Aviation Accident Analysis

1. Business Understanding

Problem Statement

A company is expanding into new industries to diversify its portfolio, with a specific interest in acquiring and operating airplanes for both commercial and private ventures. However, they lack knowledge about the potential risks associated with aircraft. The objective is to identify which aircraft pose the lowest risk for the company to enter this new market. These findings should be converted into actionable insights to guide the head of the new aviation division in making informed decisions about aircraft purchases.

Goal

The objective of this project is to employ data cleaning, imputation, analysis, and visualization to generate valuable insights for a business stakeholder interested in acquiring and operating airplanes for commercial and private ventures.

The goal is to convert these findings into actionable insights that will assist the head of the new aviation division in making informed decisions about which aircraft to purchase.

Objectives

General Objective

To determine which aircraft are least likely to be involved in accidents. This information will assist the head of the new aviation division in making informed decisions on which aircraft to purchase and operate for commercial and private ventures.

General Objectives

1. To understand the problem statement, the project's objectives, and the dataset utilized.
2. To apply data cleaning techniques to generate actionable insights.
3. To analyze the data through univariate and bivariate analysis of variables.

2. Data Understanding

Importing Libraries

Through importing various types of libraries we'll be able to understand the aviation dataset much easier.

In [1]:
```
#Pandas is especially well-suited to handling tabular data (represented as rows and co
import pandas as pd
#Numpy provides useful functionality for mathematical operations on vectors and matric
import numpy as np
#Matplotlib is tailored for the generation of simple and powerful visualizations.
import matplotlib.pyplot as plt
#Seaborn targets statistical data visualizations, which may be more time-consuming to
import seaborn as sns
#Helps display the calendar by importing the calendar module to our program.
import calendar
#Helps provides a way to control how warnings are handled within a Python script.
import warnings
warnings.filterwarnings("ignore")
```

Data Description

The data used is from the National Transportation Safety Board that includes aviation accident data from 1962 to 2023 about civil aviation accidents and selected incidents in the United States and international waters.

Loading Datasets

I will use the aviation dataset which is provided by the National Transportation Safety Board.

In [2]:
```
data = pd.read_csv('AviationData.csv', encoding='latin1')
data
```

Out[2]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Lat
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.9
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	
...	...	...	...	...	...	...	
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	34
88887	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	
88888	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	

88889 rows × 31 columns

Dataset Exploration

By exploring our data we'll be able to understand what it contains before we derive insights.

In [3]:
```
data.head()
```

Out[3]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitud
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.92222
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN

5 rows × 31 columns

In [4]:
```
data.tail()
```

Out[4]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitud
88884	20221227106491	Accident	ERA23LA093	2022-12-26	Annapolis, MD	United States	Na
88885	20221227106494	Accident	ERA23LA095	2022-12-26	Hampton, NH	United States	Na
88886	20221227106497	Accident	WPR23LA075	2022-12-26	Payson, AZ	United States	341525
88887	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	Na
88888	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	Na

5 rows × 31 columns

In [5]:
```
data.shape
```

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

The data has 88,889 rows and 31 columns.

In [6]:
```
data.columns
```

Out[6]:
```
Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Date',
       'Location', 'Country', 'Latitude', 'Longitude', 'Airport.Code',
       'Airport.Name', 'Injury.Severity', 'Aircraft.damage',
       'Aircraft.Category', 'Registration.Number', 'Make', 'Model',
       'Amateur.Built', 'Number.of.Engines', 'Engine.Type', 'FAR.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 [7]:
```
data.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

In [8]:
```
data.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
```

5 of the columns contains float values and the other 26 columns are strings. The DataFrame has some missing values, indicated by the "Non-Null Count" column.

3. Data Preparation

Data Cleaning

Data cleaning is the process of fixing or removing incorrect, corrupted, incorrectly formatted, duplicate, or incomplete data within a dataset.

Missing Values

Through this we'll be able to know which columns in our dataset have missing values.

In [9]:
```
data.isnull().sum()
```

Out[9]:
```
Event.Id                      0
Investigation.Type            0
Accident.Number               0
Event.Date                    0
Location                     52
Country                     226
Latitude                  54507
Longitude                 54516
Airport.Code              38640
Airport.Name              36099
Injury.Severity            1000
Aircraft.damage            3194
Aircraft.Category         56602
Registration.Number        1317
Make                         63
Model                        92
Amateur.Built               102
Number.of.Engines          6084
Engine.Type                7077
FAR.Description           56866
Schedule                  76307
Purpose.of.flight          6192
Air.carrier               72241
Total.Fatal.Injuries      11401
Total.Serious.Injuries    12510
Total.Minor.Injuries      11933
Total.Uninjured            5912
Weather.Condition          4492
Broad.phase.of.flight     27165
Report.Status              6381
Publication.Date          13771
dtype: int64
```

In [10]:
```
data.isnull().sum().sum()
```

Out[10]:
```
564742
```

There are 564,742 missing values. To check the percentage of missing values in each column a formula will be used:

In [11]:
```
def identify_missing_values(data):
    """A simple function to check if data has missing values"""
    # identify the total missing values per column
    # sort in order
    miss = data.isnull().sum().sort_values(ascending = False)

    # calculate percentage of the missing values
    percentage_miss = (data.isnull().sum() / len(data)).sort_values(ascending = False)

    # store in a dataframe
    missing = pd.DataFrame({"Missing Values": miss, "Percentage(%)": percentage_miss})

    # remove values that are missing
    missing.drop(missing[missing["Percentage(%)"] == 0].index, inplace = True)

    return missing
```

```
missing_data = identify_missing_values(data)
missing_data
```

Out[11]:

	Missing Values	Percentage(%)
Schedule	76307	85.845268
Air.carrier	72241	81.271023
FAR.Description	56866	63.974170
Aircraft.Category	56602	63.677170
Longitude	54516	61.330423
Latitude	54507	61.320298
Airport.Code	38640	43.469946
Airport.Name	36099	40.611324
Broad.phase.of.flight	27165	30.560587
Publication.Date	13771	15.492356
Total.Serious.Injuries	12510	14.073732
Total.Minor.Injuries	11933	13.424608
Total.Fatal.Injuries	11401	12.826109
Engine.Type	7077	7.961615
Report.Status	6381	7.178616
Purpose.of.flight	6192	6.965991
Number.of.Engines	6084	6.844491
Total.Uninjured	5912	6.650992
Weather.Condition	4492	5.053494
Aircraft.damage	3194	3.593246
Registration.Number	1317	1.481623
Injury.Severity	1000	1.124999
Country	226	0.254250
Amateur.Built	102	0.114750
Model	92	0.103500
Make	63	0.070875
Location	52	0.058500

Through this we'll be able to know if we have any repeated rows in our dataset.

Duplicates

In [12]:
```
data.duplicated().sum()
```
Out[12]:
```
0
```

There are no duplicates in the dataset before handling missing values.

Handling Missing Values

In [13]:
```
missing_data = identify_missing_values(data)
missing_data
```

Out[13]:

	Missing Values	Percentage(%)
Schedule	76307	85.845268
Air.carrier	72241	81.271023
FAR.Description	56866	63.974170
Aircraft.Category	56602	63.677170
Longitude	54516	61.330423
Latitude	54507	61.320298
Airport.Code	38640	43.469946
Airport.Name	36099	40.611324
Broad.phase.of.flight	27165	30.560587
Publication.Date	13771	15.492356
Total.Serious.Injuries	12510	14.073732
Total.Minor.Injuries	11933	13.424608
Total.Fatal.Injuries	11401	12.826109
Engine.Type	7077	7.961615
Report.Status	6381	7.178616
Purpose.of.flight	6192	6.965991
Number.of.Engines	6084	6.844491
Total.Uninjured	5912	6.650992
Weather.Condition	4492	5.053494
Aircraft.damage	3194	3.593246
Registration.Number	1317	1.481623
Injury.Severity	1000	1.124999
Country	226	0.254250
Amateur.Built	102	0.114750
Model	92	0.103500
Make	63	0.070875
Location	52	0.058500

Imputation

These columns cannot be dropped because they are important for the analysis. Imputation will be used to deal with the missing values in these columns.

In [14]:

```
fill_rows = ['Air.carrier', 'FAR.Description', 'Purpose.of.flight', 'Engine.Type', 'Br
rows_to_fill = [fill for fill in fill_rows if fill in data.columns]
data[rows_to_fill] = data[rows_to_fill].fillna(value='None')
```

Dropping Rows

Rows where columns with missing values are below 15% will be dropped as most of the data will still be retained.

In [15]:
```
Drop_rows = ['Total.Fatal.Injuries','Total.Uninjured','Total.Minor.Injuries','Aircraft
             'Injury.Severity','Location', 'Country', 'Make', 'Model', 'Amateur.Built'
             'Number.of.Engines','Total.Serious.Injuries','Aircraft.Category']
rows_to_drop = [row for row in Drop_rows if row in data.columns]
data = data.dropna(subset=rows_to_drop)
```

Dropping Columns

Columns with missing values that will not be used in the analysis are dropped.

In [16]:
```
Drop_Columns = ['Latitude', 'Longitude', 'Schedule','Registration.Number', 'Publicatic
                'Airport.Code', 'Report.Status']
columns_to_drop = [col for col in Drop_Columns if col in data.columns]
data = data.drop(columns_to_drop, axis=1)
```

In [17]:
```
missing_data = identify_missing_values(data)
missing_data
```

Out[17]:

Missing Values	Percentage(%)

In [18]:
```
data.isnull().sum()
```

Out[18]:
```
Event.Id                  0
Investigation.Type        0
Accident.Number           0
Event.Date                0
Location                  0
Country                   0
Injury.Severity           0
Aircraft.damage           0
Aircraft.Category         0
Make                      0
Model                     0
Amateur.Built             0
Number.of.Engines         0
Engine.Type               0
FAR.Description           0
Purpose.of.flight         0
Air.carrier               0
Total.Fatal.Injuries      0
Total.Serious.Injuries    0
Total.Minor.Injuries      0
Total.Uninjured           0
Weather.Condition         0
Broad.phase.of.flight     0
dtype: int64
```

In [19]:
```
data.isnull().sum().sum()
```

Out[19]:
```
0
```

There are no missing values in the dataset.

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

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

In [21]:
```
data.shape
```

Out[21]:
```
(23069, 23)
```

The dataset has 23,069 rows and 23 columns.

Checking for duplicates after handling missing values

In [22]:
```
data.duplicated().sum()
```

Out[22]:
```
1
```

There is 1 duplicate in our dataset after handling missing values

Handling Duplicates

In [23]:
```
data.drop_duplicates(inplace=True)
```

In [24]:
```
data.duplicated().sum()
```

Out[24]:
```
0
```

In [25]:
```
data.shape
```

Out[25]:
```
(23068, 23)
```

After removing the duplicate row the dataset has 23,068 rows and 23 columns.

Type Conversion

This is the process of converting data of one type to another.

In [26]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 23068 entries, 7 to 88886
Data columns (total 23 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                23068 non-null  object 
 1   Investigation.Type      23068 non-null  object 
 2   Accident.Number         23068 non-null  object 
 3   Event.Date              23068 non-null  object 
 4   Location                23068 non-null  object 
 5   Country                 23068 non-null  object 
 6   Injury.Severity         23068 non-null  object 
 7   Aircraft.damage         23068 non-null  object 
 8   Aircraft.Category       23068 non-null  object 
 9   Make                    23068 non-null  object 
 10  Model                   23068 non-null  object 
 11  Amateur.Built           23068 non-null  object 
 12  Number.of.Engines       23068 non-null  float64
 13  Engine.Type             23068 non-null  object 
 14  FAR.Description         23068 non-null  object 
 15  Purpose.of.flight       23068 non-null  object 
 16  Air.carrier             23068 non-null  object 
 17  Total.Fatal.Injuries    23068 non-null  float64
 18  Total.Serious.Injuries  23068 non-null  float64
 19  Total.Minor.Injuries    23068 non-null  float64
 20  Total.Uninjured         23068 non-null  float64
 21  Weather.Condition       23068 non-null  object 
 22  Broad.phase.of.flight   23068 non-null  object 
dtypes: float64(5), object(18)
memory usage: 4.2+ MB
```

In [27]:
```python
Int_Conversion = ['Number.of.Engines', 'Total.Fatal.Injuries', 'Total.Serious.Injuries
                  'Total.Uninjured' ]
for column in Int_Conversion:
    data[column] = data[column].astype(int)
```

In [28]:
```python
# Format the date into the pandas date format
data['Event.Date'] = pd.to_datetime(data['Event.Date'])
```

In [29]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 23068 entries, 7 to 88886
Data columns (total 23 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Event.Id               23068 non-null  object
 1   Investigation.Type     23068 non-null  object
 2   Accident.Number        23068 non-null  object
 3   Event.Date             23068 non-null  datetime64[ns]
 4   Location               23068 non-null  object
 5   Country                23068 non-null  object
 6   Injury.Severity        23068 non-null  object
 7   Aircraft.damage        23068 non-null  object
 8   Aircraft.Category      23068 non-null  object
 9   Make                   23068 non-null  object
 10  Model                  23068 non-null  object
 11  Amateur.Built          23068 non-null  object
 12  Number.of.Engines      23068 non-null  int32
 13  Engine.Type            23068 non-null  object
 14  FAR.Description        23068 non-null  object
 15  Purpose.of.flight      23068 non-null  object
 16  Air.carrier            23068 non-null  object
 17  Total.Fatal.Injuries   23068 non-null  int32
 18  Total.Serious.Injuries  23068 non-null  int32
 19  Total.Minor.Injuries   23068 non-null  int32
 20  Total.Uninjured        23068 non-null  int32
 21  Weather.Condition      23068 non-null  object
 22  Broad.phase.of.flight  23068 non-null  object
dtypes: datetime64[ns](1), int32(5), object(17)
memory usage: 3.8+ MB
```

Data Consistency

In [30]:
```
# Get a list of unique values in the 'Make' column
unique_makes = data['Make'].unique()

print("Unique makes:", unique_makes)
```

```
Unique makes: ['Cessna' 'Bellanca' 'Navion' ... 'CHILDS MICHAEL  A' 'GREG HOBBS'
 'ORLICAN S R O']
```

In [31]:
```
# Convert 'Make' column to lowercase and then capitalize the first letter
data['Make'] = data['Make'].str.lower().str.capitalize()
data['Make']
```

Out[31]:
```
7                              Cessna
8                              Cessna
12                           Bellanca
13                             Cessna
14                             Navion
                      ...
88859      Arado-flugzeugwerke gmbh
88865                          Cessna
88873             Cirrus design corp
88877                          Cessna
88886    American champion aircraft
Name: Make, Length: 23068, dtype: object
```

In [32]:
```
# Get a list of unique values in the 'Weather.Condition' column
unique_makes = data['Weather.Condition'].unique()

print("Unique makes:", unique_makes)
```

```
Unique makes: ['VMC' 'IMC' 'UNK' 'Unk']
```

In [33]:
```
# Convert 'Weather.Condition'' column to lowercase and then capitalize the first lette
data['Weather.Condition'] = data['Weather.Condition'].str.upper()
data['Weather.Condition']
```

Out[33]:
```
7        VMC
8        IMC
12       IMC
13       IMC
14       IMC
        ... 
88859    VMC
88865    VMC
88873    VMC
88877    VMC
88886    VMC
Name: Weather.Condition, Length: 23068, dtype: object
```

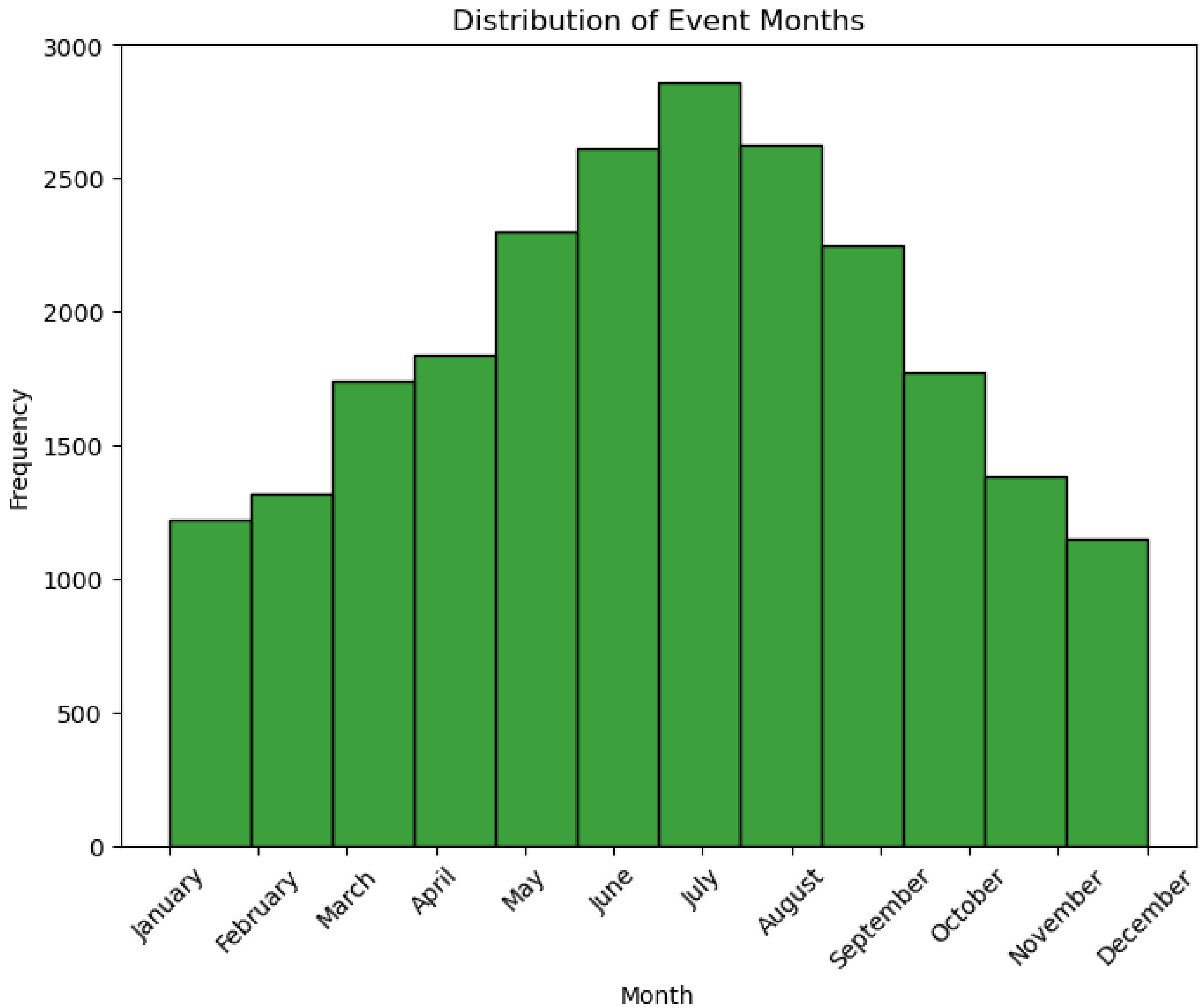
4. Data Analysis

Exploratory Data Analysis

Univariate Analysis

a) Event Month

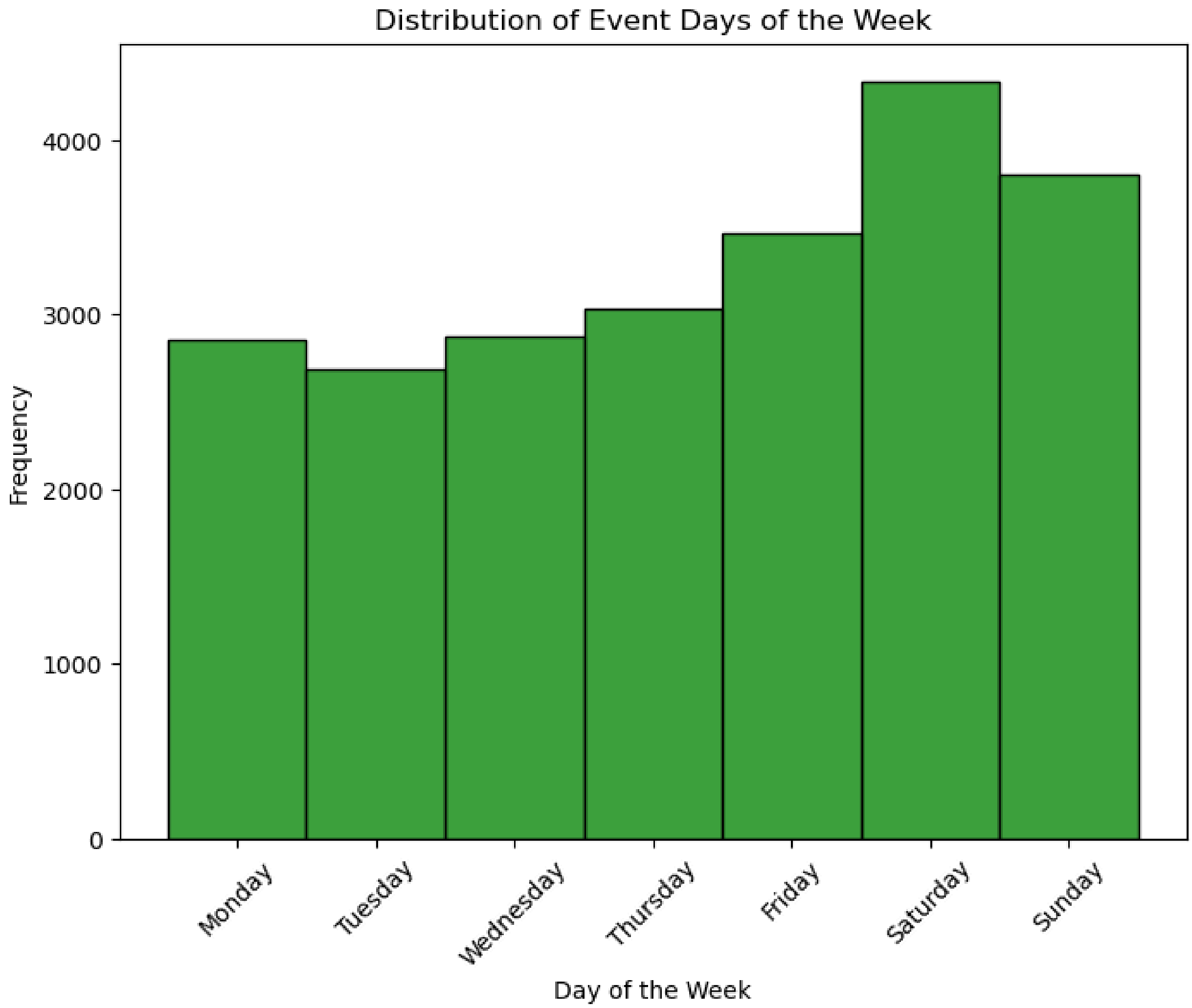
In [34]:
```
# Convert 'Event.Date' to months
data['Month'] = data['Event.Date'].dt.month

# Create a histogram
plt.figure(figsize=(8, 6))
ax = sns.histplot(data=data, x='Month', color='green', bins=12)

# Set the x-axis labels to full month names
ax.set_xticks(range(1, 13))
ax.set_xticklabels([calendar.month_name[i] for i in range(1, 13)], rotation=45)

plt.title('Distribution of Event Months')
plt.xlabel('Month')
plt.ylabel('Frequency')
plt.show()

plt.savefig('Distribution of Event Months.png');
```




```
<Figure size 640x480 with 0 Axes>
```

Most of the accidents happen between June, July and August. This can be attributed to the season of summer where most people are on holidays and are travelling more.

In [35]:
```
# Extract the day of the week from the 'Event.Date' column
data['Day_of_Week'] = data['Event.Date'].dt.day_name()

# Specify the order of days of the week
days_of_week = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'S

# Sort the data by the order of days_of_week
data['Day_of_Week'] = pd.Categorical(data['Day_of_Week'], categories=days_of_week, orc

# Create a histogram
plt.figure(figsize=(8, 6))
sns.histplot(data=data, x='Day_of_Week', color='green', bins=7, discrete=True)
plt.title('Distribution of Event Days of the Week')
plt.xlabel('Day of the Week')
plt.ylabel('Frequency')
plt.xticks(rotation=45)
plt.show()

plt.savefig('Distribution of Event Days.png');
```

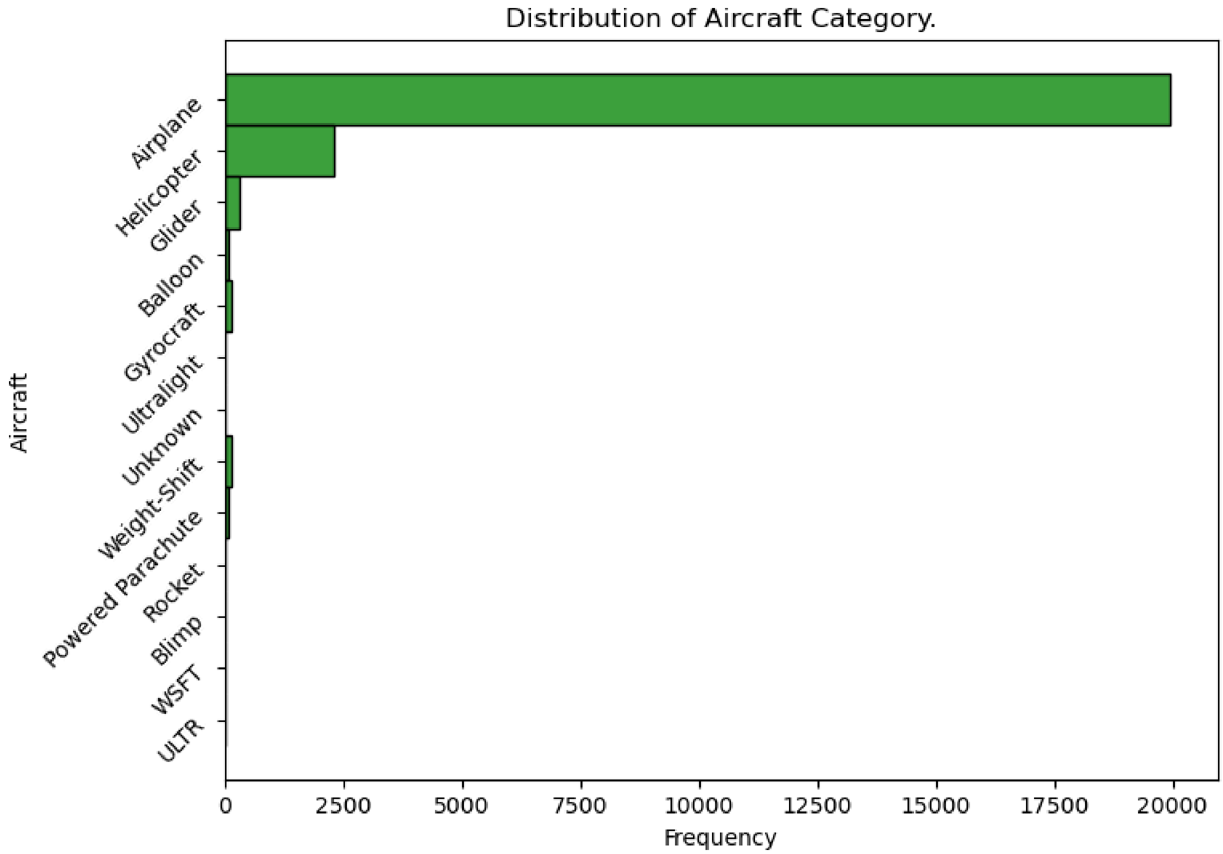



```
<Figure size 640x480 with 0 Axes>
```

Most of the accidents also happen between Friday, Saturday and Sunday. This can be attributed to the weekend where most people are also travelling more.

b) Aircraft Category

In [36]:
```
plt.figure(figsize=(8, 6))
sns.histplot(data=data, y='Aircraft.Category', color='green', bins=15)
plt.title('Distribution of Aircraft Category.')
plt.xlabel('Frequency')
plt.ylabel('Aircraft')
plt.yticks(rotation=45)
plt.show()

plt.savefig('Distribution of Aircraft Category.png');
```



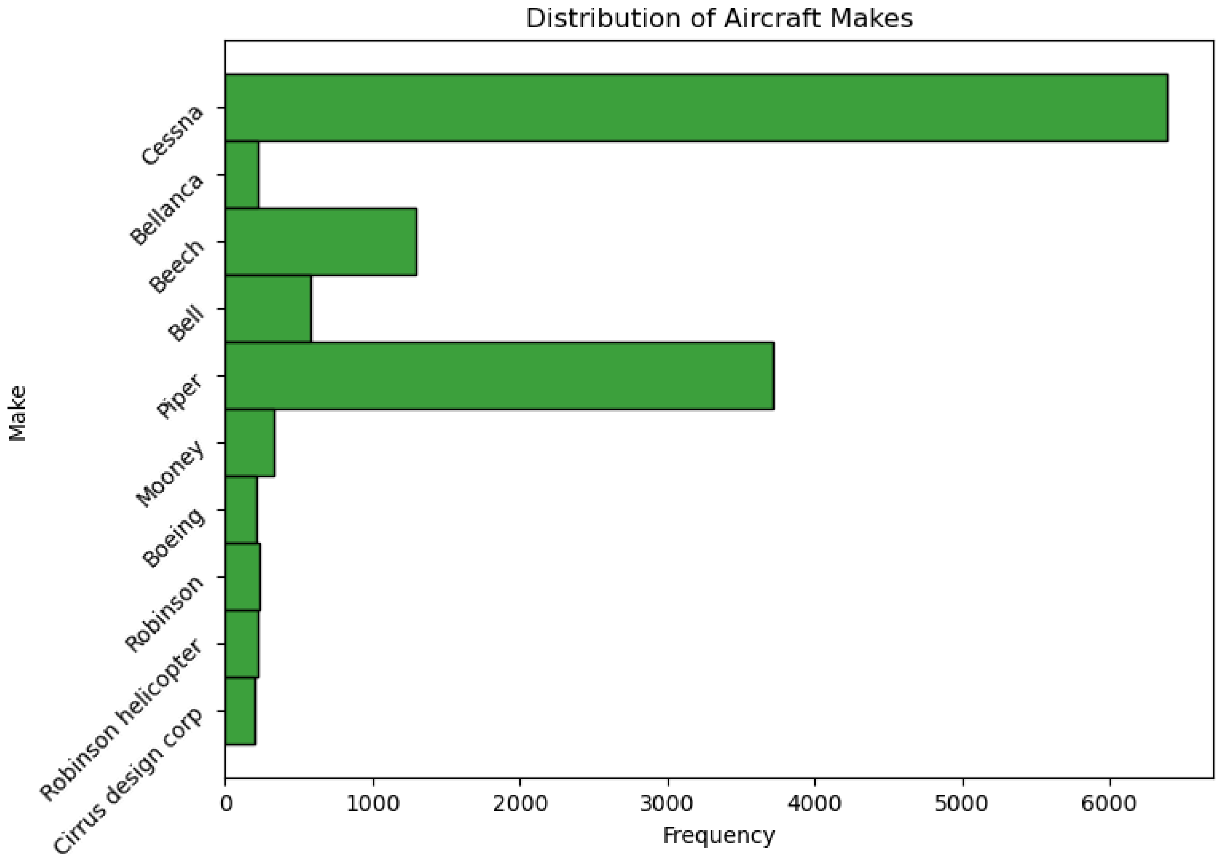

```
<Figure size 640x480 with 0 Axes>
```

Airplanes are more prone to accidents whereby Helicopters, Gliders and Gyrocraft are less likely to be in accidents.

c) Make

In [37]:

```
# Get the top 10 makes
top_10_makes = data['Make'].value_counts().head(10).index.tolist()

# Filter the data to include only the top 10 makes
top_10_data = data[data['Make'].isin(top_10_makes)]

# Plot the histogram
plt.figure(figsize=(8, 6))
sns.histplot(data=top_10_data, y='Make', color='green', bins=10)
plt.title('Distribution of Aircraft Makes')
plt.xlabel('Frequency')
plt.ylabel('Make')
plt.yticks(rotation=45)
plt.show()

plt.savefig('Distribution of Aircraft Makes.png');
```

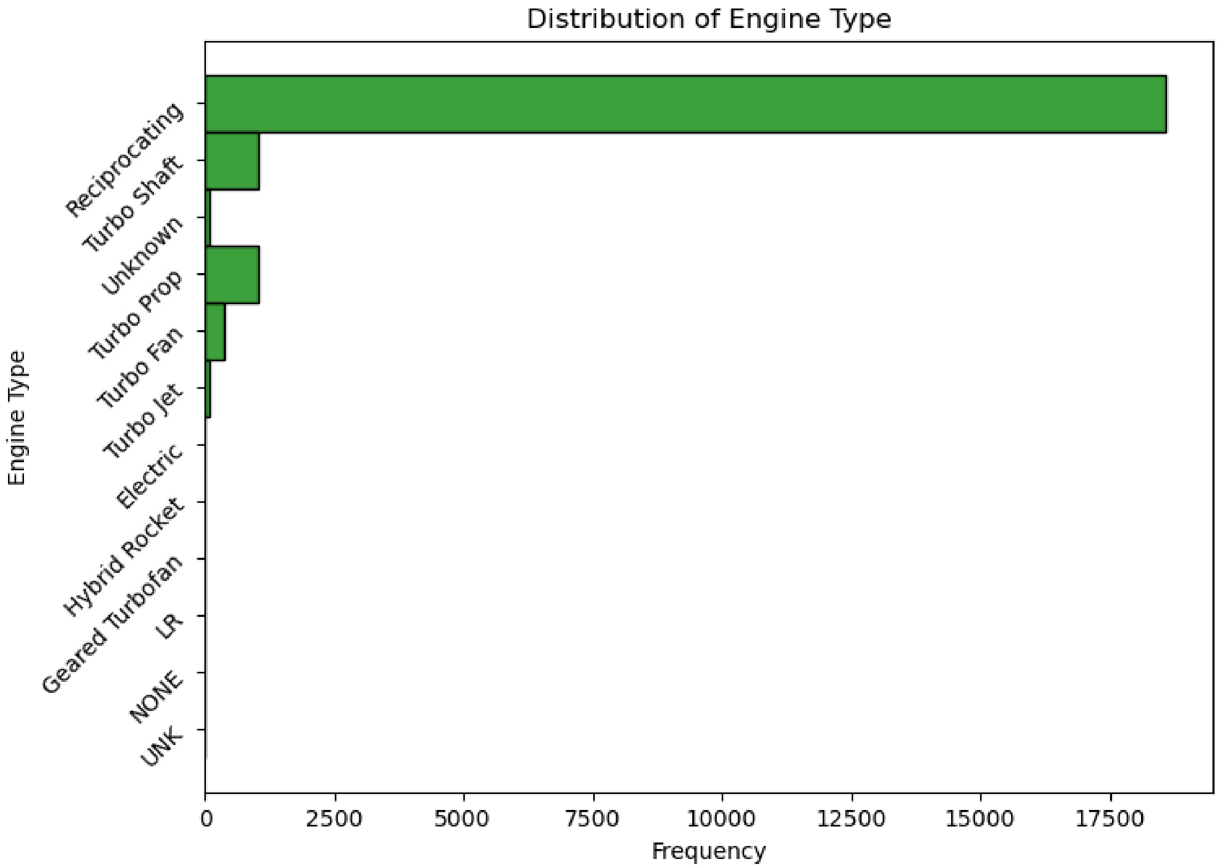



```
<Figure size 640x480 with 0 Axes>
```

Cessna, Piper, and Beech are makes of aircrafts with more aviation accidents.

d) Engine Type

In [38]:
```
# Filter out rows with 'None' in the Engine Type column
filtered_data = data[data['Engine.Type'] != 'None']

# Create a histogram
plt.figure(figsize=(8, 6))
sns.histplot(data=filtered_data, y='Engine.Type', color='green', bins=13)
plt.title('Distribution of Engine Type')
plt.ylabel('Engine Type')
plt.yticks(rotation=45)
plt.xlabel('Frequency')
plt.show()

plt.savefig('Distribution of Engine Type.png');
```

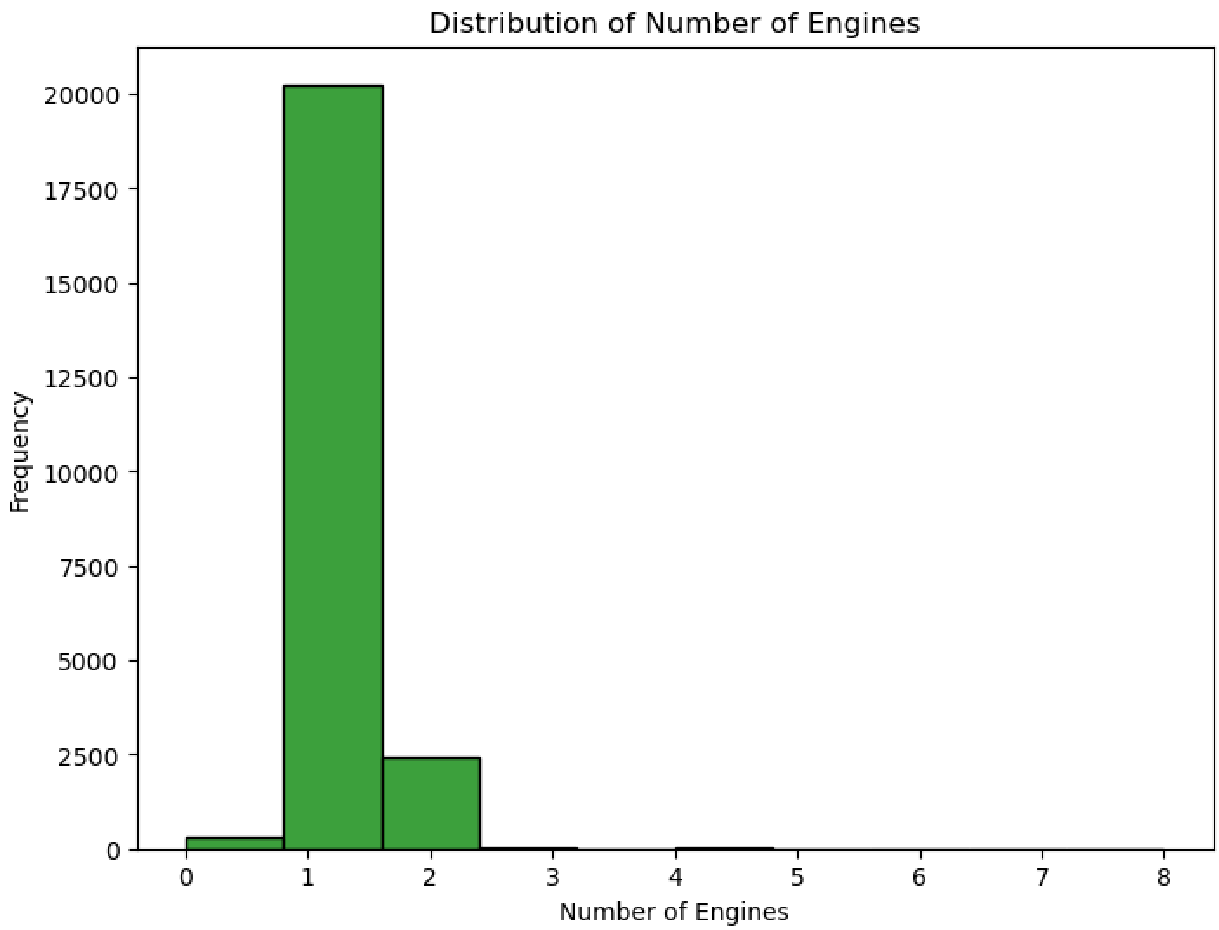



```
<Figure size 640x480 with 0 Axes>
```

Aircrafts with Reciprocating Engine Type have a high chance of being in an accident.

e) Engine Number

In [39]:
```
# Create a histogram
plt.figure(figsize=(8, 6))
sns.histplot(data=data, x='Number.of.Engines', color='green', bins=10)
plt.title('Distribution of Number of Engines')
plt.xlabel('Number of Engines')
plt.ylabel('Frequency')
plt.show()

plt.savefig('Distribution of Engine Numbers.png');
```

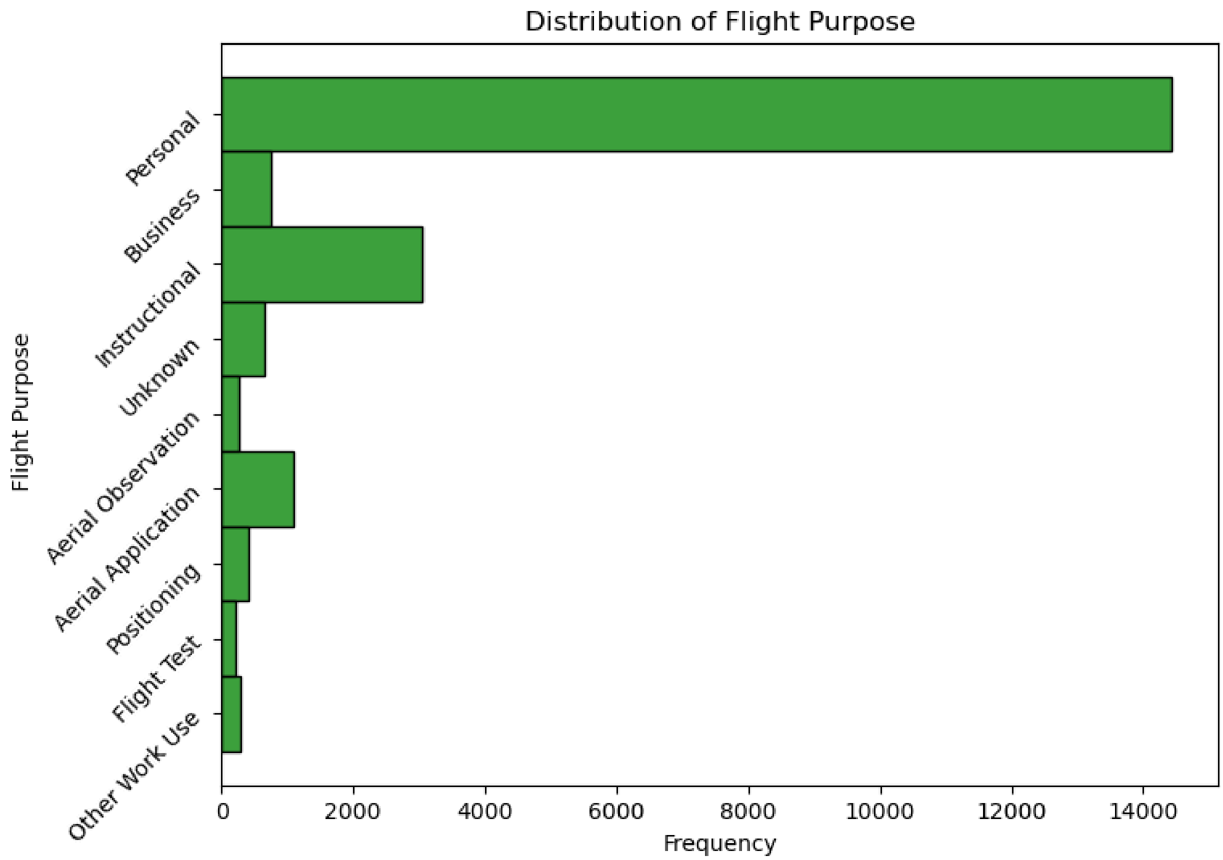



```
<Figure size 640x480 with 0 Axes>
```

1 engine aircrafts have more counts of accidents.

f) Flight Purpose

In [40]:
```
top_10 = data['Purpose.of.flight'].value_counts().head(10).index.tolist()

# Filter the data to include only the top 10 makes
top_10_data = data[data['Purpose.of.flight'].isin(top_10) &
                            (data['Purpose.of.flight'] != 'None')]

# Create a histogram
plt.figure(figsize=(8, 6))
sns.histplot(data=top_10_data, y='Purpose.of.flight', color='green', bins=10)
plt.title('Distribution of Flight Purpose')
plt.ylabel(' Flight Purpose')
plt.yticks(rotation=45)
plt.xlabel('Frequency')
plt.show()

plt.savefig('Distribution of Flight Purpose.png');
```




```
<Figure size 640x480 with 0 Axes>
```

Top five flight purposes for the aircrafts that are involved in accidents are personal, instructional, aerial application, business and positioning. Since the stakeholder is looking to purchase and operate aircrafts for commercial and private enterprises this is the main variable to be used in the bivariate analysis.

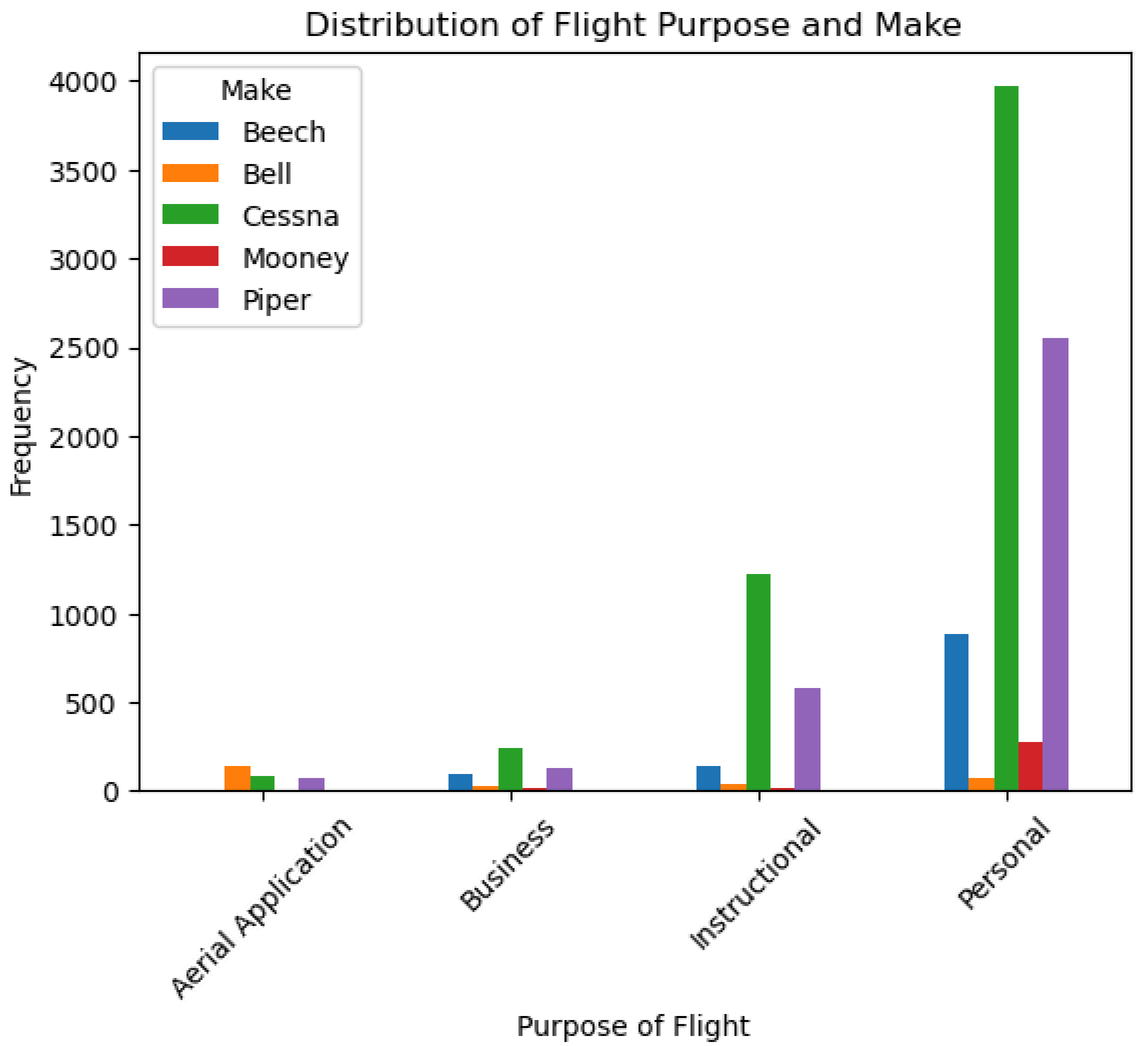
Bivariate Analysis

a) Flight Purpose and Make

In [41]:
```
# Get the top 5 values for 'Purpose of Flight' and 'Make'
top_5_purpose = data['Purpose.of.flight'].value_counts().head(5).index.tolist()
top_5_make = data['Make'].value_counts().head(5).index.tolist()

# Filter the data to include only the top 5 values for both columns and exclude 'None'
filtered_data = data[(data['Purpose.of.flight'].isin(top_5_purpose)) & (data['Purpose.
                              != 'None') & (data['Make'].isin(top_5_make)) & (data['Ma

# Create a cross-tabulation of the two columns
cross_tab = pd.crosstab(filtered_data['Purpose.of.flight'], filtered_data['Make'])

# Plot a clustered bar chart
plt.figure(figsize=(8, 6))
cross_tab.plot(kind='bar', stacked=False)
plt.title('Distribution of Flight Purpose and Make')
plt.xlabel('Purpose of Flight')
plt.ylabel('Frequency')
plt.legend(title='Make')
```

```
plt.xticks(rotation=45)
plt.show()

plt.savefig('Distribution of Flight Purpose and Make.png');
```

```
<Figure size 800x600 with 0 Axes>
```




```
<Figure size 640x480 with 0 Axes>
```

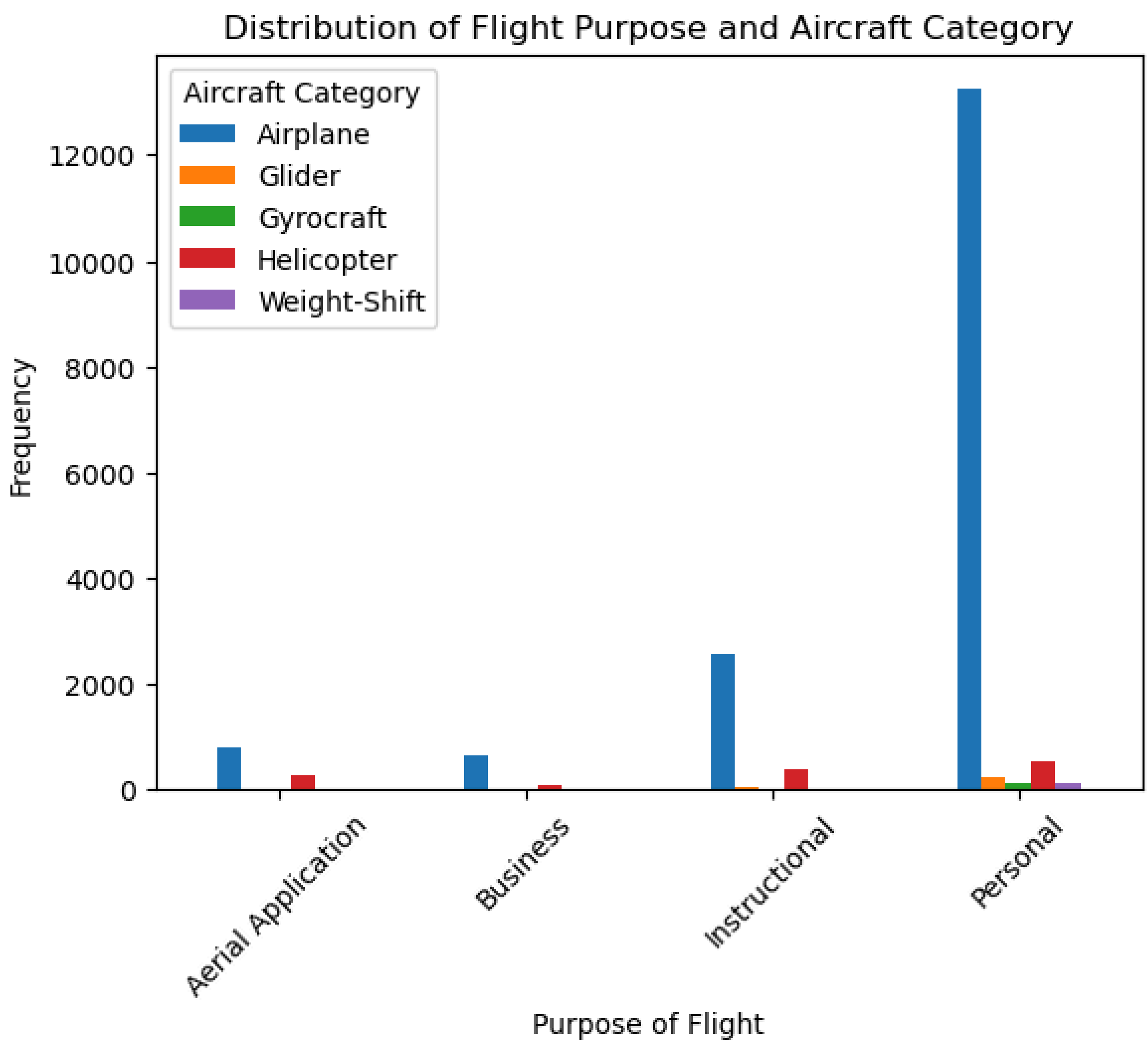
Aircrafts of the make Bell or Mooney are less prone to accidents.

b) Flight Purpose and Aircraft Category

In [42]:
```
# Get the top 5 values
top_5_purpose = data['Purpose.of.flight'].value_counts().head(5).index.tolist()
top_5_category = data['Aircraft.Category'].value_counts().head(5).index.tolist()

# Filter the data to include only the top 5 values and exclude 'None
filtered_data = data[(data['Purpose.of.flight'].isin(top_5_purpose)) & (data['Purpose.
                              != 'None') & (data['Aircraft.Category'].isin(top_5_categ

# Create a cross-tabulation of the two columns
cross_tab = pd.crosstab(filtered_data['Purpose.of.flight'], filtered_data['Aircraft.Ca

# Plot a clustered bar chart
plt.figure(figsize=(8, 6))
```

```
cross_tab.plot(kind='bar', stacked=False)
plt.title('Distribution of Flight Purpose and Aircraft Category')
plt.xlabel('Purpose of Flight')
plt.ylabel('Frequency')
plt.legend(title='Aircraft Category')
plt.xticks(rotation=45)
plt.show()

plt.savefig('Distribution of Flight Purpose and Aircraft Category.png');
```

```
<Figure size 800x600 with 0 Axes>
```




```
<Figure size 640x480 with 0 Axes>
```

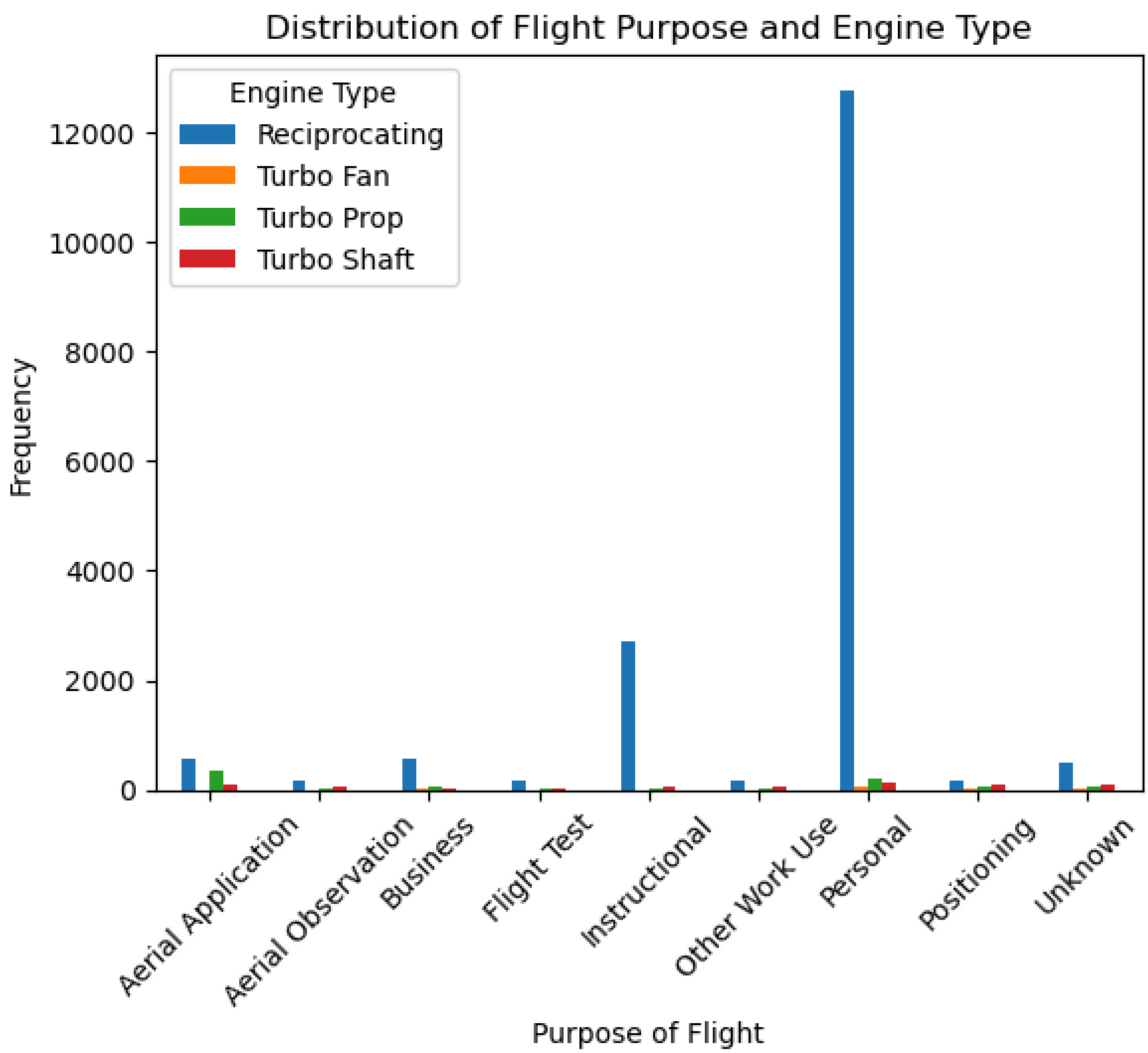
A helicopter instead of an Airplane is less risky.

c) Flight Purpose and Engine Type

In [43]:
```
# Get the top values for the columns
top_5_purpose = data['Purpose.of.flight'].value_counts().head(10).index.tolist()
top_5_type = data['Engine.Type'].value_counts().head(5).index.tolist()

# Filter the data to include only the top values and exclude 'None
filtered_data = data[(data['Purpose.of.flight'].isin(top_5_purpose)) & (data['Purpose.
                              != 'None') & (data['Engine.Type'].isin(top_5_type)) &
                              (data['Engine.Type'] != 'None')]
```

```
# Create a cross-tabulation of the two columns
cross_tab = pd.crosstab(filtered_data['Purpose.of.flight'], filtered_data['Engine.Type

# Plot a clustered bar chart
plt.figure(figsize=(8, 6))
cross_tab.plot(kind='bar', stacked=False)
plt.title('Distribution of Flight Purpose and Engine Type')
plt.xlabel('Purpose of Flight')
plt.ylabel('Frequency')
plt.legend(title='Engine Type')
plt.xticks(rotation=45)
plt.show()

plt.savefig('Distribution of Flight Purpose and Engine Type.png');
```

```
<Figure size 800x600 with 0 Axes>
```




```
<Figure size 640x480 with 0 Axes>
```

Aircrafts with engine type of Turbo Shaft, Turbo Fan, Turbo Prop are not as prone to accidents as the reciprocating engine.

5. Conclusion

For data cleaning, missing values were addressed, duplicates were eliminated, type conversions were performed, and data consistency was ensured by standardizing string formats in certain columns.

The top five flight purposes for aircraft involved in accidents were personal, instructional, aerial application, business, and positioning. Given that the stakeholder plans to purchase and operate aircraft for both commercial and private use, this variable was the focus of the bivariate analysis.

6. Recommendations

The head of the new aviation division is advised to consider the following:

1. Purchase aircrafts from the Bell or Mooney manufacturers.
2. Opt for a helicopter over an airplane.
3. Choose aircrafts with Turbo Shaft, Turbo Fan, or Turbo Prop engine types.