```
BUSINESS UNDERSTANDING
```

The main goal is to analyze and predict the risks associated with purchasing and operating airplanes for both commercial and private enterprises, as part of my company's new diversification strategy.

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PROBLEM STATEMENT
```

The goal of this analysis is to examine the AviationData dataset to identify key factors influencing the viability of a project focused on aircraft operations. Specifically, I will assess the risks associated with airplane accidents and the survival rates following such incidents.

```
OBJECTIVES
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```
1.Investigate the relationship between engine type and the frequency of accidents.
2.Examine the correlation between the number of engines per aircraft and the recorded number of accidents.
3.Identify and analyze key factors that contribute to aircraft accidents, such as weather conditions and amateur-built aircraft.
4.Develop visualizations to effectively communicate the insights and findings derived from the analysis.
```

```
REASEARCH QUESTIONS
```

```
1.What are the key aircraft characteristics that impact the likelihood of an accident?
2.Does the country of operation play a significant role in determining the probability of an airplane accident?
3.How does the phase of flight affect the survival rate in the event of an aircraft accident?
```

```
#Importing essential libraries for data analysis and visualization
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

DATA UNDERSTANDING

```
#Loading the aviation dataset from a CSV file into a pandas DataFrame and checking the top columns
import csv
Aviation_data = pd.read_csv('AviationData.csv', encoding='ISO-8859-1')
Aviation_data.head()
```

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

5 rows × 31 columns

```
#Check the last 5 Columns
Aviation_data.tail()
```

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	Airport.Na
88884	20221227106491	Accident	ERA23LA093	2022-12-26	Annapolis, MD	United States	NaN	NaN	NaN	N
88885	20221227106494	Accident	ERA23LA095	2022-12-26	Hampton, NH	United States	NaN	NaN	NaN	N
88886	20221227106497	Accident	WPR23LA075	2022-12-26	Payson, AZ	United States	341525N	1112021W	PAN	PAYS(
88887	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	NaN	NaN	NaN	N
88888	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	NaN	NaN	NaN	N

5 rows × 31 columns

```
# To get the summary information about the dataset
Aviation_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            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
```

```
#To get statistics for the numerical columns in the dataset
Aviation_data.describe()
```

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Total.Uninjured
count	82805.000000	77488.000000	76379.000000	76956.000000	82977.000000
mean	1.146585	0.647855	0.279881	0.357061	5.325440
std	0.446510	5.485960	1.544084	2.235625	27.913634
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.000000	0.000000	0.000000	1.000000
75%	1.000000	0.000000	0.000000	0.000000	2.000000
max	8.000000	349.000000	161.000000	380.000000	699.000000

```
#To get the Column names
print(list(Aviation_data.columns))
```

```
['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Date', 'Location', 'Country', 'Latitude', 'Longitude', 'Airport.Code', 'Air
```

MISSING DATA

```
# Check for missing values in the 'Aviation_data' DataFrame
# identify which columns have missing data and how many missing values each column has.
Aviation_data.isna().sum()
```

```
Event.Id                      0
Investigation.Type            0
Accident.Number               0
Event.Date                    0
Location                     52
Country                     226
Latitude                  54507
Longitude                 54516
Airport.Code              38757
Airport.Name              36185
Injury.Severity            1000
Aircraft.damage            3194
Aircraft.Category         56602
Registration.Number        1382
Make                         63
Model                        92
Amateur.Built               102
Number.of.Engines          6084
Engine.Type                7096
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              6384
Publication.Date          13771
dtype: int64
```

```
# Fill missing values (NaN) in specific columns of the 'Aviation_data' DataFrame
# Set missing values to 0
Aviation_data = Aviation_data.fillna({'Total.Fatal.Injuries': 0, 'Total.Serious.Injuries':0, 'Total.Minor.Injuries':0, 'Total.Uninjured':0,
```

```
#Replacing missing values in the Aircraft damage/Phase of flight column
Aviation_data = Aviation_data.fillna({'Aircraft.damage': 'Unknown', 'Broad.phase.of.flight': 'Unknown'})
```

```
#Additional replacement of missing values
Aviation_data = Aviation_data.fillna({'Country': 'Undefined', 'Location': 'Unknown', 'Injury.Severity': 'Unknown', 'Model': 0, 'Make': 'Unkr
```

```
#Additional replacement of missing values
Aviation_data = Aviation_data.fillna({'Country': 'Undefined', 'Location': 'Unknown', 'Injury.Severity': 'Unknown', 'Model': 0, 'Make': 'Unkr
```

```
# Check the column names before dropping
print("Original Columns:", Aviation_data.columns)

# Dropping unnecessary columns with missing data, while ignoring errors for non-existent columns
Aviation_data = Aviation_data.drop(
    ['Aircraft.Category', 'Latitude', 'Longitude', 'Airport.Code', 'FAR.Description', 'Air.carrier', 'Schedule'],
    axis=1,
    errors='ignore'
)

# Display the remaining columns after dropping
print("Updated Columns:", Aviation_data.columns)
```

```
Original Columns: 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')
Updated Columns: Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Date',
       'Location', 'Country', 'Airport.Name', 'Injury.Severity',
       'Aircraft.damage', 'Registration.Number', 'Make', 'Model',
       'Amateur.Built', 'Number.of.Engines', 'Engine.Type',
       'Purpose.of.flight', 'Total.Fatal.Injuries', 'Total.Serious.Injuries',
       'Total.Minor.Injuries', 'Total.Uninjured', 'Weather.Condition',
       'Broad.phase.of.flight', 'Report.Status', 'Publication.Date'],
      dtype='object')
```

```
Aviation_data.isna().sum()
```

```
Event.Id                    0
Investigation.Type          0
Accident.Number             0
Event.Date                  0
Location                    0
Country                     0
Airport.Name            36185
Injury.Severity             0
Aircraft.damage             0
Registration.Number      1382
Make                        0
Model                       0
Amateur.Built               0
Number.of.Engines           0
Engine.Type                 0
Purpose.of.flight           0
Total.Fatal.Injuries        0
Total.Serious.Injuries      0
Total.Minor.Injuries        0
Total.Uninjured             0
Weather.Condition           0
Broad.phase.of.flight       0
Report.Status            6384
Publication.Date        13771
dtype: int64
```

HANDLING MISSING DATA

```
#Check if we have duplicated data
Aviation_data.duplicated().sum()
```

```
0
```

```
#Check the shape of the data
Aviation_data.shape
```

```
(88889, 24)
```

DATA ANALYSIS

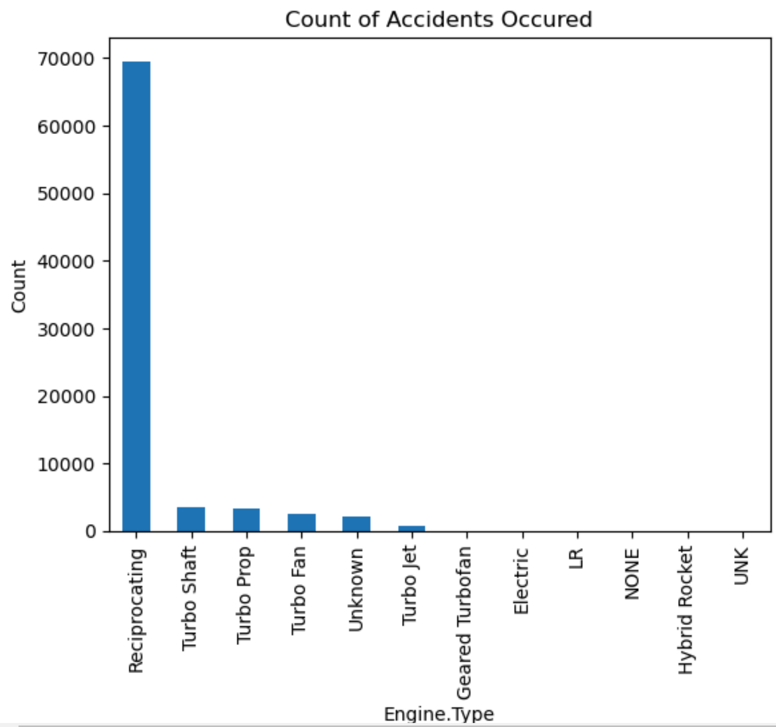
```
#Get asummary table showing the count of rows (accidents or events) for each engine type
Summary_data1 = Aviation_data.pivot_table(aggfunc='size', index='Engine.Type', fill_value=0)
print(Summary_data1)
```

```
Engine.Type
Electric             10
Geared Turbofan      12
Hybrid Rocket         1
LR                    2
NONE                  2
Reciprocating     69530
Turbo Fan          2481
Turbo Jet           703
Turbo Prop         3391
Turbo Shaft        3609
UNK                   1
Unknown            2051
dtype: int64
```

1. Engine vs Accidents

This is to comapare the relationship between the engine type and the occurance of an accident

```
Aviation_data['Engine.Type'].value_counts().plot(kind='bar')
plt.title('Count of Accidents Occured')
plt.xlabel('Engine.Type')
plt.ylabel('Count')
plt.show()
```

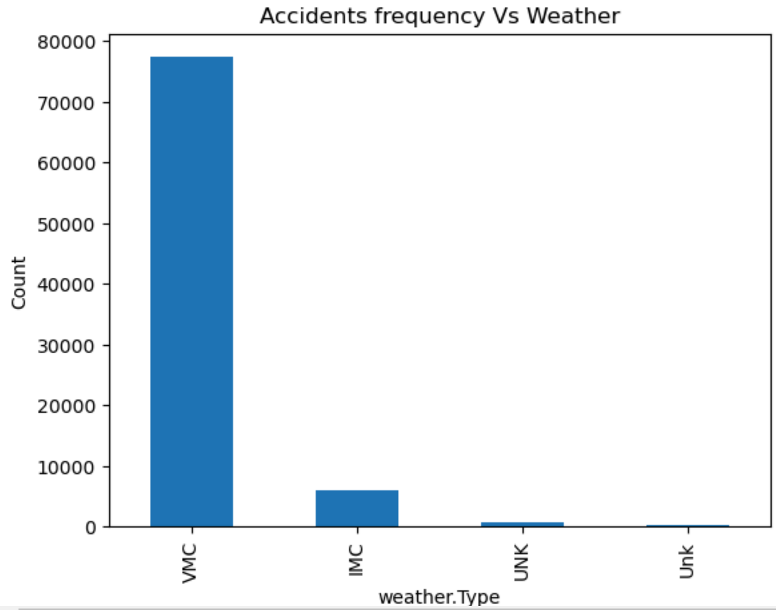


Reciprocating engines have the most accidents. This answers our first objective of checking the relationship between the engine types and the accidents occurance

2. ACCIDENTS FREQUENCY VS WEATHER`

This checks the Overal perfomance of all the aircrafts in diffrent weather Conditions

```
Aviation_data['Weather.Condition'].value_counts().plot(kind='bar')
plt.title('Accidents frequency Vs Weather')
plt.xlabel('weather.Type')
plt.ylabel('Count')
plt.show()
```

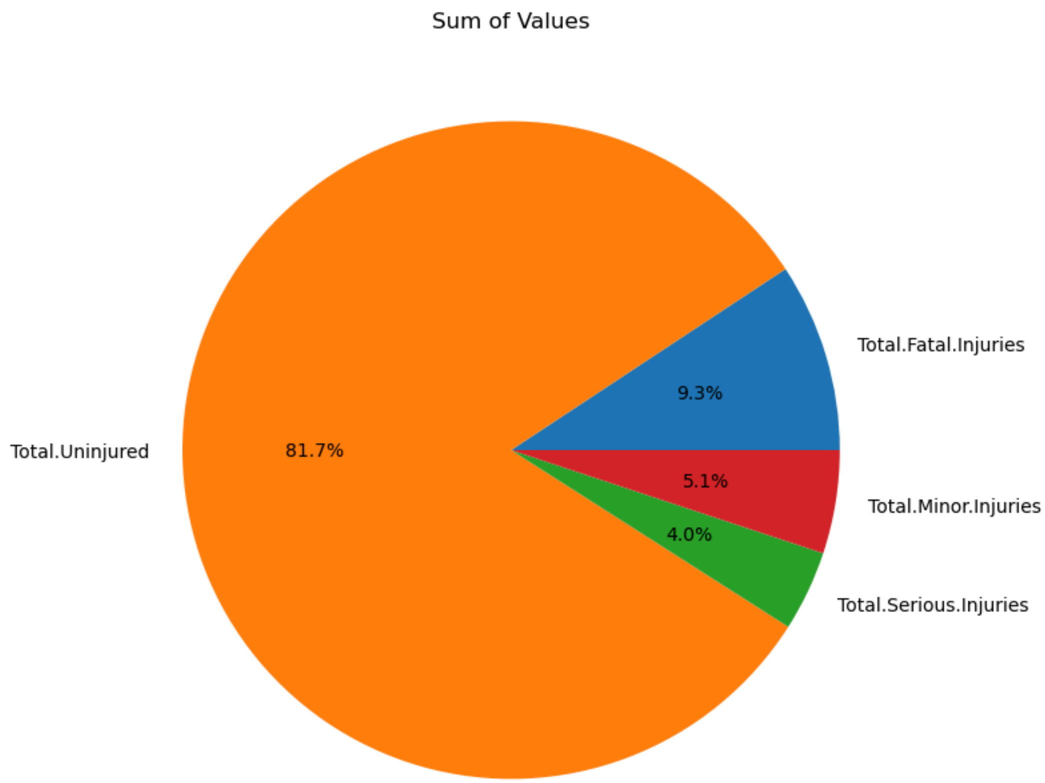


From the Visualization its clear that the VMC weather condition records the most accidents . The UNK condition records the least accidents

3. **INJURIES VISUALIZATION**

This is to give a visual on the extend of injuries on the people in the aircrafts

```
#Get total counts for fatal injuries, uninjured passengers, serious injuries, and minor injuries across all records.
Aviation_data_selected = Aviation_data[['Total.Fatal.Injuries', 'Total.Uninjured', 'Total.Serious.Injuries', 'Total.Minor.Injuries']].sum()


Aviation_data_selected.plot(kind='pie', autopct='%1.1f%%', figsize=(8, 8), title="Sum of Values")
plt.ylabel('')  # Hide the y label
plt.show()
```

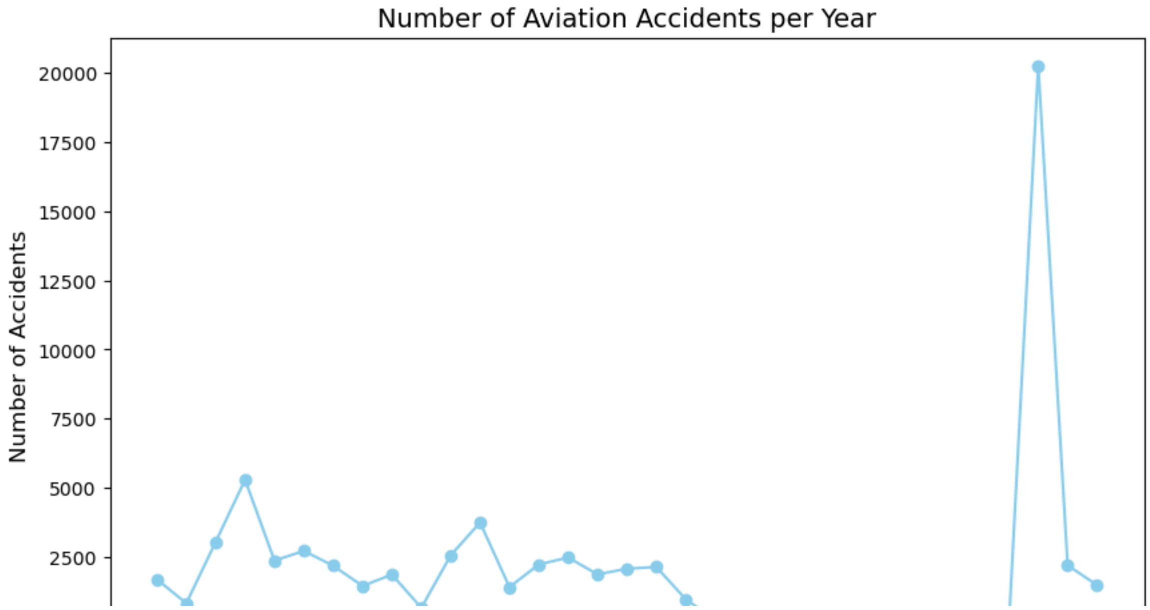


81.7 % of the passengers and crew remain uninjured. Out of the 19.7% who are injured,9.3% are fatal

4. **ACCIDENTS PER YEAR TRENDS**

To give a general overview of the frequency of accidents occurance from 1990 to 2022

```
# Compare the incidents Year to year from 1990 to 2022 in a bar chart

Aviation_data['Publication.Date'] = pd.to_datetime(Aviation_data['Publication.Date'], errors='coerce')

# Extract the year from the 'Event.Date' column
Aviation_data['Year'] = Aviation_data['Publication.Date'].dt.year

# Filter the data to only include incidents from 1990 to 2022
Aviation_data_filtered = Aviation_data[(Aviation_data['Year'] >= 1990) & (Aviation_data['Year'] <= 2022)]

# Group the data by year and count the number of incidents per year
Grouped_by_Year = Aviation_data_filtered.groupby('Year').size()

# Plot the incidents per year as a line chart
Grouped_by_Year.plot(kind='line', color='skyblue', marker='o', figsize=(10, 6))

# Generating Visuals
plt.title('Number of Aviation Accidents per Year', fontsize=14)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Number of Accidents', fontsize=12)

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



From the year 1990 to 2022. General decline in occurance however in 2020 there was a sharp rise followed by a decline.

- Majority of the accidents then happened under the VMC weather conditions

DATA LIMITATION

Reporting StandardS Variations