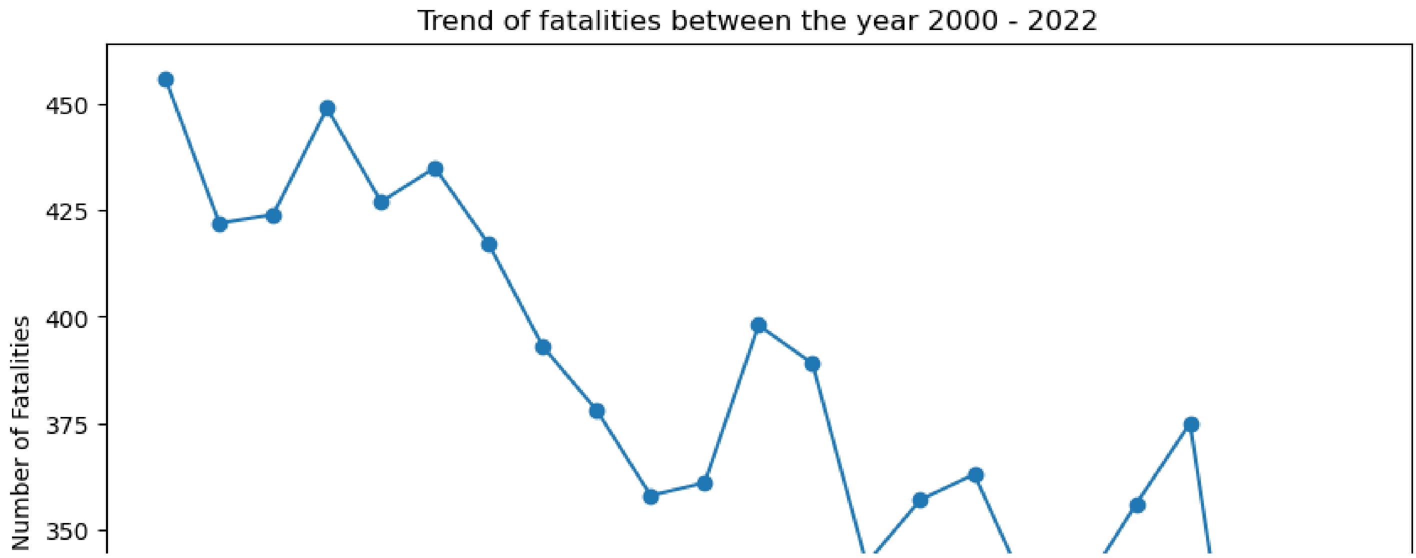
Third Objective

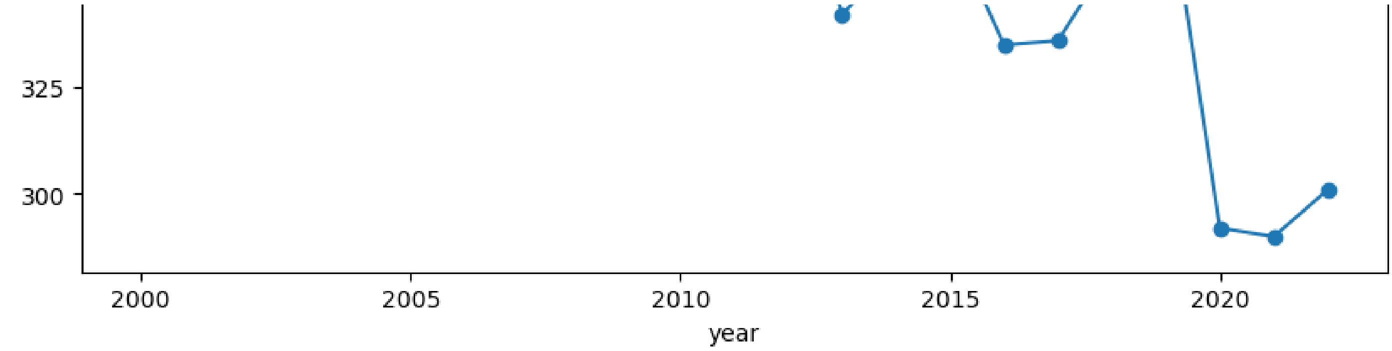
Analyzing the selected data

First, get the trajectory of fatalities recorded within the selected period (2000 - 2022) to understand the trend and how risky the sector is currently.

In [13]:

```
# create a fatalities variable
fatalities = selected_df[selected_df["Total.Fatal.Injuries"] > 0]

# group the fatalities by year

fatalities_by_year = fatalities.groupby("year").size()

# plot the trend over the years

plt.figure(figsize=(10,6))
fatalities_by_year.plot(kind="line", marker = "o")
plt.xlabel("year")
plt.ylabel("Number of Fatalities")
plt.title("Trend of fatalities between the year 2000 - 2022")
plt.grid = True
plt.show()
```





Observation

The trend of aircraft accidents that occured in the period (2000 - 2022) has continously decreased. This is probably due to improvement in aircraft technology and well trained pilots.

In order to answer the first question of which are the top 5 types of aircrafts highly susceptible to accidents; First bring together the "Make" and Aircraft.Category column via groupby function providing a clear view of how the selected columns relate with one another. Finally, plotting a line graph titled "Top 10 Make and Aircraft Category Combinations by Accident Count" allows for observation and development of insights

Observing that there is a similarity in names of the make of the aircraft and the way to differentiate them is by their model category, combining the two respective columns solves this issue. First, convert all 'Make' names to lower strings (to enhance consistency in the column), then bring together the "Make" and "Model" columns into one.

In [14]:

```
# convert all names to lowercase
selected_df["Make"] = selected_df["Make"].str.lower()

# combine and create a new column "Make_Model"
selected_df ["Make_Model"] = selected_df["Make"] + " " + selected_df["Model"]
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_10116\2778753609.py:2: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  selected_df["Make"] = selected_df["Make"].str.lower()
C:\Users\User\AppData\Local\Temp\ipykernel_10116\2778753609.py:5: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  selected_df ["Make_Model"] = selected_df["Make"] + " " + selected_df["Model"]
```

In [15]:

```
selected_df = selected_df.drop(columns=["Make", "Model"])

selected_df
```

Out[15]:

	Event.Date	Location	Country	Weather.Condition	Aircraft.damage	Aircraft.Category	Engine.Type	Number.of.E
47675	2000-01-01	HOMESTEAD, FL	United States	VMC	Substantial	unknown	Turbo Fan	
47676	2000-01-01	MONTEAGLE, TN	United States	IMC	Destroyed	unknown	Reciprocating	
[illegible]	2000-01-	VICTORVILLE,	United	[illegible]	[illegible]	[illegible]	[illegible]	

	Event.Date	Location	Country	Weather.Condition	Aircraft.damage	Aircraft.Category	Engine.Type	Number.of.E
47677	02	CA	States	VMC	Substantial	unknown	Reciprocating	
47678	2000-01-02	DOS PALOS, CA	United States	VMC	Substantial	unknown	Reciprocating	
47679	2000-01-02	CORNING, AR	United States	VMC	Substantial	unknown	Turbo Prop	
...	...	...	...	...	...	...	...	
88884	2022-12-26	Annapolis, MD	United States	unknown	unknown	unknown	NaN	
88885	2022-12-26	Hampton, NH	United States	unknown	unknown	unknown	NaN	
88886	2022-12-26	Payson, AZ	United States	VMC	Substantial	Airplane	NaN	
88887	2022-12-26	Morgan, UT	United States	unknown	unknown	unknown	NaN	
88888	2022-12-29	Athens, GA	United States	unknown	unknown	unknown	NaN	

41214 rows × 18 columns

Group the relevant columns (Make_Model and Aircraft.Category) , removing the unknown values and plot a bar chart to show the top 10 models appearing in accident report.

In [16]:

```
# group the two separate columns together
makevs_cart = selected_df[selected_df["Aircraft.Category"]!= "unknown"].groupby(["Make_M
odel", "Aircraft.Category"]).size().reset_index(name="AccidentCount")

# sort in descending order (highest to lowest) and show the first 10

top10_makevs_cart = makevs_cart.sort_values(by="AccidentCount", ascending=False).head(10
)

top10_makevs_cart
```

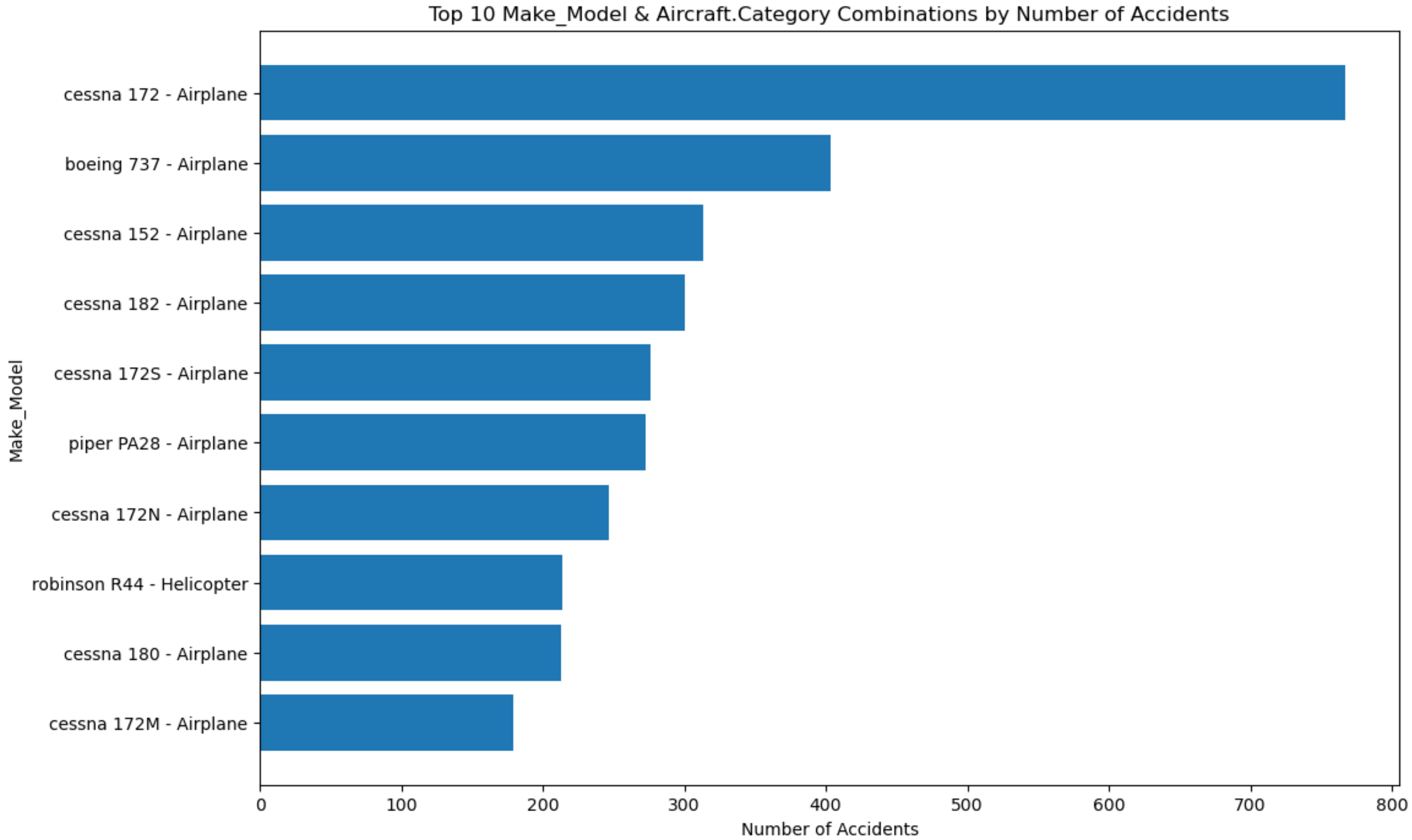
Out[16]:

	Make_Model	Aircraft.Category	AccidentCount
2230	cessna 172	Airplane	767
1523	boeing 737	Airplane	403
2220	cessna 152	Airplane	313
2293	cessna 182	Airplane	300
2266	cessna 172S	Airplane	276
6519	piper PA28	Airplane	273
2261	cessna 172N	Airplane	247
7073	robinson R44	Helicopter	214
2278	cessna 180	Airplane	213
2260	cessna 172M	Airplane	179

In [17]:

```
# Plot the data using a bar chart
plt.figure(figsize=(12, 8))
bar_plot = plt.barh(top10_makevs_cart["Make_Model"] + ' - ' + top10_makevs_cart["Aircraf
t.Category"], top10_makevs_cart["AccidentCount"])
plt.xlabel('Number of Accidents')
```

```
plt.ylabel("Make_Model")
plt.title('Top 10 Make_Model & Aircraft.Category Combinations by Number of Accidents')
plt.gca().invert_yaxis()

# y-axis inverts to display the highest value at the top
plt.show()
```



Obsevation

Based on the chart above, it is evident that the number of cessna aircrafts reported is high. Despite this significant figures, simpleflying.com describes the cessna model as the most popular among beginner pilots due to the significant low fatalities reported. Therefore, the high number of reported accidents demonstrates how popular the aircraft is within the sector.

Recommendation

Pier & Co Services Ltd should consider incorporating the cessna aircraft model among its fleet before expanding into the large commercial aircrafts.

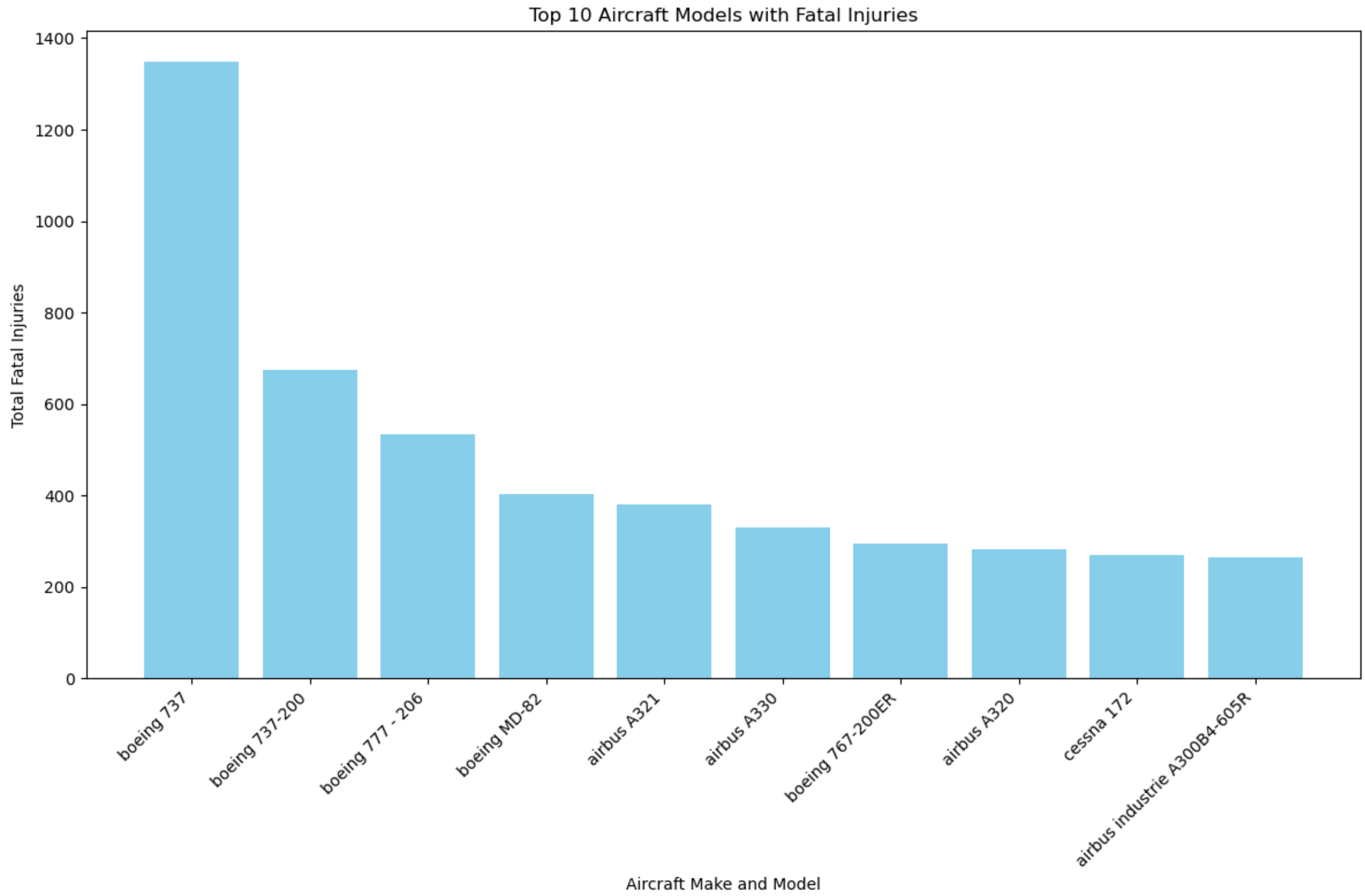
Reviewing the safety of the make and model of air crafts.

The above chart has displayed the most popular aircraft make and model in accordance to the data set. Therefore, to understand the safety of these models, plotting a chart comparing the total fatalities to the respective make provides a clearer picture of an aircraft's model suitability.

In [18]:

```
fatalities_group = selected_df.groupby('Make_Model')["Total.Fatal.Injuries"].sum().reset
_index()

top10fatal_models = fatalities_group.sort_values(by="Total.Fatal.Injuries", ascending=Fa
lse).head(10)

top10fatal_models
plt.figure(figsize=(12, 8))
plt.bar(top10fatal_models['Make_Model'], top10fatal_models["Total.Fatal.Injuries"], colo
r='skyblue')
plt.xlabel('Aircraft Make and Model')
plt.ylabel('Total Fatal Injuries')
```

```
plt.title('Top 10 Aircraft Models with Fatal Injuries')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



Observation

The bart chart above provides a summary of the top models with fatal injuries. The highest being boeing and airbus models. This explains the why most aviation stakeholders prefer the cessna models as it has better safety standards in comparison to most aircrafts.

Recommendation

Pier & Co Services Ltd should consider the safety standards as well when acquiring a new fleet for their aircraft business.

Type of Engine

Engines are an imporatn aspect in airplanes and to understand which one suits the need, extracting the top five aircraft engines from the dataset proves to be an effective approach.

In [ ]:

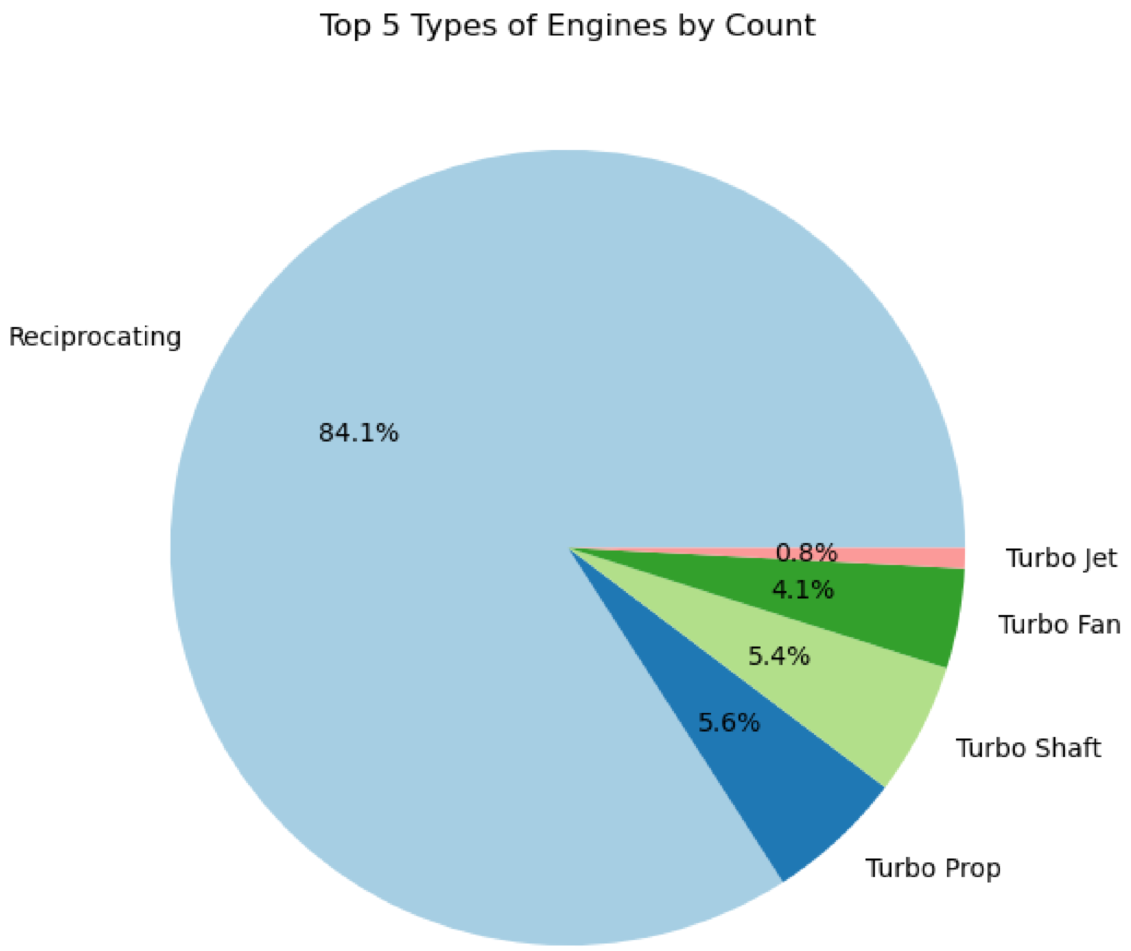
```
top5_engines = selected_df["Engine.Type"].value_counts().head(5)
top5_engines
```

Out[ ]:

```
Engine.Type
Reciprocating    28486
Turbo Prop        1900
Turbo Shaft       1826
Turbo Fan         1375
Turbo Jet          283
Name: count, dtype: int64
```

In [ ]:

```
# Plot pie chart
plt.figure(figsize=(10, 7))
plt.pie(top5_engines, labels=top5_engines.index, autopct='%1.1f%%', colors=plt.cm.Paired
.colors)
plt.title('Top 5 Types of Engines by Count')
plt.show()
```



Observation

The type of engine with the highest number of accidents reported is shown figure above to be the "Reciprocating" engine while the "Turbo jet" has the least frequency. This translates to its popularity among aviation enthusiasts. According to chapter 7 of the Federal Aviation Administration(FAA), most small aircrafts are designed with the reciprocating engine. Furthermore, the simplicity, reliability and low fuel cost factor in to how prominent this engine among small aircraft owners/airlines.

Recommendation

As a new company, Pier and Co. Services Ltd need to consider starting out with smaller aircrafts before acquiring bigger planes with expensive maintainance costs, especially the engine.

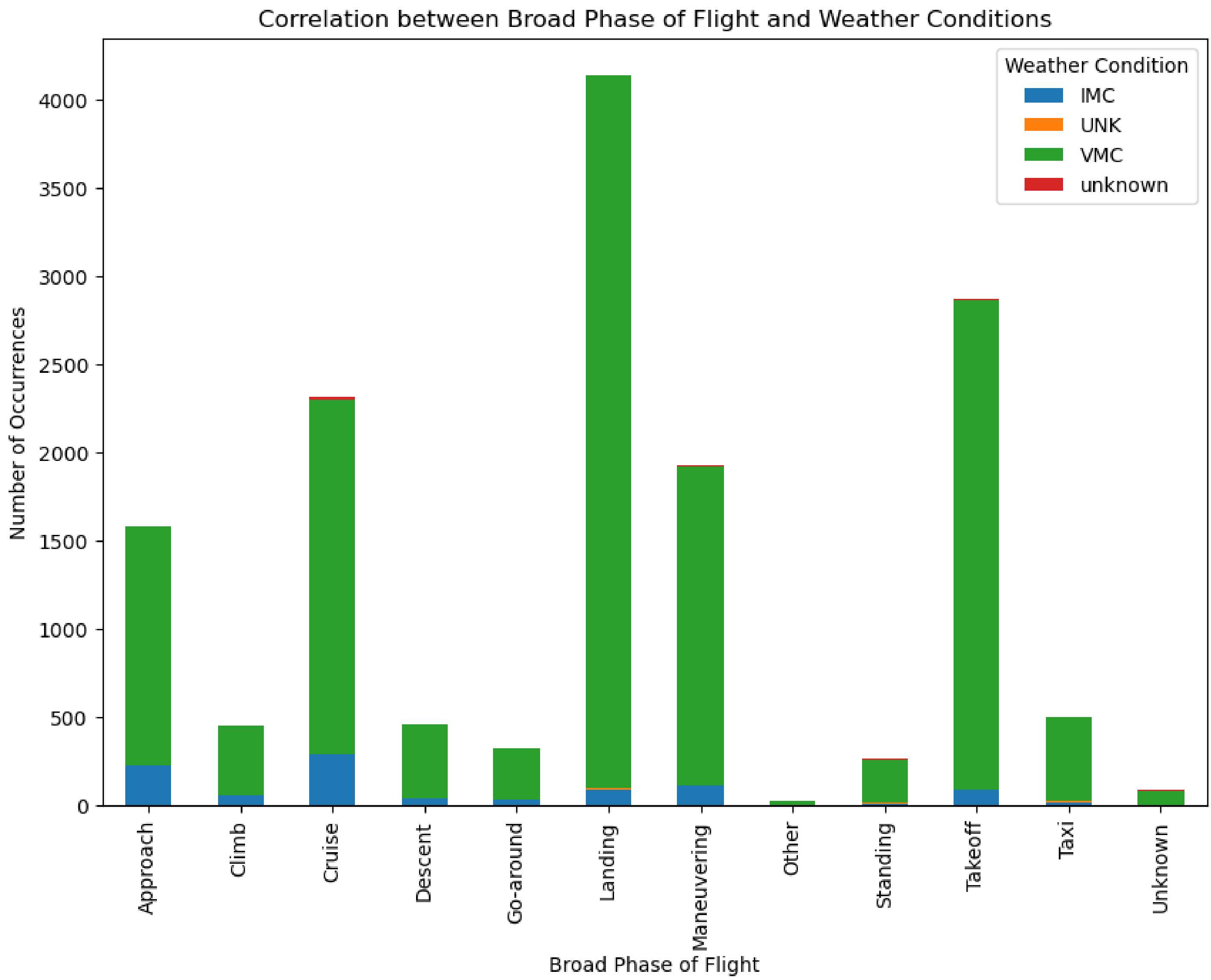
Phase of Accident

Aircraft accident occur during different phases, hence the need to know the high risk phases of an aircraft' journey.

In [20]:

```
# use value_counts method to extract the frequently reported phases of accidents
selected_df["Broad.phase.of.flight"].value_counts()

# create a new variable and group together both columns
# drop unknown
```

```
phase_by_con = selected_df[selected_df["Broad.phase.of.flight"]!= "unknown"].groupby(["B
road.phase.of.flight", "Weather.Condition"]).size().unstack().fillna(0)

# plot the heatmap to demonstrate the correlation between the columns
phase_by_con.plot(kind='bar', stacked=True, figsize=(10, 7))
plt.xlabel('Broad Phase of Flight')
plt.ylabel('Number of Occurrences')
plt.title('Correlation between Broad Phase of Flight and Weather Conditions')
plt.legend(title='Weather Condition')
plt.show()
```



Observation

With reference to the stacked bar chart above, majority of accidents occur during landing phase and interestingly while the weather conditions are favorable (VMC). The second highest occurence is observed when air crafts are taking off within similar weather conditions.

According to IATA 2022 Annual Safety Report, aircraft accidents taking place during landing and takeoff phases are attributed to overrun(aircraft continuing beyond the runway) or veering out of its lateral limits.

Recommendations

Provide scenario-based training to pilots, enhancing their competencies for effective threat and management to prevent runway excursion (e.g., contaminated runway, last minute change of runway, deterioration of weather condition).

Airlines and private plane owners should explore advanced technologies such as AI-based systems which can aid aircrew in obtaining information, and making rapid decisions.

For Airlines and Air Traffic control, they should consider recommending the execution of a go-around at any point during the approach, when there is any doubt on a safe continuation of the approach or the landing.

In [ ]:

```

```