

OVERVIEW

Ndege Holding.Inc is expanding to new horizons in order to diversify the portfolio to new markets, aviation sector has selected as the new frontier. The board has acquired crucial data from NTSB that would help make an informed decision in purchasing and operating airplanes for commercial and private enterprises.

The board lacks prior experience in aviation and therefore faces uncertainty around aircraft safety and operational risk. Poor aircraft selection could lead to increased accidents, financial losses, reputational damage, and higher insurance costs. This analysis aims to reduce those risks by identifying historically safer aircraft options.

BUSINESS UNDERSTANDING

Kamaa.Inc has been appointed to analyse the data to assist the board in making smart investments in aircrafts that are safer, more reliable, and cost-effective over time. Because the Kamaa Holding.Inc has no prior experience in aviation, leadership needs data-driven guidance to avoid costly mistakes such as: Buying aircraft models with high accident rates, investing in aircraft that require frequent repairs or have high fatality risks and choosing aircraft that may increase insurance costs and operational downtime.

Aircraft purchase and maintenance require huge financial costs, compounded by accidents, loss of life the repair, lawsuits and insurance are expensive and can damage the airline brand. By analyzing historical aviation accident data (2018–2023), we can identify patterns of risk and recommend aircraft types that historically demonstrate lower accident frequency and severity. This allows the company to make safer investment decisions backed by real data instead of assumptions.

OBJECTIVES

1. Clean and prepare data (flight) to give accurate analysis
2. Quantify aircraft risk by defining measurable indicators (frequency and severity).
3. Compare and Identify low risk aircraft based on maintenance and safety performance
4. Visualize trends and insights for high level decision makers.
5. Translate analytical findings into actionable recommendations for aircraft acquisition decisions.

```
In [16]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
In [17]: #Load the data set
df = pd.read_csv('flight.csv')
```

df

Out[17]:

	Unnamed: 0	acc.date	type	reg	operator	fat	location	dmg
0	0	3 Jan 2022	British Aerospace 4121 Jetstream 41	ZS-NRJ	SA Airlink	0	near Venetia Mine Airport	sub
1	1	4 Jan 2022	British Aerospace 3101 Jetstream 31	HR-AYY	LANHSA - Línea Aérea Nacional de Honduras S.A	0	Roatán-Juan Manuel Gálvez International Airpor...	sub
2	2	5 Jan 2022	Boeing 737-4H6	EP-CAP	Caspian Airlines	0	Isfahan-Shahid Beheshti Airport (IFN)	sub
3	3	8 Jan 2022	Tupolev Tu-204-100C	RA-64032	Cainiao, opb Aviastar-TU	0	Hangzhou Xiaoshan International Airport (HGH)	w/o
4	4	12 Jan 2022	Beechcraft 200 Super King Air	NaN	private	0	Machakilha, Toledo District, Grahem Creek area	w/o
...
2495	1245	20 Dec 2018	Cessna 560 Citation V	N188CW	Chen Aircrafts LLC	4	2 km NE of Atlanta-Fulton County Airport, GA (...)	w/o
2496	1246	22 Dec 2018	PZL-Mielec M28 Skytruck	GNB-96107	Guardia Nacional Bolivariana de Venezuela - GNBV	0	Kamarata Airport (KTV)	sub
2497	1247	24 Dec 2018	Antonov An-26B	9T-TAB	Air Force of the Democratic Republic of the Congo	0	Beni Airport (BNC)	w/o
2498	1248	31 Dec 2018	Boeing 757-2B7 (WL)	N938UW	American Airlines	0	Charlotte-Douglas International Airport, NC (C...	sub
2499	1249	unk. date 2018	Rockwell Sabreliner 80	N337KL	private	0	Eugene Airport, OR (EUG)	sub

2500 rows x 8 columns

DATA UNDERSTANDING

In [18]:

```
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2500 entries, 0 to 2499
Data columns (total 8 columns):
```

#	Column	Non-Null Count	Dtype
0	Unnamed: 0	2500 non-null	int64
1	acc.date	2500 non-null	object
2	type	2500 non-null	object
3	reg	2408 non-null	object
4	operator	2486 non-null	object
5	fat	2488 non-null	object
6	location	2500 non-null	object
7	dmg	2500 non-null	object

dtypes: int64(1), object(7)
memory usage: 156.4+ KB

```
In [4]: #Noticed I deleted 'fat' column want to bring it back.
df = pd.read_csv("flight.csv")

#Missing fatality values were treated as zero under the assumption that unrecorded
```

```
In [19]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2500 entries, 0 to 2499
Data columns (total 8 columns):
#   Column      Non-Null Count  Dtype
---  ---
0   Unnamed: 0   2500 non-null   int64
1   acc.date     2500 non-null   object
2   type         2500 non-null   object
3   reg          2408 non-null   object
4   operator     2486 non-null   object
5   fat          2488 non-null   object
6   location     2500 non-null   object
7   dmg          2500 non-null   object
dtypes: int64(1), object(7)
memory usage: 156.4+ KB
```

```
In [20]: #creating a new column 'year', dropping missing data and changing from data type
#for easier analysis.
df['year'] = (
    pd.to_datetime(df['acc.date'], errors='coerce')
    .dt.year
)

df = df.dropna(subset=['year'])
df.loc[:, 'year'] = df['year'].astype(int)
```

/Users/jane/miniconda3/envs/learn-env/lib/python3.8/site-packages/pandas/core/indexing.py:1745: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
isetter(ilocs[0], value)

Created a new column 'year' to analyse the trends annually. This makes it easier to sum p yearly counts as opposed to dates.

```
In [21]: df.head()
```

Out [21]:

	Unnamed: 0	acc.date	type	reg	operator	fat	location	dmg	year
0	0	3 Jan 2022	British Aerospace 4121 Jetstream 41	ZS-NRJ	SA Airlink	0	near Venetia Mine Airport	sub	2022
1	1	4 Jan 2022	British Aerospace 3101 Jetstream 31	HR-AYY	LANHSA - Línea Aérea Nacional de Honduras S.A	0	Roatán-Juan Manuel Gálvez International Airpor...	sub	2022
2	2	5 Jan 2022	Boeing 737-4H6	EP-CAP	Caspian Airlines	0	Isfahan-Shahid Beheshti Airport (IFN)	sub	2022
3	3	8 Jan 2022	Tupolev Tu-204-100C	RA-64032	Cainiao, opb Aviastar-TU	0	Hangzhou Xiaoshan International Airport (HGH)	w/o	2022
4	4	12 Jan 2022	Beechcraft 200 Super King Air	NaN	private	0	Machakilha, Toledo District, Graham Creek area	w/o	2022

In [8]:

df.tail()

Out [8]:

	Unnamed: 0	acc.date	type	reg	operator	fat	location	dmg	year
2494	1244	20 Dec 2018	Antonov An-26B	9S-AGB	Gomair	7	ca 37 km from Kinshasa-N'Djili Airport (FIH)	w/o	2018
2495	1245	20 Dec 2018	Cessna 560 Citation V	N188CW	Chen Aircrafts LLC	4	2 km NE of Atlanta-Fulton County Airport, GA (...)	w/o	2018
2496	1246	22 Dec 2018	PZL-Mielec M28 Skytruck	GNB-96107	Guardia Nacional Bolivariana de Venezuela - GNBV	0	Kamarata Airport (KTV)	sub	2018
2497	1247	24 Dec 2018	Antonov An-26B	9T-TAB	Air Force of the Democratic Republic of the Congo	0	Beni Airport (BNC)	w/o	2018
2498	1248	31 Dec 2018	Boeing 757-2B7 (WL)	N938UW	American Airlines	0	Charlotte-Douglas International Airport, NC (C...	sub	2018

DATA CLEANING

Data cleaning methods explored various steps, for example:

- 1.Checking for missing values
- 2.Checking for duplicated values
- 3.Converting objects to intergers
- 4.Creating data uniformity

```
In [22]: #Missing values
df.isna().sum().sort_values(ascending=False)
```

Out[22]: reg 90
operator 14
fat 12
year 0
dmg 0
location 0
type 0
acc.date 0
Unnamed: 0 0
dtype: int64

```
In [10]: #Checking the data after dropping the missing values.
df.info()
# columns are 8 and rows have dropped to 2494
```

<class 'pandas.core.frame.DataFrame'>
Int64Index: 2494 entries, 0 to 2498
Data columns (total 9 columns):
Column Non-Null Count Dtype

0 Unnamed: 0 2494 non-null int64
1 acc.date 2494 non-null object
2 type 2494 non-null object
3 reg 2404 non-null object
4 operator 2480 non-null object
5 fat 2482 non-null object
6 location 2494 non-null object
7 dmg 2494 non-null object
8 year 2494 non-null int64
dtypes: int64(2), object(7)
memory usage: 194.8+ KB

```
In [23]: #Selecting key columns to work with
#key data columns to work with
key_data_columns = ['year', 'type','fat', 'dmg']
df = df[key_data_columns]
df
```

Out[23]:

	year		type	fat	dmg
0	2022	British Aerospace 4121 Jetstream 41		0	sub
1	2022	British Aerospace 3101 Jetstream 31		0	sub
2	2022	Boeing 737-4H6		0	sub
3	2022	Tupolev Tu-204-100C		0	w/o
4	2022	Beechcraft 200 Super King Air		0	w/o
...
2494	2018	Antonov An-26B		7	w/o
2495	2018	Cessna 560 Citation V		4	w/o

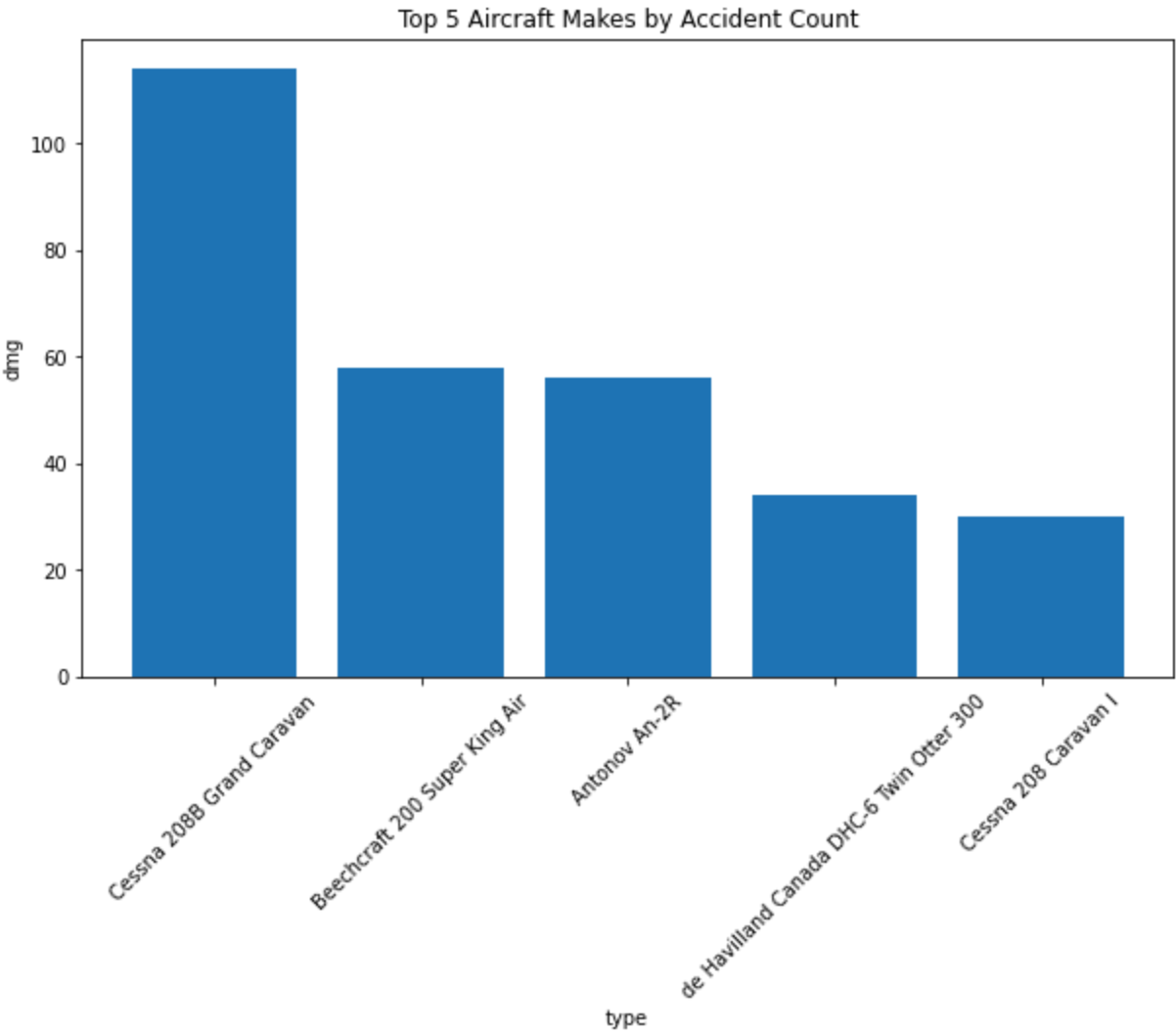
	year		type	fat	dmg
2496	2018	PZL-Mielec M28 Skytruck		0	sub
2497	2018	Antonov An-26B		0	w/o
2498	2018	Boeing 757-2B7 (WL)		0	sub

2494 rows x 4 columns

DATA ANALYSIS

```
In [27]: #Top 5 aircraft type accidents counts
top_makes_acc = df['type'].value_counts().head(5)

fig, ax = plt.subplots(figsize=(10,6))
ax.bar(top_makes_acc.index, top_makes_acc.values)
ax.set_title("Top 5 Aircraft Makes by Accident Count")
ax.set_xlabel("type")
ax.set_ylabel("dmg")
plt.xticks(rotation=45)
plt.show()
```

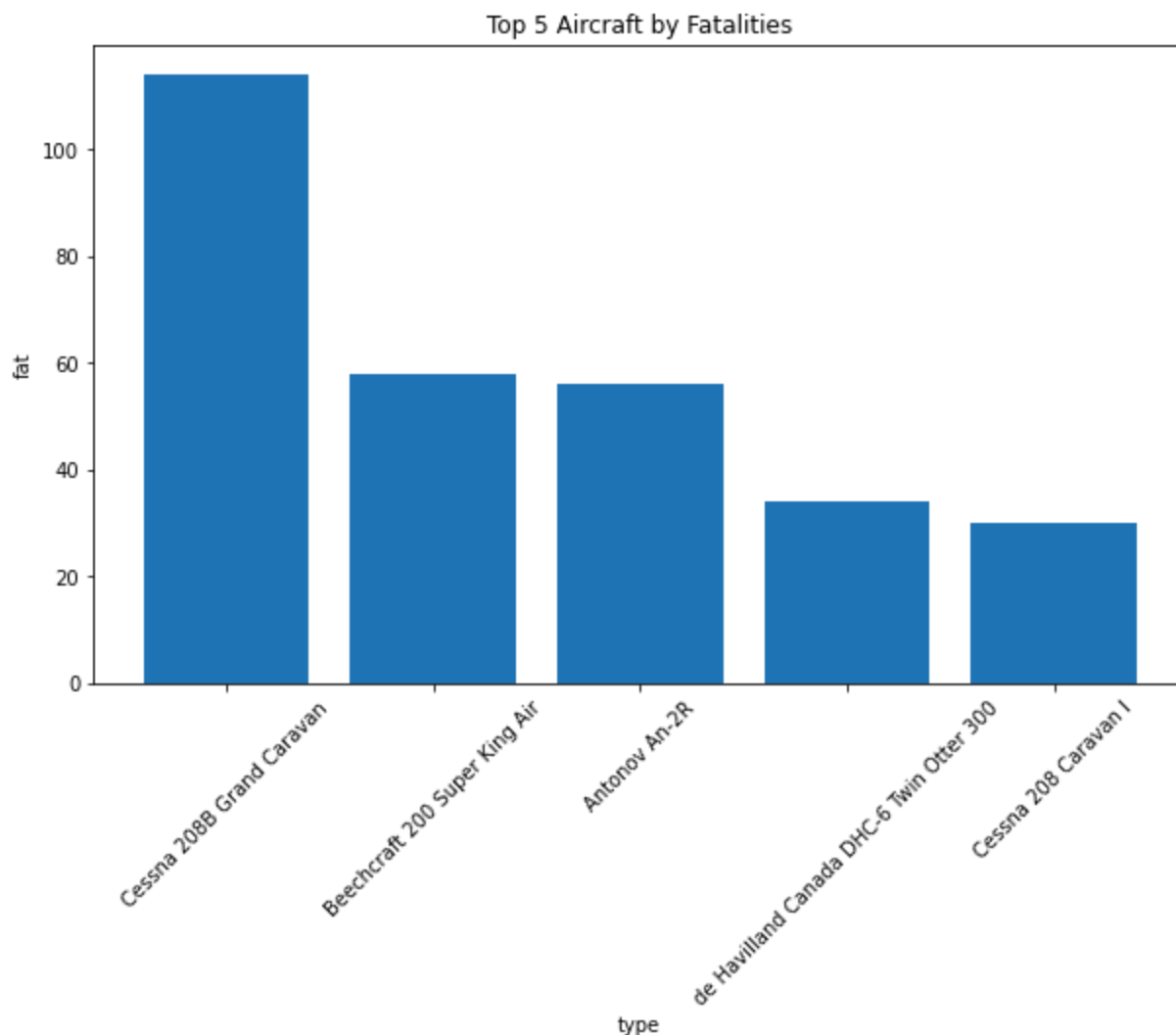


The bar chart shows that certain aircraft types consistently account for higher fatality counts, indicating elevated safety risk compared to others.Cessna 208B had the highest accidents,

followed by Beechcraft 200 and Cessna 208 the last among the top 5 aircrafts.

```
In [28]: top_makes_fat = df['type'].value_counts().head(5)

fig, ax = plt.subplots(figsize=(10,6))
ax.bar(top_makes_fat.index, top_makes_fat.values)
ax.set_title("Top 5 Aircraft by Fatalities")
ax.set_xlabel("type")
ax.set_ylabel("fat")
plt.xticks(rotation=45)
plt.show()
```



From the graph above, Cessna 208B had the highest fatalities and Cessna 208 the least among the top 5 aircrafts.

```
In [30]: #Fatalities per year
#The fatality column has str (97+1) and int, I want to convert all to int.
#This involved data cleaning to create data uniformity

def eval_sum(x):

    #Converts strings leaves integers as-is.

    if isinstance(x, str) and '+' in x:
        try:
```

```

        return sum(int(i) for i in x.split('+'))
    except:
        return 0 # fallback for malformed strings
    try:
        return int(x)
    except:
        return 0 # fallback for anything else

```

```

# Apply to the 'fat' column
df['fat'] = df['fat'].apply(eval_sum)

```

```

In [31]: #Checking the above equation if works.
#This specific data set had '97+1'
df.iloc[540]

```

```

Out[31]: year          2020
type      Airbus A320-214
fat         98
dmg         w/o
Name: 542, dtype: object

```

```

In [32]: #Fatalities per year
fatalities_per_year = (
    df.groupby('year')['fat']
    .sum()
    .reset_index())

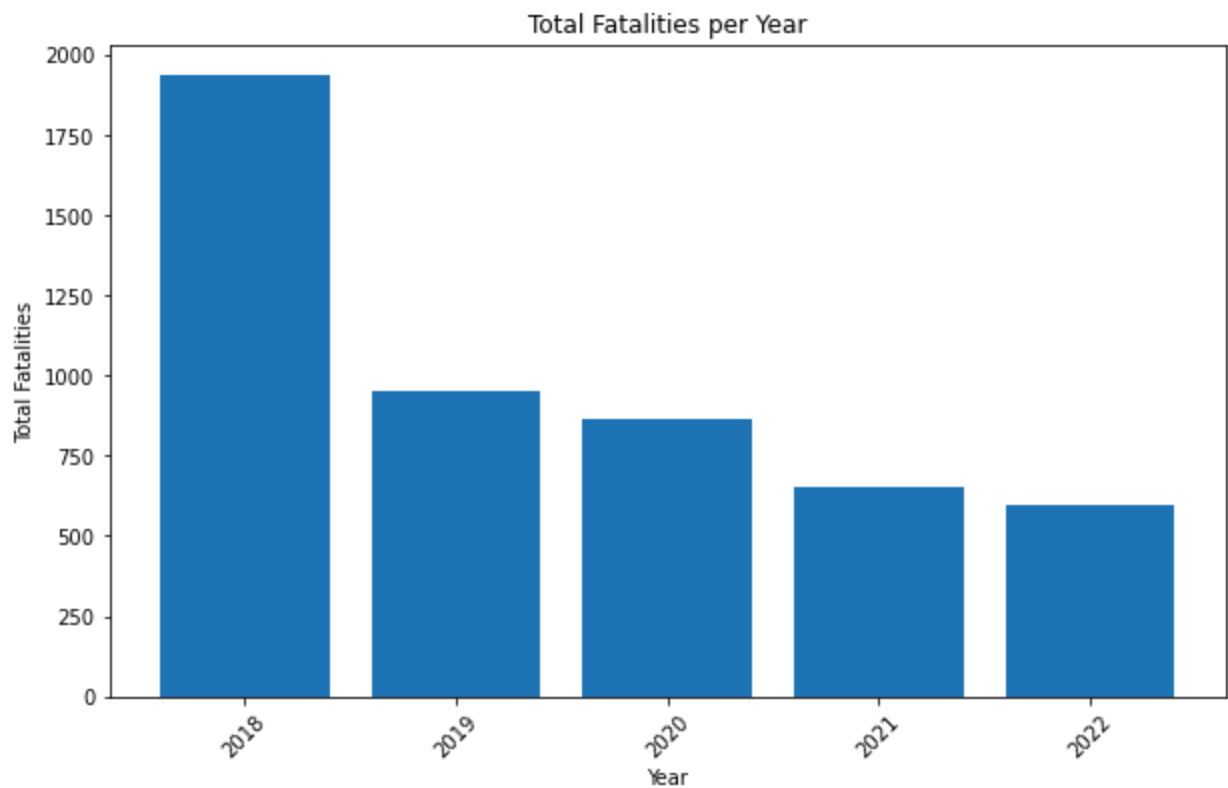
fig, ax = plt.subplots(figsize=(10,6))

ax.bar(fatalities_per_year['year'],
      fatalities_per_year['fat'])

ax.set_title("Total Fatalities per Year")
ax.set_xlabel("Year")
ax.set_ylabel("Total Fatalities")

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

```

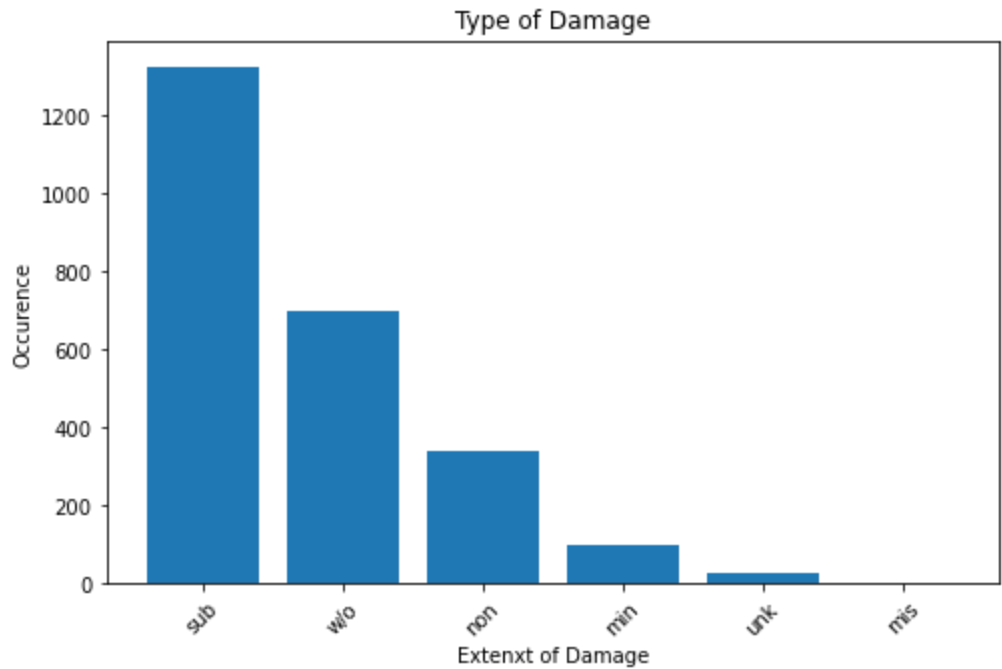



The above graph shows decreasing accidents fatalities over the years from 2018 to 2022.

```
In [34]: #Severity of Aircraft damages

damage_counts = df['dmg'].value_counts()

fig, ax = plt.subplots(figsize=(8,5))
ax.bar(damage_counts.index, damage_counts.values)
ax.set_title("Type of Damage")
ax.set_xlabel("Extenxt of Damage")
ax.set_ylabel("Occurence")
plt.xticks(rotation=45)
plt.show()
```



The graph above shows of the aircraft recorded substantial damage, while others were written off meaning total loss.

```
In [ ]: df.to_csv("flight_clean.csv", index=False)
```

```
In [49]: #Summary of Total_Flight data for top 5 aircraft for tableau analysis
Total_Flight_Summary = (
    df
    .groupby('type', as_index=False)
    .agg(
        dmg=('type', 'count'),
        fat=('fat', 'sum'),
    )
    .sort_values('dmg', ascending=False)
)
Total_Flight_Summary = Total_Flight_Summary.head(5)
Total_Flight_Summary
```

Out[49]:

	type	dmg	fat
289	Cessna 208B Grand Caravan	114	86
88	Beechcraft 200 Super King Air	58	16
69	Antonov An-2R	56	46
506	de Havilland Canada DHC-6 Twin Otter 300	34	86
287	Cessna 208 Caravan I	30	8

```
In [42]: Total_Flight_Summary.to_csv("Total_Flight_Summary.csv", index=False)
```

KEY INSIGHTS

1. Fatalities patterns vary significantly by aircraft type with small aircrafts contributing significantly to large porportion of total fatalities.
2. Fatality trends show a decline suggesting aviation safety improvement, however outliers exist indicating persisent risk.
3. Aircraft type though a good indicator doesn't necesarily a strong indicator, this could also imply that small aircraft have been purchased in high numbers hence correlating to high number of accidents and vice-versa also applies.
4. Aircraft operators practices and maintenance play crucial role in damages and fatalities and not necessarily linked to aircraft type.

CONCLUSION AND RECOMMENDATIONS

This analytical summary of avitaion accident data seeks to inform aircraft safety risk and inform data droven decision making. The data was cleaned, and ket data sets selected were the year of the accident, type of aircraft, number of fatalities and the extent of the aircraft damage. The data shows aviation safety and risk is not direct linked to aircraft types or year. Safety has improved overtime, and small aircraft consistently show disproportionate share of fatalities, higher opertional and safety risk.

1. Prioritize aircrafts with low-risk fatalities and fewer accidents. This offers a safer entry point into aviation operations, aircrafts with elevated fatalities pose safety, financial and reputations risk.
2. Continous aviation safety monitoring should be buttressed in the new aviation division. Risk assessment should continue beyond acquistion, as operations and maintenance do contribute to fatalities and damage.
3. More analysis is required on the reason for declining fatalities and accidents over the years, has safety aviation increased?

Annexes

Tableau Link

https://public.tableau.com/authoring/Total_flight_data/TotalAccidentsperAircraft/Total_flights_data_
