Final Project Submission

Please fill out:

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- Scheduled project review date/time:
- Instructor name: Nikita Njoroge
- Blog post URL:

In [40]:
```
# Your code here - remember to use markdown cells for comments as well!
```

BUSINESS UNDERSTANDING

INTRODUCTION

The company is seeking to diversify its operations by acquiring and operating private and commercial aircrafts. In the case, the company seeks data driven insights to determine which aircrafts present the lowest operational risk to venture in.

In this notebook will provide intense data cleaning, analysis and visualization to address the business problem of determining the lowest-risk aircraft for the company to venture in within the aviation industry. The goal is to leverage historical aviation accident data to generate insights and recommendations to the Head of the New Aviation Division. The insights should help the business decide on which aircraft to purchase.

DATA UNDERSTANDING

This analysis will be leverage comprehensive aviation dataset provided by the National Transport Safety Board(NTSB)

The data collected from 1962 to 2023 File: Aviation_Data csv in the data folder The dataset contains 90348 rows of data and 31 columns to provide content on aviation safety

This dataset from NTSB is highly suitable for this project as it provides historical, comprehesive and standard records of aviation accidents and incidents in US and International waters which is directly relevant to this project to determine which aircrafts pose the lowest operational risk.

Some essential features in the dataset include

```
Aircraft Make

Aircraft Model

Injury Severity

Total Fatal Injury

Purpose of Flight

Aircraft Damage
```

However, the dataset is suitable for the project but has some limitations and implications that must be managed

```
1. The dataset lacks some operational data. In the case this dataset provides
only accident data such as aircraft category by Accident but doesnt not
provide content such as total no. of flight hours , total departures for a
given make/ model over a period of time

2. Lack of data Consistency:The naming conventions in the aviation industry
have changed over time since 1962. There are variations like past years there
was a model 737 which changed the convention naming to B737-300 after some
time.
```

The steps will be loading dataset, inspecting and understanding the dataset and later to data cleaning, analysis and visualization.

Import Relevant Libraries

In [41]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [42]:
```
#Loading dataset in csv format
aviation=pd.read_csv('data/Aviation_Data.csv', encoding='latin-1', low_memory=False)
aviation.head()
```

Out[42]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longit
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	N
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	N
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.922223	-81.878
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	N
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	N

5 rows × 31 columns

In [43]:
```
#The number of rows and columns in the dataset
aviation.shape
```

Out[43]:
```
(90348, 31)
```

In [44]:
```
# Take a look at the columns in the dataset
aviation.columns
```

Out[44]:
```
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 [45]:
```
#Drop columns that are irrelevant in achieving the data analysis objectives
aviation.drop(['Event.Id', 'Accident.Number', 'Event.Date',
        'Location', 'Country', 'Latitude', 'Longitude', 'Airport.Code',
        'Airport.Name', 'Registration.Number','Amateur.Built','FAR.Description',
        'Schedule', 'Air.carrier','Broad.phase.of.flight', 'Report.Status',
        'Publication.Date'],
        axis=1,
        inplace=True)
```

In [46]:
```
#Checking missing values for the remaining columns
aviation.columns
```

Out[46]:
```
Index(['Investigation.Type', 'Injury.Severity', 'Aircraft.damage',
       'Aircraft.Category', 'Make', 'Model', 'Number.of.Engines',
       'Engine.Type', 'Purpose.of.flight', 'Total.Fatal.Injuries',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured',
       'Weather.Condition'],
      dtype='object')
```

In [47]:
```
# Checking the total sum of missing values in columns
aviation.isna().sum()
```

Out[47]:
```
Investigation.Type            0
Injury.Severity            2459
Aircraft.damage            4653
Aircraft.Category         58061
Make                       1522
Model                      1551
Number.of.Engines          7543
Engine.Type                8536
Purpose.of.flight          7651
Total.Fatal.Injuries      12860
Total.Serious.Injuries    13969
Total.Minor.Injuries      13392
Total.Uninjured            7371
Weather.Condition          5951
dtype: int64
```

In [48]:
```
#Lets iterate over every column and calculate the relative frequency of the top five
#An important step in Exploratory Data Analysis.
for col in aviation.columns:
    print(col, '\n', aviation[col].value_counts(normalize=True).head(), '\n\n')
```

```
Investigation.Type
 Accident      0.940973
Incident      0.042879
25-09-2020    0.007770
26-09-2020    0.000664
02-02-2021    0.000432
Name: Investigation.Type, dtype: float64


Injury.Severity
 Non-Fatal    0.766387
Fatal(1)     0.070168
Fatal        0.059871
Fatal(2)     0.042224
Incident     0.025248
Name: Injury.Severity, dtype: float64


Aircraft.damage
 Substantial    0.748562
Destroyed      0.217317
Minor          0.032732
Unknown        0.001389
Name: Aircraft.damage, dtype: float64


Aircraft.Category
 Airplane      0.855360
Helicopter    0.106544
Glider        0.015734
Balloon       0.007155
Gyrocraft     0.005358
Name: Aircraft.Category, dtype: float64


Make
 Cessna    0.250231
Piper     0.135422
CESSNA    0.055412
Beech     0.048747
PIPER     0.031984
Name: Make, dtype: float64


Model
 152          0.026656
172          0.019775
172N         0.013109
PA-28-140    0.010496
150          0.009336
Name: Model, dtype: float64


Number.of.Engines
 1.0    0.840312
2.0    0.133796
0.0    0.014806
3.0    0.005833
4.0    0.005205
Name: Number.of.Engines, dtype: float64


Engine.Type
 Reciprocating    0.849875
Turbo Shaft      0.044113
Turbo Prop       0.041449
Turbo Fan        0.030326
Unknown          0.025070
Name: Engine.Type, dtype: float64


Purpose.of.flight
 Personal              0.597942
Instructional         0.128191
Unknown               0.082252
Aerial Application    0.056979
Business              0.048587
Name: Purpose.of.flight, dtype: float64


Total.Fatal.Injuries
 0.0    0.770119
1.0    0.114637
2.0    0.066759
3.0    0.020506
4.0    0.014234
Name: Total.Fatal.Injuries, dtype: float64


Total.Serious.Injuries
 0.0    0.828618
1.0    0.119470
2.0    0.036856
3.0    0.008235
4.0    0.003378
Name: Total.Serious.Injuries, dtype: float64


Total.Minor.Injuries
 0.0    0.798560
1.0    0.134103
2.0    0.046468
3.0    0.010188
4.0    0.004834
Name: Total.Minor.Injuries, dtype: float64


Total.Uninjured
 0.0    0.360088
1.0    0.302506
2.0    0.192680
3.0    0.051978
4.0    0.032081
Name: Total.Uninjured, dtype: float64


Weather.Condition
 VMC    0.915945
IMC    0.070808
UNK    0.010143
Unk    0.003104
Name: Weather.Condition, dtype: float64
```

Dealing with Missing values

In [49]:
```
# Lets deal with Categorical columns
#1. Engine type column
aviation['Engine.Type'].unique()
# there placeholder values ['nan',None,NONE,UNK,Unknown]
```

Out[49]:
```
array(['Reciprocating', nan, 'Turbo Fan', 'Turbo Shaft', 'Unknown',
       'Turbo Prop', 'Turbo Jet', 'None', 'Electric', 'Hybrid Rocket',
       'Geared Turbofan', 'LR', 'NONE', 'UNK'], dtype=object)
```

In [50]:
```
#Fill missing values in Engine type column with unknown
aviation['Engine.Type'].fillna(value='NOT KNOWN', inplace=True)
```

In [51]:
```
#Lets replace the placeholders "Unknown,nan,None,NONE and UNK" with 'NOT KNOWN'
aviation['Engine.Type']=aviation['Engine.Type'].map(lambda x: 'NOT KNOWN'if  x=='UNK'
```

In [52]:
```
#Lets execute the Purpose of flight and Aircraft Damage columns
#By imputing nan values with NOT KNOWN
# Assuming your DataFrame is named 'df'
aviation['Purpose.of.flight'].fillna(value='NOT KNOWN', inplace=True)
aviation['Aircraft.damage'].fillna(value='NOT KNOWN', inplace=True)
aviation['Aircraft.damage'] = aviation['Aircraft.damage'].map(lambda x: 'NOT KNOWN' i
```

In [53]:
```
#since the make and model category hae small amount of missing values
#Lets drop missing rows in the columns
aviation=aviation.dropna(subset=['Make','Model'])
```

In [54]:
```
# FILL nan values in the weather column with NOT KNOWN
aviation['Weather.Condition'].unique
```

Out[54]:
```
<bound method Series.unique of 0        UNK
1        UNK
2        IMC
3        IMC
4        VMC
        ...
90343    NaN
90344    NaN
90345    VMC
90346    NaN
90347    NaN
Name: Weather.Condition, Length: 88777, dtype: object>
```

In [55]:
```
#There are place holders values "UNK" and Unk
#Will replace the placeholder values with NOT KNOWN
aviation['Weather.Condition'].fillna(value='NOT KNOWN', inplace=True)
```

In [56]:
```
aviation['Weather.Condition']=aviation['Weather.Condition'].map(lambda x: 'NOT KNOWN'
```

In [57]:
```
aviation= aviation[aviation['Aircraft.Category']=='Airplane']
aviation['Aircraft.Category'].value_counts()
```

Out[57]:
```
Airplane    27580
Name: Aircraft.Category, dtype: int64
```

IMPUTING MISSING VALUES IN THE NUMERIC COLUMNS WITH THEIR MEDIAN

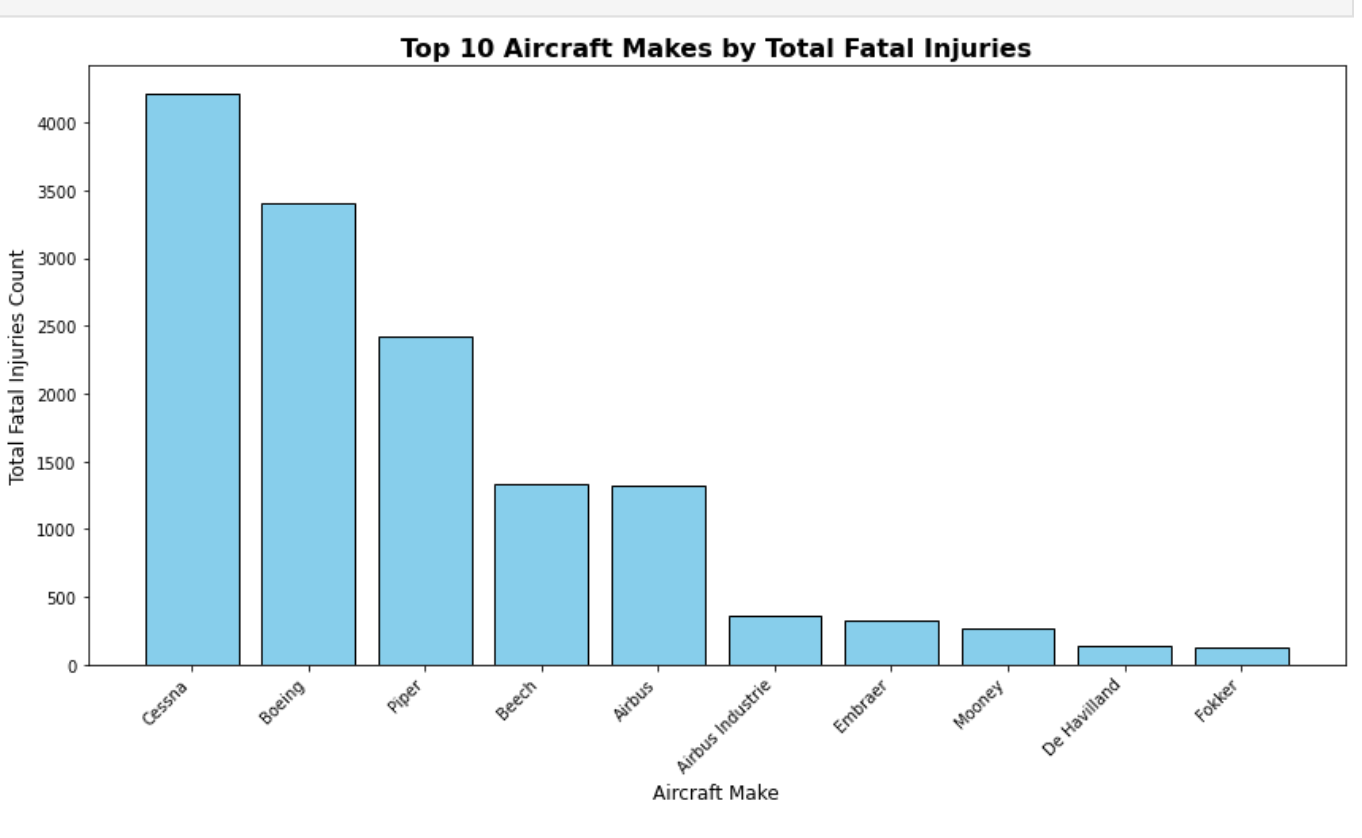
In [58]:
```
#Lets deal with the numeric Categories
#Number of engines, Total serious injuries, total minor injuries, total uninjured
aviation.fillna(value=aviation['Number.of.Engines'].median(),inplace=True)
aviation.fillna(value=aviation['Total.Serious.Injuries'].median(),inplace=True)
aviation.fillna(value=aviation['Total.Minor.Injuries'].median(),inplace=True)
aviation.fillna(value=aviation['Total.Uninjured'].median(),inplace=True)
aviation.fillna(value=aviation['Total.Fatal.Injuries'].median(),inplace=True)
```

In [59]:
```
#Lets Standardize the make and model columns
aviation['Make'] = aviation['Make'].str.title()
aviation['Model'] = aviation['Model'].str.title()
```

DATA ANALYSIS

Which makes are more prone to fatal injuries?

In [60]:
```
#Group by Airplane Make by the Total.Fatal.Injuries
fatal_injuries_by_make = (
    aviation.groupby('Make')['Total.Fatal.Injuries']
    .sum()
    .sort_values(ascending=False)
    .head(10)
)
#Visualizing a bar chart
plt.figure(figsize=(12, 7))
bars = plt.bar(
    fatal_injuries_by_make.index,
    fatal_injuries_by_make.values,
    color='skyblue',
    edgecolor='black'
)
plt.title(
    'Top 10 Aircraft Makes by Total Fatal Injuries',
    fontsize=16,
    fontweight='bold'
)
plt.xlabel('Aircraft Make', fontsize=12)
plt.ylabel('Total Fatal Injuries Count', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



Insights gained

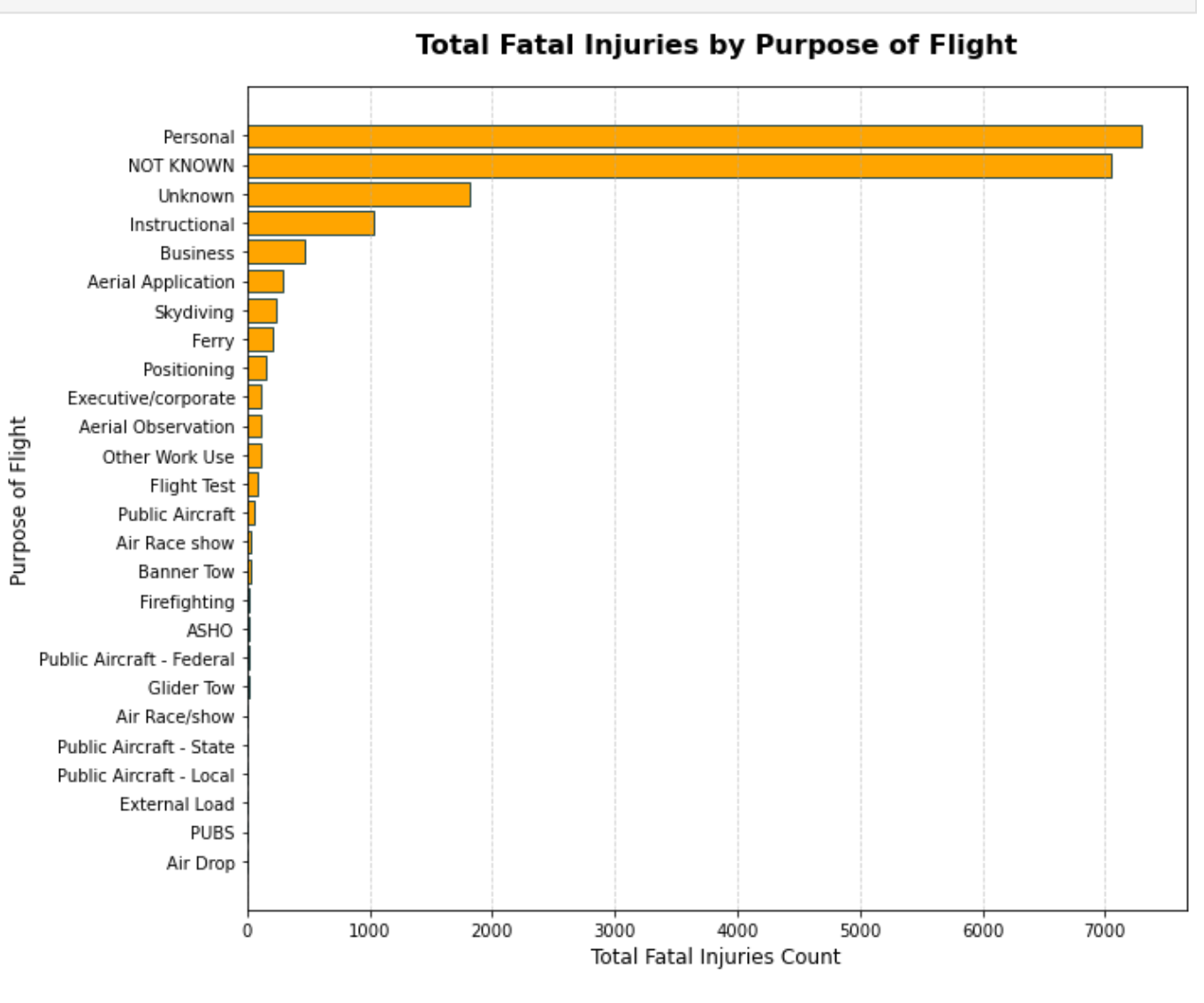
The bar chart analyzes the top 10 makes by total fatal injuries. From the chart. It is clear that CESSNA has the highest risk of fatality incase an acident occurs. On the other hand, FOKKER has the lowest risk to fatality incase an accident occurs.

Recommendation

It is recommended that the company invests in Aircrafts makes such as DE HAVILLAND Aand FOKKER which have a lower risk of fatality

Insight 2: Number of Fatal Injuries by Purpose of Flight

In [61]:
```
# Grouping Purpose of flights by The total fatal injuries
fatal_injuries_by_purpose = (
    aviation.groupby('Purpose.of.flight')['Total.Fatal.Injuries']
    .sum()
    .sort_values(ascending=True)
)
plt.figure(figsize=(10, 8))
bars = plt.barh(
    fatal_injuries_by_purpose.index,
    fatal_injuries_by_purpose.values,
    color='Orange',
    edgecolor='darkslategray'
)
plt.title(
    'Total Fatal Injuries by Purpose of Flight',
    fontsize=16,
    fontweight='bold',
    pad=20
)
plt.xlabel('Total Fatal Injuries Count', fontsize=12)
plt.ylabel('Purpose of Flight', fontsize=12)
plt.grid(axis='x', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```



Total Fatal Injuries by Purpose of Flight
Purpose of Flight
Personal
NOT KNOWN
Unknown
Instructional
Business
Aerial Application
Skydiving
Ferry
Positioning
Executive/corporate
Aerial Observation
Other Work Use
Flight Test
Public Aircraft
Air Race show
Banner Tow
Firefighting
ASHO
Public Aircraft - Federal
Glider Tow
Air Race/show
Public Aircraft - State
Public Aircraft - Local
External Load
PUBS
Air Drop
0
1000
2000
3000
4000
5000
6000
7000
Total Fatal Injuries Count

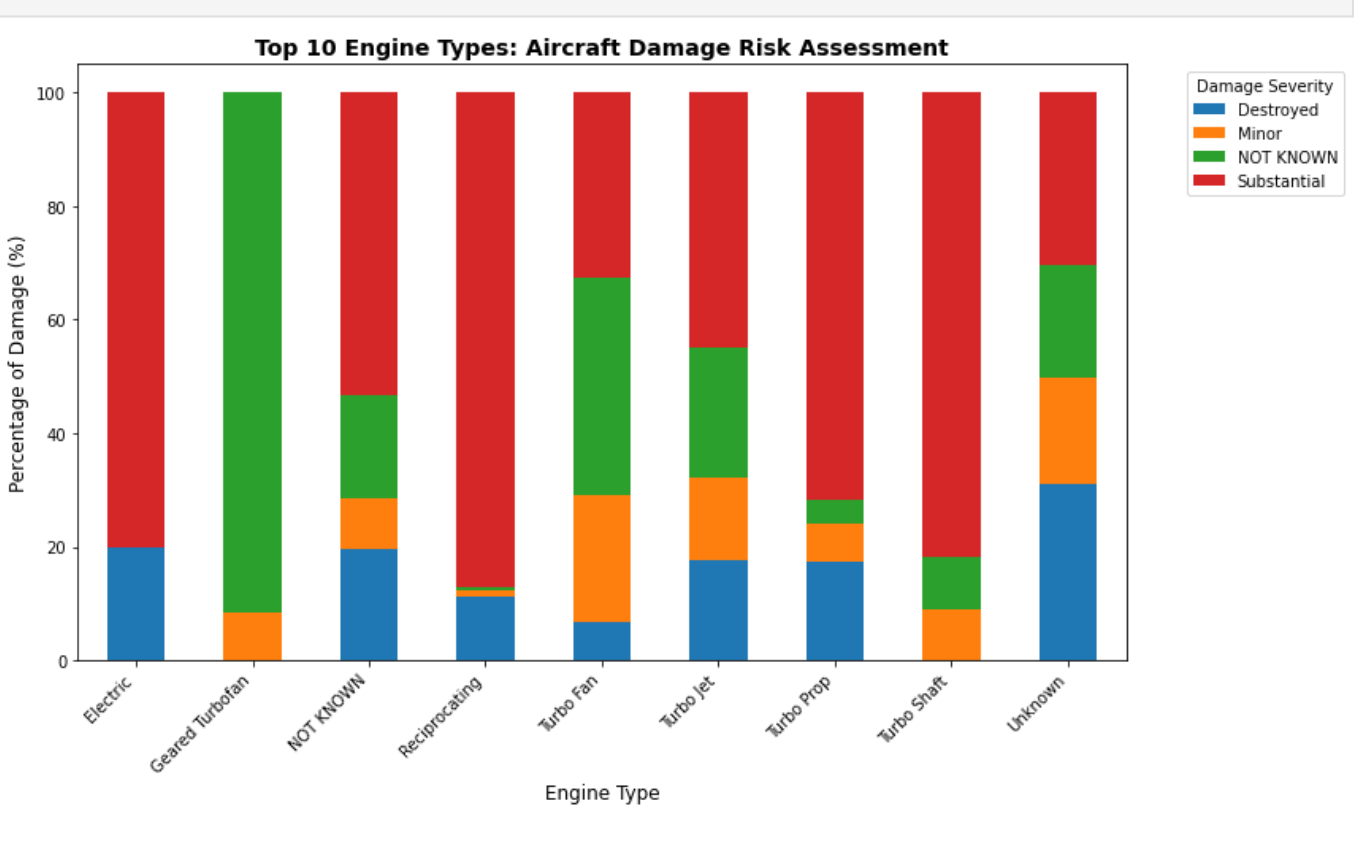
Insights Gained

From the chart above, it is evident that Aircrafts used for personal purpose have the highest risk to fatal injuries. Hence its not recommended for the company to venture in aircrafts for personal and private use.

Recommendation The company company to the aviation industry for commercial purposes, either for ASHO, as Public crafts and also for business purposes since their risks to fatal injuries is low

How is the Aircraft Type based on their engine Type? For the company to decide on which engines to invest on

In [62]:
```
#  Identify the Top 10 Most Frequent Engine Types
top_10_engines = aviation['Engine.Type'].value_counts().head(10).index
df_filtered = aviation[aviation['Engine.Type'].isin(top_10_engines)]
risk_data_top_10 = pd.crosstab(
    df_filtered['Engine.Type'],
    df_filtered['Aircraft.damage'],
    normalize='index'
) * 100
risk_data_top_10.plot(
    kind='bar',
    stacked=True,
    figsize=(12, 7)
)
plt.title(
    'Top 10 Engine Types: Aircraft Damage Risk Assessment',
    fontsize=14,
    fontweight='bold'
)
plt.ylabel('Percentage of Damage (%)', fontsize=12)
plt.xlabel('Engine Type', fontsize=12)
plt.xticks(rotation=45, ha='right') # Rotate for better visibility of the 10 labels
plt.legend(title='Damage Severity', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



Top 10 Engine Types: Aircraft Damage Risk Assessment
Percentage of Damage (%)
100
80
60
40
20
0
Electric
Geared Turbofan
NOT KNOWN
Reciprocating
Turbo Fan
Turbo Jet
Turbo Prop
Turbo Shaft
Unknown
Engine Type
Damage Severity
Destroyed
Minor
NOT KNOWN
Substantial

Insights Gained

From the chart above, Reciprocating engine have the highest risk of Aircraft damage hence not a good venture to dive in. Similar engines such as Electric,Turbo Prop and Turbo Shaft have high substastial damage. Air crafts with Turbo fan engines are highly recommended

Exporting the cleaned dataset to csv

In [63]:
```
aviation.to_csv('cleaned_data.csv', index=False)
```