Business Problem:

The company is expanding in to new industries to diversify its portfolio. Specifically, they are interested in purchasing and operating airplanes for commercial and private enterprises, but do not know anything about the potential risks of aircraft. You are charged with determining which aircraft are the lowest risk for the company to start this new business endeavor. You must then translate your findings into actionable insights that the head of the new aviation division can use to help decide which aircraft to purchase.

Aim and Goals:

This project analyzes aviation accident data from 1962 to 2023 to identify the safest aircraft models. By understanding accident trends, risk factors, and aircraft performance, we aim to provide actionable insights that guide the company in selecting low-risk aircraft for its new aviation division. Project Goals:

- Identify aircraft models with the lowest accident rates.
- Highlight key risk factors contributing to aviation accidents.
- Provide data-backed recommendations for safe aircraft investment

1. Understanding the data

Understanding the data helps to clearly grasp what the dataset entails, including what each column represents, the types of values contained, and how complete or consistent it is. This clarity allows you to identify relevant patterns, spot missing or incorrect entries, to ultimately ensures that you conduct accurate and meaningful analyses.

```python
# loading the data
import pandas as pd
aviationdata = pd.read_csv("Aviation_Data /AviationData.csv",
encoding='cp1252')
```

```
/var/folders/3s/d5pt38l9793djb6wv9n_4d6w0000gn/T/
ipykernel_76904/3486649267.py:3: DtypeWarning: Columns (6,7,28) have
mixed types. Specify dtype option on import or set low_memory=False.
  aviationdata = pd.read_csv("Aviation_Data /AviationData.csv",
encoding='cp1252')
```

The warning means that pandas found columns containing mixed data types (strings and numbers). It's a common warning with large or unstructured datasets which now brings us to the next step of cleaning the data

```python
# viewing the first five rows
aviationdata.head()
```

```
         Event.Id Investigation.Type Accident.Number  Event.Date  \
0  20001218X45444           Accident      SEA87LA080  1948-10-24   
1  20001218X45447           Accident      LAX94LA336  1962-07-19   
2  20061025X01555           Accident      NYC07LA005  1974-08-30   
3  20001218X45448           Accident      LAX96LA321  1977-06-19   
4  20041105X01764           Accident      CHI79FA064  1979-08-02   

          Location        Country   Latitude  Longitude 
Airport.Code  \
0  MOOSE CREEK, ID  United States        NaN        NaN          NaN   

1   BRIDGEPORT, CA  United States        NaN        NaN          NaN   

2    Saltville, VA  United States  36.922223 -81.878056          NaN   

3       EUREKA, CA  United States        NaN        NaN          NaN   

4       Canton, OH  United States        NaN        NaN          NaN   


  Airport.Name  ... Purpose.of.flight Air.carrier Total.Fatal.Injuries
\
0          NaN  ...          Personal         NaN                  2.0   

1          NaN  ...          Personal         NaN                  4.0   

2          NaN  ...          Personal         NaN                  3.0   

3          NaN  ...          Personal         NaN                  2.0   

4          NaN  ...          Personal         NaN                  1.0   


  Total.Serious.Injuries Total.Minor.Injuries Total.Uninjured  \
0                    0.0                  0.0             0.0   
1                    0.0                  0.0             0.0   
2                    NaN                  NaN             NaN   
3                    0.0                  0.0             0.0   
4                    2.0                  NaN             0.0   

  Weather.Condition  Broad.phase.of.flight   Report.Status 
Publication.Date  
0               UNK                 Cruise  Probable Cause  
NaN  
1               UNK                Unknown  Probable Cause       19-
09-1996  
2               IMC                 Cruise  Probable Cause       26-
02-2007  
3               IMC                 Cruise  Probable Cause       12-
09-2000  
4               VMC               Approach  Probable Cause       16-
```

```
04-1980

[5 rows x 31 columns]

# viewing the general info of the data
aviationdata.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
```

The above general infomation helps to quickly understand the data I am working on in my case:

- The dataset contains 88,889 entries and 31 columns.
- Reveals the type of data if its text ,numbers or floats in each column.

- Identifies columns with missing data.
- Reveals the current data type of data each column.

2. Data Cleaning

Data cleaning is crucial as it ensures our data is clean, structured, and reliable to perform accurate analysis and extract meaningful insights. This process will include:

- Handling missing values
- Dealing with duplicates
- Correcting data types
- standardizing the date forma rts

```
''' Creating a copy of my data so as to work on the copy instead of of
original data'''
avidatacopy = aviationdata.copy()

avidatacopy.head(n=3)
```

```
         Event.Id Investigation.Type Accident.Number  Event.Date  \
0  20001218X45444           Accident      SEA87LA080  1948-10-24
1  20001218X45447           Accident      LAX94LA336  1962-07-19
2  20061025X01555           Accident      NYC07LA005  1974-08-30

          Location        Country   Latitude  Longitude
Airport.Code  \
0  MOOSE CREEK, ID  United States        NaN        NaN          NaN

1   BRIDGEPORT, CA  United States        NaN        NaN          NaN

2    Saltville, VA  United States  36.922223 -81.878056          NaN


  Airport.Name  ... Purpose.of.flight Air.carrier Total.Fatal.Injuries
\
0          NaN  ...          Personal         NaN                  2.0

1          NaN  ...          Personal         NaN                  4.0

2          NaN  ...          Personal         NaN                  3.0


  Total.Serious.Injuries Total.Minor.Injuries Total.Uninjured  \
0                    0.0                  0.0             0.0
1                    0.0                  0.0             0.0
2                    NaN                  NaN             NaN

  Weather.Condition  Broad.phase.of.flight   Report.Status
Publication.Date
```

```
0                UNK                 Cruise  Probable Cause
NaN
1                UNK                Unknown  Probable Cause       19-
09-1996
2                IMC                 Cruise  Probable Cause       26-
02-2007

[3 rows x 31 columns]
```

i) Handling missing values

```
# Checking for all the columns with missing values and the count of
values missing
avidatacopy.isnull().sum()[avidatacopy.isnull().sum()>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
```

- Replacing the Location missing values with "Unknown" since we do not know the location names

```
# Handling missing values in the Location column
avidatacopy["Location"]= avidatacopy["Location"].fillna("Unknown")
```

```
avidatacopy["Location"].isnull().sum()

0
```

- Filling the missing country names with the most frequent country occuring

```
#The most frequent country is United States
avidatacopy["Country"].value_counts()

Country
United States                               82248
Brazil                                        374
Canada                                        359
Mexico                                        358
United Kingdom                                344
                                             ...
Seychelles                                      1
Palau                                           1
Libya                                           1
Saint Vincent and the Grenadines                1
Turks and Caicos Islands                        1
Name: count, Length: 219, dtype: int64

#filling the missing values with the mode()
frequent_country = avidatacopy["Country"].mode().iloc[0]
frequent_country

'United States'

# replacing the missing values withe mode()
avidatacopy["Country"] =
avidatacopy["Country"].fillna(frequent_country)

avidatacopy["Country"].isnull().sum()

0
```

- Dropping both the Latitude and longitude columns since they have alot of missing values
- In my analysis I will use the Locations and country instead of the latitude and longitude

```
#Dropping both the latitude and longitude columns
avidatacopy.drop(columns=['Latitude', 'Longitude'], inplace=True)
```

- Dropping the Airport.Code column for it has alot of missing values

```
avidatacopy["Airport.Code"].value_counts()

Airport.Code
NONE    1488
PVT      485
APA      160
ORD      149
```

```
MRI       137
        ...
7NJ9        1
CWV         1
5QA         1
M55         1
EIKH        1
Name: count, Length: 10374, dtype: int64
```

```
avidatacopy = avidatacopy.drop(columns = ["Airport.Code"])

# Checking the remaining columns after dropping some of them
avidatacopy.columns
```

```
Index(['Event.Id', 'Investigation.Type', 'Accident.Number',
'Event.Date',
       'Location', 'Country', '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')
```

- filling the Airport.Name missing values with "Unknown" since we were not given the Airport.Names

```
avidatacopy["Airport.Name"] =
avidatacopy["Airport.Name"].fillna("Unknown")

# Confirming the data information so far after the changes.
avidatacopy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 28 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                88889 non-null  object
 5   Country                 88889 non-null  object
 6   Airport.Name            88889 non-null  object
 7   Injury.Severity         87889 non-null  object
 8   Aircraft.damage         85695 non-null  object
 9   Aircraft.Category       32287 non-null  object
```

```
 10  Registration.Number     87507 non-null  object
 11  Make                    88826 non-null  object
 12  Model                   88797 non-null  object
 13  Amateur.Built           88787 non-null  object
 14  Number.of.Engines       82805 non-null  float64
 15  Engine.Type             81793 non-null  object
 16  FAR.Description         32023 non-null  object
 17  Schedule                12582 non-null  object
 18  Purpose.of.flight       82697 non-null  object
 19  Air.carrier             16648 non-null  object
 20  Total.Fatal.Injuries    77488 non-null  float64
 21  Total.Serious.Injuries  76379 non-null  float64
 22  Total.Minor.Injuries    76956 non-null  float64
 23  Total.Uninjured         82977 non-null  float64
 24  Weather.Condition       84397 non-null  object
 25  Broad.phase.of.flight   61724 non-null  object
 26  Report.Status           82505 non-null  object
 27  Publication.Date        75118 non-null  object
dtypes: float64(5), object(23)
memory usage: 19.0+ MB
```

Dropping the numbers in brackets after Fatal to categorize all the fatal as "Fatal" and filling the missing values with the mode().

```
#viewing the column to understand how it looks like
avidatacopy["Injury.Severity"].value_counts()

Injury.Severity
Non-Fatal     67357
Fatal(1)       6167
Fatal          5262
Fatal(2)       3711
Incident       2219
              ...
Fatal(270)        1
Fatal(60)         1
Fatal(43)         1
Fatal(143)        1
Fatal(230)        1
Name: count, Length: 109, dtype: int64

# Dropping the numbers in brackets after the Fatal and accounting for
different values in the column including NaN
def cleaned_injury_severity(data):
    cleaned_data = []
    for word in data:
        if isinstance(word, float):
            cleaned_data.append(None)
        elif word == "Fatal":
```

```
            cleaned_data.append(word)
        elif "Fatal" in word:
            cleaned_data.append(word.split("(")[0])
        else:
            cleaned_data.append(word)
    return cleaned_data

avidatacopy["Injury.Severity"] =
cleaned_injury_severity(avidatacopy["Injury.Severity"])

#Confirming the code has changed and worked
avidatacopy["Injury.Severity"].value_counts()

Injury.Severity
Non-Fatal      67357
Fatal          17826
Incident        2219
Minor            218
Serious          173
Unavailable       96
Name: count, dtype: int64

# Checking the missing values
avidatacopy["Injury.Severity"].isnull().sum()

1000
```

- We have 1000 missing values from the avidatacopy["Injury.Severity"].
- To make sure the values are uniform I will fill the missing values with "Unavailable" since we were not given the severity of the accident.
- Incident is not clear whether injury occured and was not recorded or there was no injury *It required further investigation*
- "Incidents" in the column is meant to represent injury severity, but it suggests that either the data entry is inconsistent or that the information is being misclassified
- Non-Fatal does not indicate whether the injuries were serious or minor ,it only conculdes that the accident did not lead to death.
- To investigate this column I will use the Total.Fatal.Injuries ,Total.Serious.Injuries ,Total.Minor.Injuries ,Total.Uninjured columns to determine the Injury .Severity.
- I will create another column to clasiffy the Severity as [Fatal,Serious injuries,Minor injuries,Uninjured,Unknown] This will give a clear view of the severity while clasiffying even the Unknown ones.

To achieve the above I first have to ensure the columns ["Total.Fatal.Injuries","Total.Serious.Injuries","Total.Minor.Injuries","Total.Uninjured"] Do not have missing values and if they have I will use the placeholder of "Unknow" to avoiding assuming the counts

```
# Checking for missing values in the column Total.Fatal.Injuries
injury_cols = ['Total.Fatal.Injuries', 'Total.Serious.Injuries',
'Total.Minor.Injuries', 'Total.Uninjured']
missing_value_sum = avidatacopy[injury_cols].isnull().sum()
missing_value_sum

Total.Fatal.Injuries      11401
Total.Serious.Injuries    12510
Total.Minor.Injuries      11933
Total.Uninjured            5912
dtype: int64
```

The above code prints the sum of all the missing values in the columns I am working with.To ensure I get the expected results the missing values will be filled with "Unknown" to avoid using 0 and assuming

```
# Filling the missing values of the columns with "unknown"
filling_severity =
avidatacopy[["Total.Fatal.Injuries","Total.Serious.Injuries","Total.Mi
nor.Injuries","Total.Uninjured"]].fillna('Unknown')
avidatacopy[["Total.Fatal.Injuries","Total.Serious.Injuries","Total.Mi
nor.Injuries","Total.Uninjured"]] = filling_severity
```

- After filling the missing values with "Unknown" ,I will now create a new column which will classify the severity according to the above columns
- To achieve that and know where each accident fall ,I will take the column with the maximum number to define to classification.If all the columns are Unknown then the Accident falls under Unknown.

```
# A function to loop through the columns and classify them
def Classification(row):
    injury_cols = ['Total.Fatal.Injuries', 'Total.Serious.Injuries',
'Total.Minor.Injuries', 'Total.Uninjured']
    Severity_labels = ["Fatal", "Serious injuries", "Minor injuries",
"Uninjured", "Unknown"]
    if all(row[col] == 'Unknown' for col in injury_cols):
        return "Unknown"
    max_value = -1
    max_col = None
    for col in injury_cols:
        if row[col] != 'Unknown' and float(row[col]) > max_value:
            max_value = float(row[col])
            max_col = col

    return Severity_labels[injury_cols.index(max_col)] if max_col else
"Unknown"
avidatacopy["Severity"] = avidatacopy.apply(Classification, axis=1)
```

```
#Confirming the column was added and classification was done as
expected
avidatacopy.head()
```

```
         Event.Id Investigation.Type Accident.Number  Event.Date  \
0  20001218X45444           Accident      SEA87LA080  1948-10-24
1  20001218X45447           Accident      LAX94LA336  1962-07-19
2  20061025X01555           Accident      NYC07LA005  1974-08-30
3  20001218X45448           Accident      LAX96LA321  1977-06-19
4  20041105X01764           Accident      CHI79FA064  1979-08-02

          Location        Country Airport.Name Injury.Severity  \
0  MOOSE CREEK, ID  United States      Unknown           Fatal
1   BRIDGEPORT, CA  United States      Unknown           Fatal
2    Saltville, VA  United States      Unknown           Fatal
3       EUREKA, CA  United States      Unknown           Fatal
4       Canton, OH  United States      Unknown           Fatal

  Aircraft.damage Aircraft.Category  ... Air.carrier
Total.Fatal.Injuries  \
0       Destroyed               NaN  ...         NaN
2.0
1       Destroyed               NaN  ...         NaN
4.0
2       Destroyed               NaN  ...         NaN
3.0
3       Destroyed               NaN  ...         NaN
2.0
4       Destroyed               NaN  ...         NaN
1.0

  Total.Serious.Injuries Total.Minor.Injuries  Total.Uninjured  \
0                    0.0                  0.0              0.0
1                    0.0                  0.0              0.0
2                Unknown              Unknown          Unknown
3                    0.0                  0.0              0.0
4                    2.0              Unknown              0.0

  Weather.Condition Broad.phase.of.flight   Report.Status
Publication.Date  \
0               UNK                Cruise  Probable Cause
NaN
1               UNK               Unknown  Probable Cause       19-09-
1996
2               IMC                Cruise  Probable Cause       26-02-
2007
3               IMC                Cruise  Probable Cause       12-09-
2000
4               VMC              Approach  Probable Cause       16-04-
1980
```

```
           Severity
0             Fatal
1             Fatal
2             Fatal
3             Fatal
4  Serious injuries

[5 rows x 29 columns]

#Checking the number of occurrencies of the new column values
avidatacopy["Severity"].value_counts()

Severity
Uninjured           49793
Fatal               18048
Minor injuries      11042
Serious injuries     9783
Unknown               223
Name: count, dtype: int64
```

- Since I have the Severity column I will drop the Initially Injury.Severity column since it had inconsistent values.
- In my analysis I will be using the Severity column

```
avidatacopy.drop("Injury.Severity",axis = 1,inplace = True)

#Confirming the column is dropped
avidatacopy.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 28 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                88889 non-null  object
 5   Country                 88889 non-null  object
 6   Airport.Name            88889 non-null  object
 7   Aircraft.damage         85695 non-null  object
 8   Aircraft.Category       32287 non-null  object
 9   Registration.Number     87507 non-null  object
 10  Make                    88826 non-null  object
 11  Model                   88797 non-null  object
 12  Amateur.Built           88787 non-null  object
 13  Number.of.Engines       82805 non-null  float64
 14  Engine.Type             81793 non-null  object
```

```
 15  FAR.Description         32023 non-null  object
 16  Schedule                12582 non-null  object
 17  Purpose.of.flight       82697 non-null  object
 18  Air.carrier             16648 non-null  object
 19  Total.Fatal.Injuries    88889 non-null  object
 20  Total.Serious.Injuries  88889 non-null  object
 21  Total.Minor.Injuries    88889 non-null  object
 22  Total.Uninjured         88889 non-null  object
 23  Weather.Condition       84397 non-null  object
 24  Broad.phase.of.flight   61724 non-null  object
 25  Report.Status           82505 non-null  object
 26  Publication.Date        75118 non-null  object
 27  Severity                88889 non-null  object
dtypes: float64(1), object(27)
memory usage: 19.0+ MB
```

Using "Unknown" to replace the missing values in the Aircraft.damage column

```
#checking the already available values
avidatacopy["Aircraft.damage"].value_counts()

Aircraft.damage
Substantial    64148
Destroyed      18623
Minor           2805
Unknown          119
Name: count, dtype: int64

avidatacopy.loc[:, "Aircraft.damage"] =
avidatacopy["Aircraft.damage"].fillna("Unknown")

avidatacopy["Aircraft.damage"].isnull().sum()

0
```

For the ;

- Aircraft.Category
- Registration
- Engine.Type
- Report.Status
- Broad.phase.of.flight I will Use "Unknown" to replace the missing values in the column

```
# Getting a view of the available values
avidatacopy["Aircraft.Category"].value_counts()

Aircraft.Category
Airplane              27617
Helicopter             3440
Glider                  508
```

```
Balloon                    231
Gyrocraft                  173
Weight-Shift               161
Powered Parachute           91
Ultralight                  30
Unknown                     14
WSFT                         9
Powered-Lift                 5
Blimp                        4
UNK                          2
Rocket                       1
ULTR                         1
Name: count, dtype: int64
```

```python
avidatacopy.loc[:, "Aircraft.Category"] =
avidatacopy["Aircraft.Category"].fillna("Unknown")

avidatacopy["Aircraft.Category"].isnull().sum()
```

```
0
```

```python
avidatacopy.loc[:, "Registration.Number"] =
avidatacopy["Registration.Number"].fillna("Unknown")

avidatacopy["Registration.Number"].isnull().sum()
```

```
0
```

```python
avidatacopy["Engine.Type"].value_counts()
```

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

```python
#since there is  2051 unknown Engine.Type I will add the other missing
values as unknown
avidatacopy.loc[:, "Engine.Type"] =
avidatacopy["Engine.Type"].fillna("Unknown")

avidatacopy["Broad.phase.of.flight"].value_counts()
```

```
Broad.phase.of.flight
Landing        15428
Takeoff        12493
Cruise         10269
Maneuvering     8144
Approach        6546
Climb           2034
Taxi            1958
Descent         1887
Go-around       1353
Standing         945
Unknown          548
Other            119
Name: count, dtype: int64
```

```
avidatacopy.loc[:, "Broad.phase.of.flight"] =
avidatacopy["Broad.phase.of.flight"].fillna("Unknown")

avidatacopy.loc[:, "Report.Status"] =
avidatacopy["Report.Status"].fillna("Unknown")
```

Dropping columns with many missing values such as;

- FAR.Description
- Schedule,Air.carrier

```
avidatacopy.drop(columns=["FAR.Description",
"Schedule","Air.carrier"], inplace=True)

#checking the data info and confirming the columns have been dropped
avidatacopy.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 25 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                88889 non-null  object
 5   Country                 88889 non-null  object
 6   Airport.Name            88889 non-null  object
 7   Aircraft.damage         88889 non-null  object
 8   Aircraft.Category       88889 non-null  object
 9   Registration.Number     88889 non-null  object
 10  Make                    88826 non-null  object
 11  Model                   88797 non-null  object
 12  Amateur.Built           88787 non-null  object
 13  Number.of.Engines       82805 non-null  float64
```

```
 14   Engine.Type              88889 non-null   object
 15   Purpose.of.flight        82697 non-null   object
 16   Total.Fatal.Injuries     88889 non-null   object
 17   Total.Serious.Injuries   88889 non-null   object
 18   Total.Minor.Injuries     88889 non-null   object
 19   Total.Uninjured          88889 non-null   object
 20   Weather.Condition        84397 non-null   object
 21   Broad.phase.of.flight    88889 non-null   object
 22   Report.Status            88889 non-null   object
 23   Publication.Date         75118 non-null   object
 24   Severity                 88889 non-null   object
dtypes: float64(1), object(24)
memory usage: 17.0+ MB
```

- Filling this columns with most frequent value
- Make
- Model
- Amateur.Built
- Number.of.Engines
- Purpose.of.flight
- Weather.Condition

```
avidatacopy.loc[:, "Make"] =
avidatacopy["Make"].fillna(avidatacopy["Make"].mode()[0])

avidatacopy.loc[:, "Model"] =
avidatacopy["Model"].fillna(avidatacopy["Model"].mode()[0])

avidatacopy.loc[:, "Purpose.of.flight"] =
avidatacopy["Purpose.of.flight"].fillna(avidatacopy["Purpose.of.flight
"].mode()[0])

avidatacopy.loc[:, "Amateur.Built"] =
avidatacopy["Amateur.Built"].fillna(avidatacopy["Amateur.Built"].mode(
)[0])

avidatacopy.loc[:, "Number.of.Engines"] =
avidatacopy["Number.of.Engines"].fillna(avidatacopy["Number.of.Engines
"].mode()[0])

avidatacopy.loc[:, "Weather.Condition"] =
avidatacopy["Weather.Condition"].fillna(avidatacopy["Weather.Condition
"].mode()[0])
```

- For the Publication.Date in order to handel the missing values ,I will use the Event.Date column which has no missing values.
- With Event.Date I will calculate the difference between publication_date and event_date for records where both exist.

- Using the gap between the two dates of the dates available I will be able to get the average gap and use it to fill in missing publication_date by adding the average gap to event_date.

To achieve the above the columns should be in datetype data type

```
avidatacopy["Event.Date"].dtype

dtype('O')

avidatacopy["Event.Date"]

0        1948-10-24
1        1962-07-19
2        1974-08-30
3        1977-06-19
4        1979-08-02
            ...
88884    2022-12-26
88885    2022-12-26
88886    2022-12-26
88887    2022-12-26
88888    2022-12-29
Name: Event.Date, Length: 88889, dtype: object

#converting Event.Date column to datetime since it's stored as object.
avidatacopy["Event.Date"] =
pd.to_datetime(avidatacopy["Event.Date"],format = "%Y-%m-%d")

avidatacopy["Publication.Date"].dtype

dtype('O')

# standardizing my publication date column since it has both (/)and
(-) as the seperators of the date
avidatacopy["Publication.Date"] =
avidatacopy["Publication.Date"].astype(str).str.replace("/", "-")
avidatacopy["Publication.Date"]

0               nan
1        19-09-1996
2        26-02-2007
3        12-09-2000
4        16-04-1980
            ...
88884    29-12-2022
88885           nan
88886    27-12-2022
88887           nan
88888    30-12-2022
Name: Publication.Date, Length: 88889, dtype: object
```

```
avidatacopy["Publication.Date"] =
pd.to_datetime(avidatacopy["Publication.Date"],format = "%d-%m-%Y")

print(avidatacopy["Event.Date"].dtype)

datetime64[ns]

print(avidatacopy["Publication.Date"].dtype)

datetime64[ns]

#Calculating the dates gap
avidatacopy["gap"]= (avidatacopy["Publication.Date"] -
avidatacopy["Event.Date"]).dt.days
avidatacopy["gap"]

0            NaN
1        12481.0
2        11868.0
3         8486.0
4          258.0
          ...
88884        3.0
88885        NaN
88886        1.0
88887        NaN
88888        1.0
Name: gap, Length: 88889, dtype: float64

#Checking for the extreem days executed
avidatacopy.loc[avidatacopy["gap"] > 10000, ["Publication.Date",
"Event.Date", "gap"]].head()

    Publication.Date Event.Date      gap
1         1996-09-19 1962-07-19  12481.0
2         2007-02-26 1974-08-30  11868.0
5         2017-09-19 1979-09-17  13882.0
260       2011-05-05 1982-02-07  10679.0
293       2017-10-30 1982-02-11  13045.0

#The average time it takes from when an event happens to when its
publicated
average_gap = avidatacopy["gap"].mean()  # Mean gap in days
print(f"Average gap between Event and Publication: {average_gap}
days")

Average gap between Event and Publication: 1025.3769669054022 days

# Using the average days to fill in the missing values in the
publication date column
missing_dates = avidatacopy["Publication.Date"].isna()
```

```
avidatacopy.loc[missing_dates, "Publication.Date"] =
avidatacopy["Event.Date"] + pd.Timedelta(days=average_gap)

avidatacopy["Event.Date"].isnull().sum()

0

# Dropping the gap column after filling the missing values
avidatacopy.drop(columns=["gap"], inplace=True)
```

- confirming the data Information has no missing values after all the modification

```
avidatacopy.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 25 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  datetime64[ns]
 4   Location                88889 non-null  object
 5   Country                 88889 non-null  object
 6   Airport.Name            88889 non-null  object
 7   Aircraft.damage         88889 non-null  object
 8   Aircraft.Category       88889 non-null  object
 9   Registration.Number     88889 non-null  object
 10  Make                    88889 non-null  object
 11  Model                   88889 non-null  object
 12  Amateur.Built           88889 non-null  object
 13  Number.of.Engines       88889 non-null  float64
 14  Engine.Type             88889 non-null  object
 15  Purpose.of.flight       88889 non-null  object
 16  Total.Fatal.Injuries    88889 non-null  object
 17  Total.Serious.Injuries  88889 non-null  object
 18  Total.Minor.Injuries    88889 non-null  object
 19  Total.Uninjured         88889 non-null  object
 20  Weather.Condition       88889 non-null  object
 21  Broad.phase.of.flight   88889 non-null  object
 22  Report.Status           88889 non-null  object
 23  Publication.Date        88889 non-null  datetime64[ns]
 24  Severity                88889 non-null  object
dtypes: datetime64[ns](2), float64(1), object(22)
memory usage: 17.0+ MB
```

ii) Handling the datatypes

Handling datatypes correctly is crucial because it ensures:

- Reduces memory consumption.
- Avoiding type errors when working with different datas
- It increases data accuracy

```
avidatacopy.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 25 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  datetime64[ns]
 4   Location                88889 non-null  object
 5   Country                 88889 non-null  object
 6   Airport.Name            88889 non-null  object
 7   Aircraft.damage         88889 non-null  object
 8   Aircraft.Category       88889 non-null  object
 9   Registration.Number     88889 non-null  object
 10  Make                    88889 non-null  object
 11  Model                   88889 non-null  object
 12  Amateur.Built           88889 non-null  object
 13  Number.of.Engines       88889 non-null  float64
 14  Engine.Type             88889 non-null  object
 15  Purpose.of.flight       88889 non-null  object
 16  Total.Fatal.Injuries    88889 non-null  object
 17  Total.Serious.Injuries  88889 non-null  object
 18  Total.Minor.Injuries    88889 non-null  object
 19  Total.Uninjured         88889 non-null  object
 20  Weather.Condition       88889 non-null  object
 21  Broad.phase.of.flight   88889 non-null  object
 22  Report.Status           88889 non-null  object
 23  Publication.Date        88889 non-null  datetime64[ns]
 24  Severity                88889 non-null  object
dtypes: datetime64[ns](2), float64(1), object(22)
memory usage: 17.0+ MB

avidatacopy.head()

        Event.Id Investigation.Type Accident.Number Event.Date  \
0  20001218X45444           Accident      SEA87LA080 1948-10-24
1  20001218X45447           Accident      LAX94LA336 1962-07-19
2  20061025X01555           Accident      NYC07LA005 1974-08-30
3  20001218X45448           Accident      LAX96LA321 1977-06-19
4  20041105X01764           Accident      CHI79FA064 1979-08-02

         Location        Country Airport.Name Aircraft.damage  \
0  MOOSE CREEK, ID  United States      Unknown       Destroyed
1   BRIDGEPORT, CA  United States      Unknown       Destroyed
```

```
2    Saltville, VA  United States      Unknown       Destroyed
3       EUREKA, CA  United States      Unknown       Destroyed
4       Canton, OH  United States      Unknown       Destroyed

  Aircraft.Category Registration.Number  ... Purpose.of.flight  \
0           Unknown              NC6404  ...          Personal
1           Unknown              N5069P  ...          Personal
2           Unknown              N5142R  ...          Personal
3           Unknown              N1168J  ...          Personal
4           Unknown               N15NY  ...          Personal

  Total.Fatal.Injuries Total.Serious.Injuries  Total.Minor.Injuries  \
0                  2.0                    0.0                   0.0
1                  4.0                    0.0                   0.0
2                  3.0                Unknown               Unknown
3                  2.0                    0.0                   0.0
4                  1.0                    2.0               Unknown

  Total.Uninjured Weather.Condition Broad.phase.of.flight
Report.Status  \
0             0.0               UNK                Cruise  Probable
Cause
1             0.0               UNK               Unknown  Probable
Cause
2         Unknown               IMC                Cruise  Probable
Cause
3             0.0               IMC                Cruise  Probable
Cause
4             0.0               VMC              Approach  Probable
Cause

               Publication.Date          Severity
0 1951-08-15 09:02:49.940626752             Fatal
1 1996-09-19 00:00:00.000000000             Fatal
2 2007-02-26 00:00:00.000000000             Fatal
3 2000-09-12 00:00:00.000000000             Fatal
4 1980-04-16 00:00:00.000000000  Serious injuries

[5 rows x 25 columns]
```

```python
# Column Investigation.Type is object but can be converted to
categorical data type
avidatacopy['Investigation.Type'] =
avidatacopy['Investigation.Type'].astype('category')

# changing column Aircraft.damage from object to categorical datattype
,it has limited set of unique values
avidatacopy['Aircraft.damage'] =
avidatacopy['Aircraft.damage'].astype('category')
```

```
# changing Amateur.Built from object to boolen since it has only "yes
and "No" values
avidatacopy['Amateur.Built'] = (avidatacopy['Amateur.Built'] ==
'Yes').astype(bool)

#Changing Severity column from object to categorical data type
avidatacopy['Severity'] = avidatacopy['Severity'].astype('category')

#Changing the Total.Fatal.Injuries to floats and since it has the
"Unknown' that will be converted to NaN
avidatacopy['Total.Fatal.Injuries'] =
pd.to_numeric(avidatacopy['Total.Fatal.Injuries'], errors='coerce')

#Changing the Total.Serious.Injuries to floats to ease analysis
avidatacopy['Total.Serious.Injuries'] =
pd.to_numeric(avidatacopy['Total.Serious.Injuries'], errors='coerce')

#Coercing the Total.Minor.Injuries to floats
avidatacopy['Total.Minor.Injuries'] =
pd.to_numeric(avidatacopy['Total.Minor.Injuries'], errors='coerce')

#Coercing the Total.Uninjured to floats
avidatacopy['Total.Uninjured'] =
pd.to_numeric(avidatacopy['Total.Uninjured'], errors='coerce')

#Checking if all the data types has been changed and if I missing any
avidatacopy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 25 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                88889 non-null  object
 1   Investigation.Type      88889 non-null  category
 2   Accident.Number         88889 non-null  object
 3   Event.Date              88889 non-null  datetime64[ns]
 4   Location                88889 non-null  object
 5   Country                 88889 non-null  object
 6   Airport.Name            88889 non-null  object
 7   Aircraft.damage         88889 non-null  category
 8   Aircraft.Category       88889 non-null  object
 9   Registration.Number     88889 non-null  object
 10  Make                    88889 non-null  object
 11  Model                   88889 non-null  object
 12  Amateur.Built           88889 non-null  bool
 13  Number.of.Engines       88889 non-null  float64
 14  Engine.Type             88889 non-null  object
 15  Purpose.of.flight       88889 non-null  object
 16  Total.Fatal.Injuries    77488 non-null  float64
 17  Total.Serious.Injuries  76379 non-null  float64
```

```
 18   Total.Minor.Injuries    76956 non-null   float64
 19   Total.Uninjured         82977 non-null   float64
 20   Weather.Condition       88889 non-null   object
 21   Broad.phase.of.flight   88889 non-null   object
 22   Report.Status           88889 non-null   object
 23   Publication.Date        88889 non-null   datetime64[ns]
 24   Severity                88889 non-null   category
dtypes: bool(1), category(3), datetime64[ns](2), float64(5),
object(14)
memory usage: 14.6+ MB
```

```python
#Saving the clean data as CSV
avidatacopy.to_csv("avidatacopy.csv",index = False)
```

3. EDA

i) General Accidents Assesement

i.a) The basic summary statistics (mean, median, range) for injury counts.

```python
avidatacopy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 25 columns):
 #    Column                  Non-Null Count   Dtype
---   ------                  --------------   -----
 0    Event.Id                88889 non-null   object
 1    Investigation.Type      88889 non-null   category
 2    Accident.Number         88889 non-null   object
 3    Event.Date              88889 non-null   datetime64[ns]
 4    Location                88889 non-null   object
 5    Country                 88889 non-null   object
 6    Airport.Name            88889 non-null   object
 7    Aircraft.damage         88889 non-null   category
 8    Aircraft.Category       88889 non-null   object
 9    Registration.Number     88889 non-null   object
 10   Make                    88889 non-null   object
 11   Model                   88889 non-null   object
 12   Amateur.Built           88889 non-null   bool
 13   Number.of.Engines       88889 non-null   float64
 14   Engine.Type             88889 non-null   object
 15   Purpose.of.flight       88889 non-null   object
 16   Total.Fatal.Injuries    77488 non-null   float64
 17   Total.Serious.Injuries  76379 non-null   float64
 18   Total.Minor.Injuries    76956 non-null   float64
```

```
 19  Total.Uninjured         82977 non-null  float64
 20  Weather.Condition       88889 non-null  object
 21  Broad.phase.of.flight   88889 non-null  object
 22  Report.Status           88889 non-null  object
 23  Publication.Date        88889 non-null  datetime64[ns]
 24  Severity                88889 non-null  category
dtypes: bool(1), category(3), datetime64[ns](2), float64(5),
object(14)
memory usage: 14.6+ MB
```

```
#The distribution of injuries
avidatacopy[["Total.Fatal.Injuries","Total.Serious.Injuries","Total.Minor.Injuries","Total.Uninjured"]].describe()
```

```
       Total.Fatal.Injuries  Total.Serious.Injuries
Total.Minor.Injuries  \
count          77488.000000            76379.000000
76956.000000
mean               0.647855                0.279881
0.357061
std                5.485960                1.544084
2.235625
min                0.000000                0.000000
0.000000
25%                0.000000                0.000000
0.000000
50%                0.000000                0.000000
0.000000
75%                0.000000                0.000000
0.000000
max              349.000000              161.000000
380.000000

       Total.Uninjured
count     82977.000000
mean          5.325440
std          27.913634
min           0.000000
25%           0.000000
50%           1.000000
75%           2.000000
max         699.000000
```

The above results shows ;

- The counts vary slightly across the variables this is beacuse we had some missing values in the dataset
- The high max values suggest that certain events result in large numbers of injuries and fatalities.
- 50% of incidents have zero injuries suggesting many incidents do not result in injuries.

- Most incidents have few injuries, but some extreme cases cause many casualties.

i.b) Over what time period do the accidents occur?

```
# using the Event.Date and Publication.Date to get the time period
when the accidents occur
avidatacopy['Year'] = avidatacopy['Event.Date'].dt.year
yearly_accidents = avidatacopy.groupby('Year').size()

yearly_accidents
```

```
Year
1948       1
1962       1
1974       1
1977       1
1979       2
1981       1
1982    3593
1983    3556
1984    3457
1985    3096
1986    2880
1987    2828
1988    2730
1989    2544
1990    2518
1991    2462
1992    2355
1993    2313
1994    2257
1995    2309
1996    2187
1997    2148
1998    2226
1999    2209
2000    2220
2001    2063
2002    2020
2003    2085
2004    1952
2005    2031
2006    1851
2007    2016
2008    1893
2009    1783
2010    1786
2011    1850
2012    1835
2013    1561
```

```
2014    1535
2015    1582
2016    1664
2017    1638
2018    1681
2019    1624
2020    1392
2021    1545
2022    1607
dtype: int64
```

In the above data it shows :

- Very few incidents were recorded before 1982
- There is a sharp increase of incidents from year 1982–2005
- From 2005 -2015 there is a decrease of incidents indicating possible flight safety measures implementations.
- From 2015 there is a slight increase of the incidents .
- 2020 has fewer reported incidents indicating that less fligts were used and thus less incidents

```
avidatacopy['Month'] = avidatacopy['Event.Date'].dt.month
monthly_accidents = avidatacopy.groupby('Month').size()

monthly_accidents
```

```
Month
1      4985
2      5285
3      6686
4      7248
5      8514
6      9561
7     10698
8      9986
9      8346
10     6982
11     5538
12     5060
dtype: int64
```

- June (9,561), July (10,698), and August (9,986) have the highest accident counts
- January (4,985) and February (5,285) have the lowest accident counts indicating possible less travel after the holiday season.
- After August, the number of incidents declines indicating fewer flights thus less accidents.

i.c) How many accidents are recorded per aircraft category

```
aircraft_accidents =
avidatacopy.groupby(['Aircraft.Category']).size().sort_values(ascendin
g=False)
print(aircraft_accidents)
```

```
Aircraft.Category
Unknown              56616
Airplane             27617
Helicopter            3440
Glider                 508
Balloon                231
Gyrocraft              173
Weight-Shift           161
Powered Parachute       91
Ultralight              30
WSFT                     9
Powered-Lift             5
Blimp                    4
UNK                      2
Rocket                   1
ULTR                     1
dtype: int64
```

- The largest category is "Unknown" due to missing values in the data set
- Most accidents are from airplanes (27,617 cases), followed by helicopters (3,440 cases),this is expected since airplanes are the most commonly used.
- Other Aircrafts such as Glider and ballons accidents maybe due to weather conditions or pilots errors.

i.d) What percentage of accidents are fatal, serious, minor, or non-severe?

```
severity_counts = avidatacopy['Severity'].value_counts()
severity_percentages = (severity_counts / severity_counts.sum()) * 100

severity_summary = pd.DataFrame({'Count': severity_counts,
'Percentage': severity_percentages.round(2)})

severity_summary
```

Severity	Count	Percentage
Uninjured	49793	56.02
Fatal	18048	20.30
Minor injuries	11042	12.42
Serious injuries	9783	11.01
Unknown	223	0.25

- 56% of accidents resulted in no injuries
- 20% of cases were fatal, showing that a significant portion of accidents have serious
- 12% were minor injuries & 11% were serious injuries

i.e) Are most accidents during takeoff, cruising, landing, or taxiing?

```
phase_accidents = avidatacopy['Broad.phase.of.flight'].value_counts()
print(phase_accidents)

Broad.phase.of.flight
Unknown        27713
Landing        15428
Takeoff        12493
Cruise         10269
Maneuvering     8144
Approach        6546
Climb           2034
Taxi            1958
Descent         1887
Go-around       1353
Standing         945
Other            119
Name: count, dtype: int64
```

- Landing (17%) & Takeoff (14%) are the riskiest phases
- Go-around, taxi, and standing are soe of the low-risk phases

i.f) Are accidents more frequent in commercial flights, private flights, or training flights?

```
flight_purpose_accidents =
avidatacopy['Purpose.of.flight'].value_counts()
print(flight_purpose_accidents)

Purpose.of.flight
Personal                     55640
Instructional                10601
Unknown                       6802
Aerial Application            4712
Business                      4018
Positioning                   1646
Other Work Use                1264
Ferry                          812
Aerial Observation             794
Public Aircraft                720
Executive/corporate            553
Flight Test                    405
Skydiving                      182
External Load                  123
Public Aircraft - Federal      105
```

```
Banner Tow                       101
Air Race show                     99
Public Aircraft - Local           74
Public Aircraft - State           64
Air Race/show                     59
Glider Tow                        53
Firefighting                      40
Air Drop                          11
ASHO                               6
PUBS                               4
PUBL                               1
Name: count, dtype: int64
```

- Personal flights have the highest accident count likely due to less experienced pilots
- Instructional flights accidents are common in training flights as they occur under supervision.
- Aerial Application accidents may be due to low-altitude flying and exposure to chemicals.

i.g)Are certain countries or regions more prone to accidents?

```python
country_accidents = avidatacopy['Country'].value_counts().head(10)
print(country_accidents)
```

```
Country
United States     82474
Brazil              374
Canada              359
Mexico              358
United Kingdom      344
Australia           300
France              236
Spain               226
Bahamas             216
Germany             215
Name: count, dtype: int64
```

- Recorded accidents in the U.S lead maybe due to increased flights.

i.h) Under which weather condition do most accidents happen

```python
weather_accidents = 
avidatacopy.groupby('Weather.Condition').size().sort_values(ascending=
False)
print(weather_accidents)
```

```
Weather.Condition
VMC    81795
IMC     5976
UNK      856
```

```
Unk       262
dtype: int64
```

- VMC (Visual Meteorological Conditions) – 81,795 incidents is leading This means weather is not the leading factor in most cases.
- IMC (Instrument Meteorological Conditions) – 5,976 incidents These accidents occurred in poor weather conditions where pilots had to rely on instruments and maybe there were turbulence errors.

i.i) aircraft incidents by damage severity across my data

```
avidatacopy["Aircraft.damage"].value_counts()

Aircraft.damage
Substantial    64148
Destroyed      18623
Unknown         3313
Minor           2805
Name: count, dtype: int64
```

- Majority of aircraft accidents cause significant damage but may not necessarily result in a total loss.
- The Unknown category with 3,313 cases indicates there is missing data
- The Destroyed category with 18623 indicates that accidents occur aircraft destruction is likely to happen.

```
avidatacopy["Number.of.Engines"]

0        1.0
1        1.0
2        1.0
3        1.0
4        1.0
        ...
88884    1.0
88885    1.0
88886    1.0
88887    1.0
88888    1.0
Name: Number.of.Engines, Length: 88889, dtype: float64
```

i.j) Do aircraft with fewer engines have a higher risk per engine compared to those with more engines?

To achive this i will use this fomular ;

Risk per Engine= Total Incidents/ Total Number of Engines

```
#Grouping number of engines and count incidents
engine_risk =
avidatacopy.groupby('Number.of.Engines').size().reset_index(name='Tota
l Incidents')
engine_risk
```

```
   Number.of.Engines  Total Incidents
0                0.0             1226
1                1.0            75666
2                2.0            11079
3                3.0              483
4                4.0              431
5                6.0                1
6                8.0                3
```

```
# Calculating risk per engine
engine_risk['Risk per Engine'] = engine_risk['Total Incidents'] /
engine_risk['Number.of.Engines']
engine_risk['Risk per Engine']
```

```
0             inf
1    7.566600e+04
2    5.539500e+03
3    1.610000e+02
4    1.077500e+02
5    1.666667e-01
6    3.750000e-01
Name: Risk per Engine, dtype: float64
```

```
# combining my results
engine_risk = engine_risk.sort_values(by='Number.of.Engines')
engine_risk
```

```
   Number.of.Engines  Total Incidents  Risk per Engine
0                0.0             1226              inf
1                1.0            75666     7.566600e+04
2                2.0            11079     5.539500e+03
3                3.0              483     1.610000e+02
4                4.0              431     1.077500e+02
5                6.0                1     1.666667e-01
6                8.0                3     3.750000e-01
```

- Single-engine aircraft are the riskiest in terms of accidents per engine, so if safety is a priority, they may not be the best investment
- Multi-engine aircraft have significantly lower risk per engine, making them more reliable for operations
- Having more engines greatly reduces risk per engine, reinforcing the idea that multi-engine aircraft provide more safety.

i.k) Do amateur-built aircraft exhibit risk compared to professionally built aircraft?

```
amateur_risk =
avidatacopy.groupby('Amateur.Built').size().reset_index(name='Total
Incidents')
amateur_risk
```

	Amateur.Built	Total Incidents
0	False	80414
1	True	8475

```
fatality_stats = avidatacopy.groupby('Amateur.Built')
['Total.Fatal.Injuries'].sum().reset_index()
fatality_stats
```

	Amateur.Built	Total.Fatal.Injuries
0	False	47041.0
1	True	3160.0

```
fatality_stats['Fatality Rate'] =
fatality_stats['Total.Fatal.Injuries'] / amateur_risk['Total
Incidents']
fatality_stats
```

	Amateur.Built	Total.Fatal.Injuries	Fatality Rate
0	False	47041.0	0.584985
1	True	3160.0	0.372861

- Incidents involving professionally built aircraft result in a higher fatality rate per incident compared to amateur-built aircraft
- Professionally built aircraft may be involved in more severe accidents
- Amateur-built aircraft account for about 3160 of total fatalities.

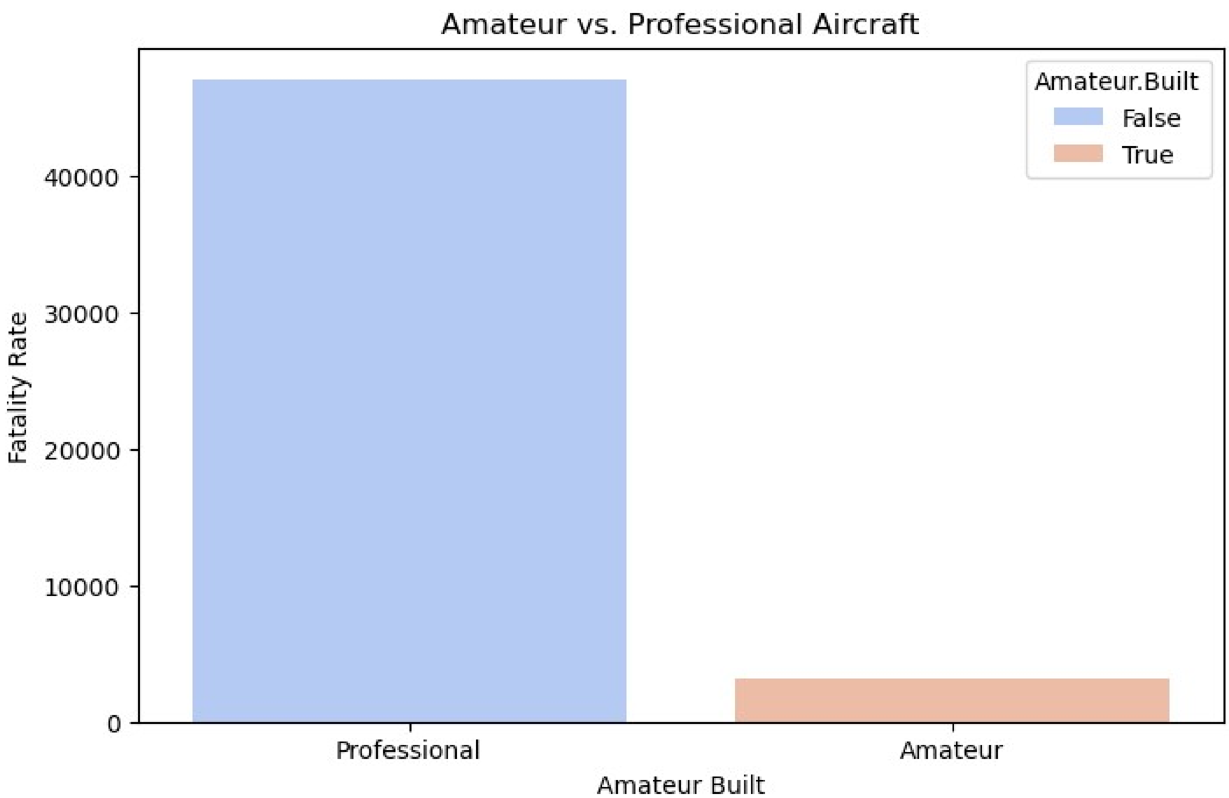
4 .Visualization

```
import matplotlib.pyplot as plt
import seaborn as sns
```

1) Do amateur built aircraft have a higher fatality rate than professionally built aircraft?

```
plt.figure(figsize=(8,5))
sns.barplot(x=fatality_stats["Amateur.Built"],
            y=fatality_stats["Total.Fatal.Injuries"],
            hue=fatality_stats["Amateur.Built"],
            palette = "coolwarm")
```

```
plt.xlabel("Amateur Built")
plt.ylabel("Fatality Rate")
plt.title("Amateur vs. Professional Aircraft")
plt.xticks([0, 1], ["Professional", "Amateur"])
plt.show()
```

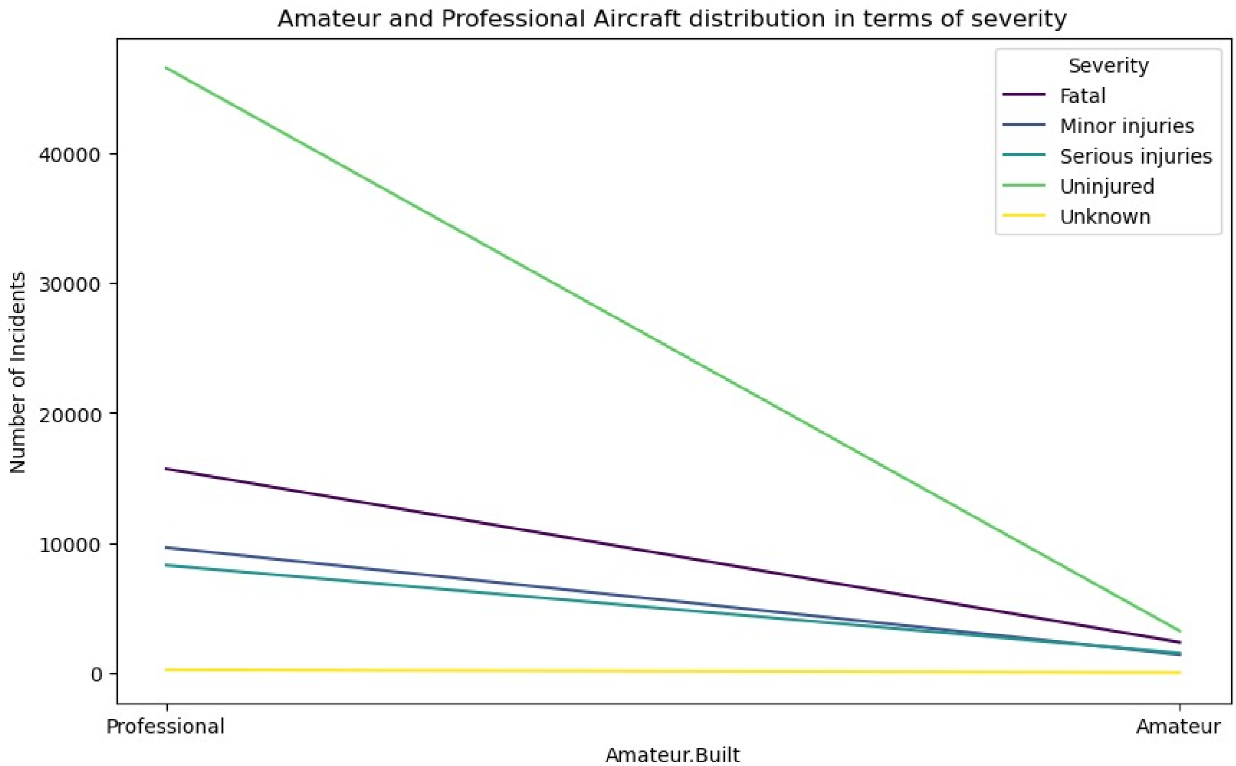


- The professional aircraft appear to have a higher fatality rate compared to amateur-built aircrafts.

2)How severe are incidents based on aircraft built?

```
# Distribution of 'Amateur.Built', 'Severity' in terms of severity
severity_counts = avidatacopy.groupby(["Amateur.Built",
"Severity"],observed=False).size().unstack()

severity_counts.plot(kind="line",figsize=(10,6), colormap="viridis")
plt.ylabel("Number of Incidents")
plt.title("Amateur and Professional Aircraft distribution in terms of
severity")
plt.xticks([0, 1], ["Professional", "Amateur"])
plt.legend(title="Severity")
plt.show()
```



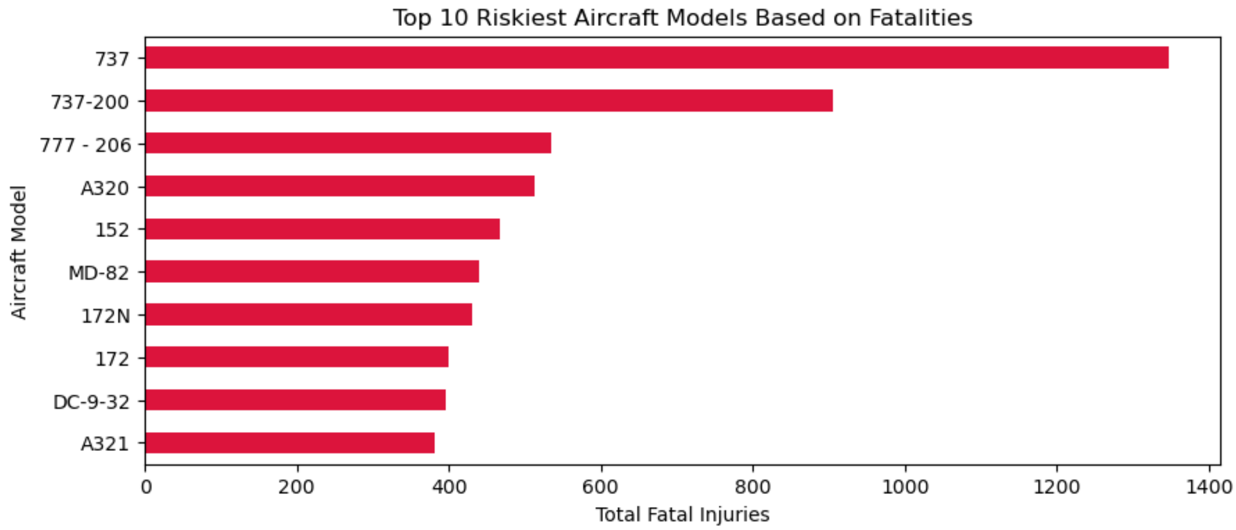
- For every severity category, the number of incidents is higher for Professional aircraft than for Amateur-built
- All lines slope downward from “Professional” to “Amateur,” indicating that Professional aircraft have more total incidents recorded.
- Since professional aircraft are more numerous and fly more frequently, it is expected they would have a higher count of incidents across all severity levels.

3) What are the riskiest flights model based on fatalities?

```
top_models = avidatacopy.groupby("Model")
["Total.Fatal.Injuries"].sum().nlargest(10)

plt.figure(figsize=(10, 4))
top_models.sort_values().plot(kind="barh", color="crimson")

plt.xlabel("Total Fatal Injuries")
plt.ylabel("Aircraft Model")
plt.title("Top 10 Riskiest Aircraft Models Based on Fatalities")
plt.show()
```



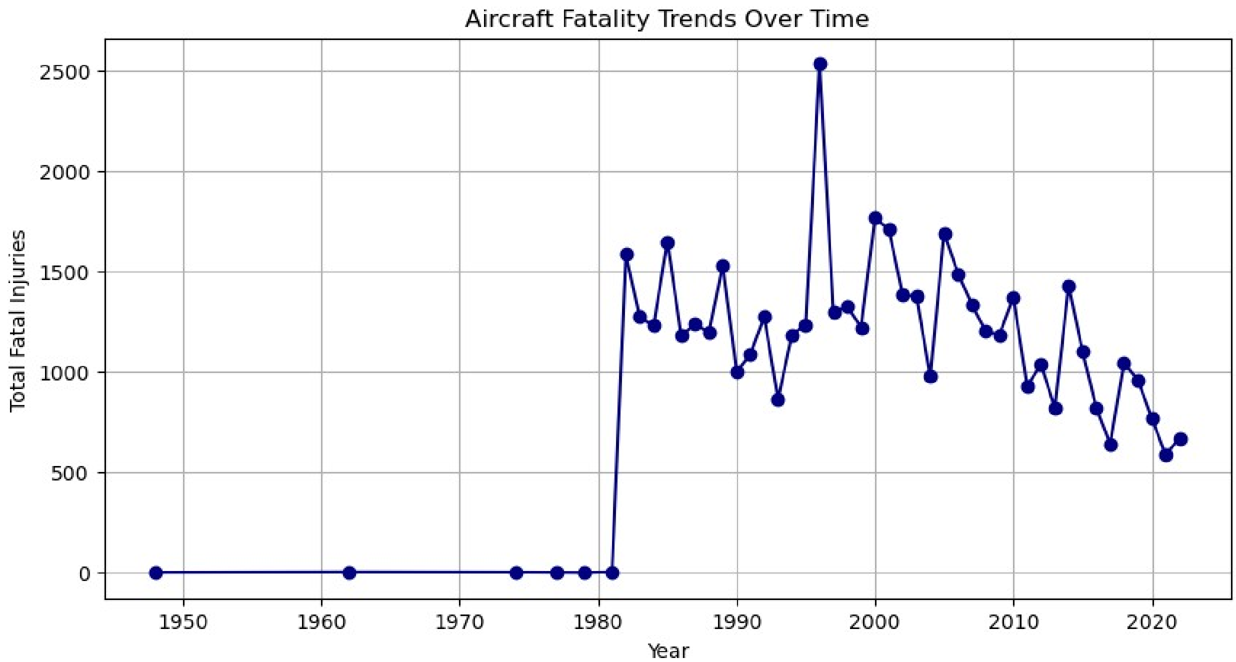
- The aircraft model 737 at the top has the highest number of total fatal injuries this could also indicate its mostly used
- The chart identifies which aircraft models have the highest absolute number of fatal injuries in the dataset.

4)How do aircraft accident trends change over time?

```
avidatacopy["Year"] =
pd.to_datetime(avidatacopy["Event.Date"]).dt.year
yearly_trends = avidatacopy.groupby("Year")
["Total.Fatal.Injuries"].sum()

plt.figure(figsize=(10, 5))
plt.plot(yearly_trends.index, yearly_trends.values, marker="o",
linestyle="-", color="navy")

plt.xlabel("Year")
plt.ylabel("Total Fatal Injuries")
plt.title("Aircraft Fatality Trends Over Time")
plt.grid(True)
plt.show()
```

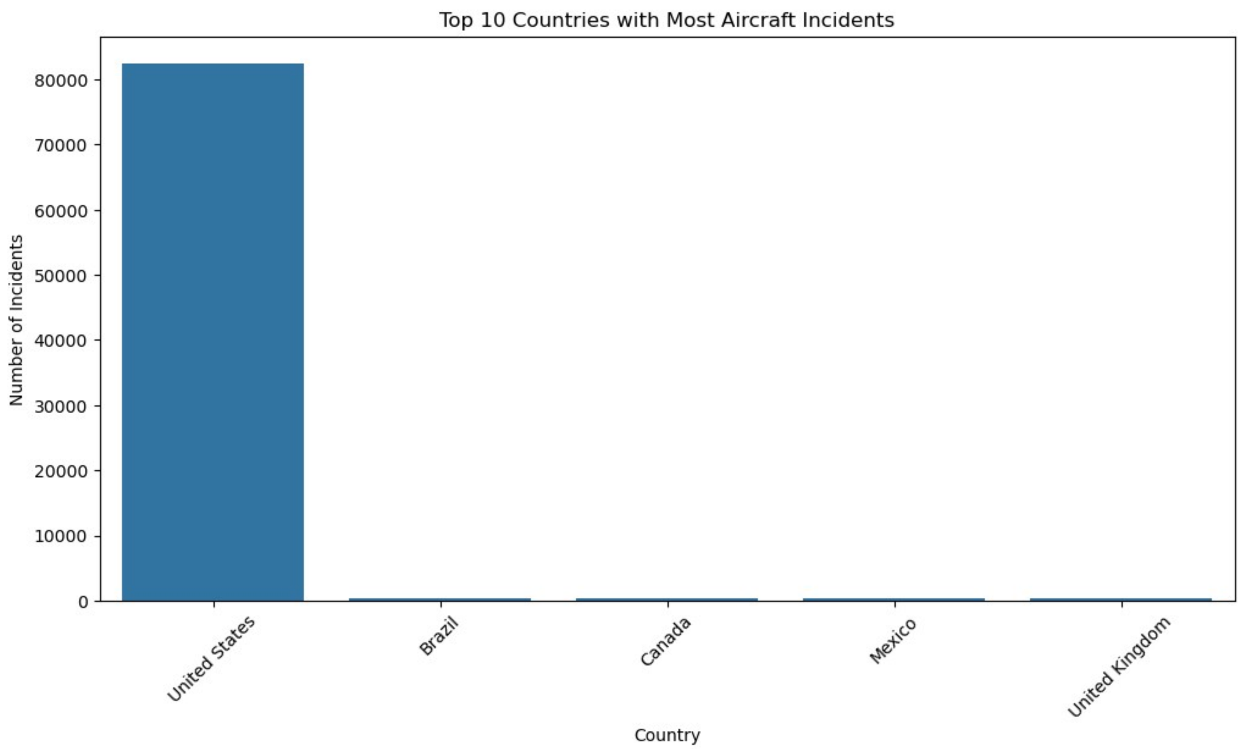


- By 1980 , the fatality count increases significantly, reaching over 1500 fatalities in some years.
- The highest peaks are observed in the 1990s with over 2500 recorded incidents
- By the early 2010s, the numbers are consistently decreasing compared to earlier peaks.
- Improvements in aviation safety, regulations, and technology could be contributing factors to the downward trend.

5) Top 10 Countries with the Most Accidents

```
# Countries accidents distribution
plt.figure(figsize=(12, 6))
sns.barplot(x=country_counts.index, y=country_counts.values)

plt.title("Top 10 Countries with Most Aircraft Incidents")
plt.xlabel("Country")
plt.ylabel("Number of Incidents")
plt.xticks(rotation=45)
plt.show()
```

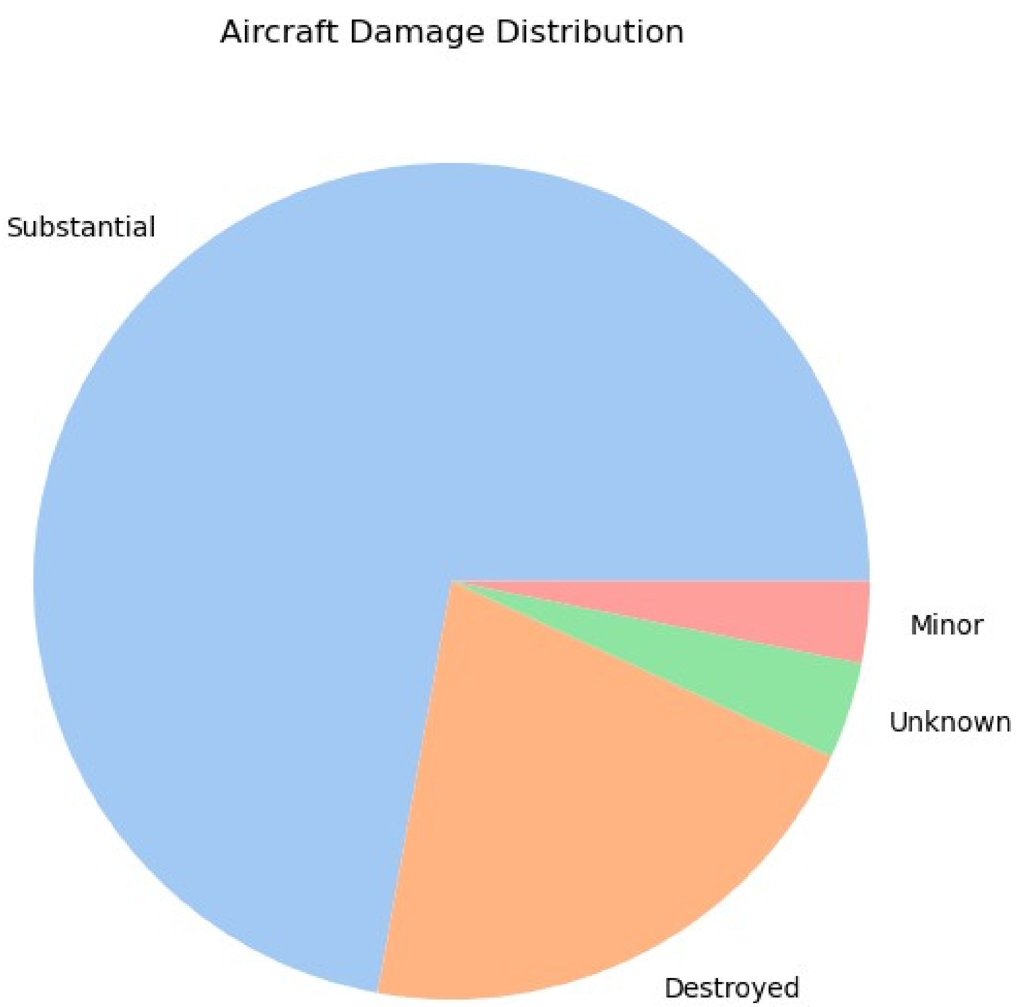


- Overall United States recorded the most numbers of incidents

6)What is the Aircraft Damage Distribution

```
# Aircraft damage distribution
damage_counts = avidatacopy["Aircraft.damage"].value_counts()

plt.figure(figsize=(7, 7))
plt.pie(damage_counts, labels=damage_counts.index,
colors=sns.color_palette("pastel"))
plt.title("Aircraft Damage Distribution")
plt.show()
```

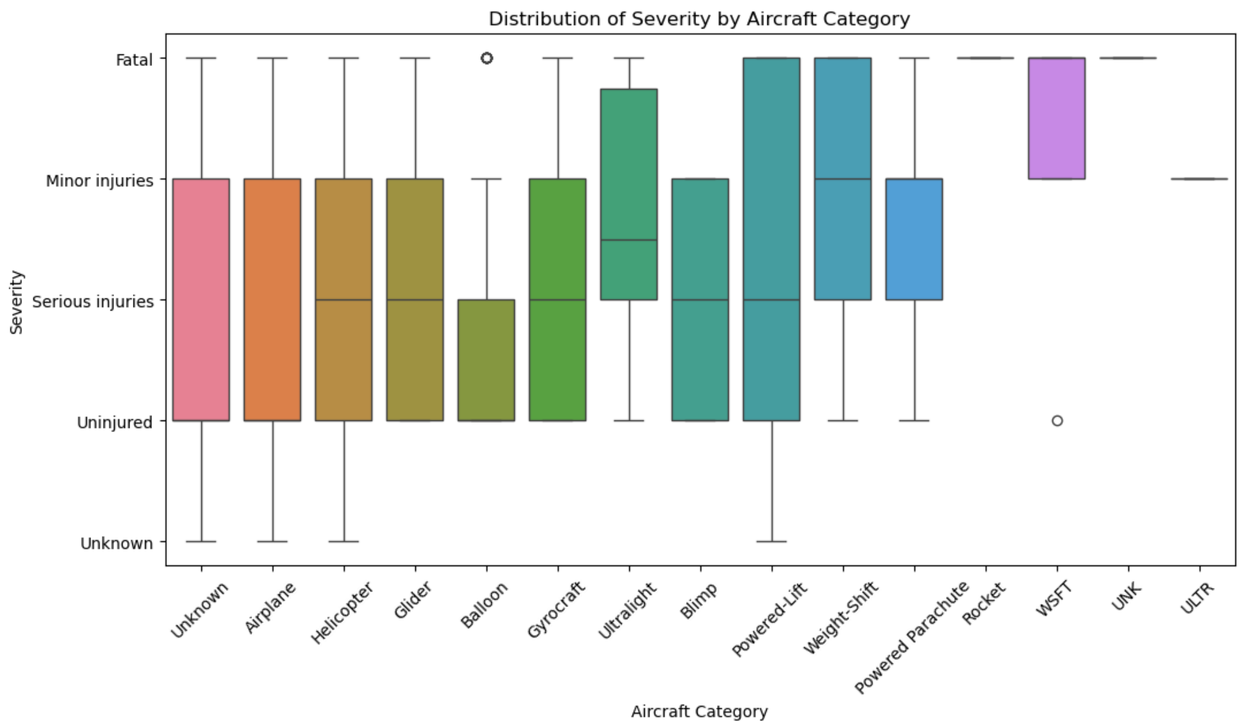


- The biggest slice of the pie chart represents aircraft sustaining “Substantial” damage, indicating that most recorded incidents lead to significant structural harm but not total destruction
- Minor damage forms a smaller slice, suggesting fewer incidents where aircraft only incur minor damage.
- A Segment labeled “Unknown” reflectS instances where the extent of damage was not clearly recorded.
- A noticeable share of incidents results in the aircraft being Destroyed.

7)visualizing the severity distribution for each aircraft category

```
plt.figure(figsize=(12, 6))
sns.boxplot(data=avidatacopy, x="Aircraft.Category",
y="Severity",hue="Aircraft.Category")
```

```
plt.title("Distribution of Severity by Aircraft Category")
plt.xlabel("Aircraft Category")
plt.ylabel("Severity")
plt.xticks(rotation=45)
plt.show()
```



- The plot represents the middle 50% of severity outcomes , while the “whiskers” and any outliers show the full spread of data.
- Airplanes and helicopters span from no injuries at all (uninjured) to fatal injuries, indicating a broad distribution of accident outcomes.
- airplanes may have a much larger number of reported incidents than others balloons or ultralights influencing the spread of the data.
- The “Unknown” severity category contains incidents for which injury details weren’t reported (missing data)

5.Recommendations

Recommendations to determine the lowest-risk aircraft for the company's new aviation division to guide purchasing decisions for both commercial and private enterprises.

- Airplanes account for 27,617 incidents, making them the most commonly involved aircraft in accidents and also the commonly used commercial aircraft. The company should focus on acquiring airplanes, as they are the most common category with data for risk assessment and with the highest traffic.
- Smaller aircraft may be risky due to operational challenges and some weather affected.

- The company can consider Helicopter for private usage since it has lower incidents.
- Aircraft with advanced safety features during landing, takeoff, and cruise should be prioritized with over 15,428 incidents in landing and 12,493 incidents in Takeoff investing in training and safety protocols can reduce accidents in these phases.
- Ensuring aircraft have weather detection technology to minimize risks in poor visibility conditions since we had 5,976 IMC incidents .
- The company should consider acquiring business and executive aircraft, as they have lower accident rates compared to personal and instructional flights , there are only 4,018 incidents in business and 553 incidents in executive flights, compare to personal with over 55,640 incidents.
- Choose aircraft with higher durability and safety records to reduce financial losses and increase passenger safety.Aicrafts sustained substantial damage amount to upto 64,148, and the completely damaged aircrafts amount to 18,623 this can be reduced with quality aircrafts.
- Opting for twin-engine or multi-engine aircraft for enhanced safety in case of engine failure.Aircrafts with a single engine aircraft account for the majority of incidents over 75,666 suggesting higher risk due to reliance on a single engine.
- Consider a mix of certified and well-built amateur aircraft, but opt for factory built aircraft with strong safety records to minimize risks ,factory built aircraft had 47,041 fatal injuries, while amateur-built aircraft had only 3,160.
- Modern aircraft are safer due to improvements in technology, maintenance, and training as after 2005, there was a gradual decline in incidents, with fewer incidents per year by 2010.
- By 2020, incidents dropped to around 1,392, showing a significant improvement in aviation safety over time and newer models should be prioritized, as aviation safety standards have strengthened over time.
- The company should priotize aircraft manufactured after 2010, as they have more stricter safety regulations, improved maintenance standards, and technological advancements.