Final Project Submission

Please fill out:

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- Student pace: full time
- Scheduled project review date/time: 3/10/2025
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- Blog post URL:

1: Background

The company is expanding its portfolio by entering the aviation industry, focusing on both commercial and private air travel. However, aviation carries inherent safety and financial risks, especially when it comes to aircraft accidents, reliability, and maintenance. To ensure a successful and sustainable entry into this industry, the company requires an evidence-based assessment of aircraft safety and associated risks.

2: Project Overview

This project leverages historical accident data from the National Transportation Safety Board (NTSB), covering civil aviation accidents and selected incidents from 1962 to 2023. By analyzing this dataset, we aim to identify aircraft types with the lowest safety risks. The insights generated will guide business stakeholders in making informed decisions on which aircraft are most suitable for purchase and operation, minimizing risk exposure and maximizing operational reliability.

3: Business Understanding

Goal: Determine which aircraft types are associated with the lowest risk for accidents/incidents.

Objectives:

1. To assess the distribution and severity of aircraft accidents across different aircraft models and manufacturers.
2. To analyze the relationship between accident characteristics (fatalities, damage level, risk category) and the likelihood of aircraft being involved in fatal incidents.

3. To identify trends in aviation accident frequency and severity over time and across geographical locations.

4: Data Understanding

a).Set up the environment and import libraries

In [1]:
```
# Basic libraries
import pandas as pd
import numpy as np
# Visualization libraries
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
# Display settings
pd.set_option("display.max_columns", None)
```

b).Load Data

In [2]:
```
# Load dataset
df = pd.read_csv("data/Aviation_Data.csv", low_memory= False)
df.head()
```

Out[2]:

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

c). Initial Data Exploration

In [3]:
```
# Shape
df.shape
```

Out[3]: (90348, 31)

In [4]:
```
# Basic information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                88889 non-null  object 
 1   Investigation.Type      90348 non-null  object 
 2   Accident.Number         88889 non-null  object 
 3   Event.Date              88889 non-null  object 
 4   Location                88837 non-null  object 
 5   Country                 88663 non-null  object 
 6   Latitude                34382 non-null  object 
 7   Longitude               34373 non-null  object 
 8   Airport.Code            50249 non-null  object 
 9   Airport.Name            52790 non-null  object 
 10  Injury.Severity         87889 non-null  object 
 11  Aircraft.damage         85695 non-null  object 
 12  Aircraft.Category       32287 non-null  object 
 13  Registration.Number     87572 non-null  object 
 14  Make                    88826 non-null  object 
 15  Model                   88797 non-null  object 
 16  Amateur.Built           88787 non-null  object 
 17  Number.of.Engines       82805 non-null  float64
 18  Engine.Type             81812 non-null  object 
 19  FAR.Description         32023 non-null  object 
 20  Schedule                12582 non-null  object 
 21  Purpose.of.flight       82697 non-null  object 
 22  Air.carrier             16648 non-null  object 
 23  Total.Fatal.Injuries    77488 non-null  float64
 24  Total.Serious.Injuries  76379 non-null  float64
 25  Total.Minor.Injuries    76956 non-null  float64
 26  Total.Uninjured         82977 non-null  float64
 27  Weather.Condition       84397 non-null  object 
 28  Broad.phase.of.flight   61724 non-null  object 
 29  Report.Status           82508 non-null  object 
 30  Publication.Date        73659 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.4+ MB
```

In [5]:

```
# Summary statistics for all columns
df.describe(include="all").T
```

Out[5]:

	count	unique	top	freq	mean	std	min
Event.Id	88889	87951	20001212X19172	3	NaN	NaN	NaN
Investigation.Type	90348	71	Accident	85015	NaN	NaN	NaN
Accident.Number	88889	88863	DCA22LA135	2	NaN	NaN	NaN
Event.Date	88889	14782	2000-07-08	25	NaN	NaN	NaN
Location	88837	27758	ANCHORAGE, AK	434	NaN	NaN	NaN
Country	88663	219	United States	82248	NaN	NaN	NaN
Latitude	34382	25589	332739N	19	NaN	NaN	NaN
Longitude	34373	27154	0112457W	24	NaN	NaN	NaN
Airport.Code	50249	10375	NONE	1488	NaN	NaN	NaN
Airport.Name	52790	24871	Private	240	NaN	NaN	NaN
Injury.Severity	87889	109	Non-Fatal	67357	NaN	NaN	NaN
Aircraft.damage	85695	4	Substantial	64148	NaN	NaN	NaN
Aircraft.Category	32287	15	Airplane	27617	NaN	NaN	NaN
Registration.Number	87572	79105	NONE	344	NaN	NaN	NaN
Make	88826	8237	Cessna	22227	NaN	NaN	NaN
Model	88797	12318	152	2367	NaN	NaN	NaN
Amateur.Built	88787	2	No	80312	NaN	NaN	NaN
Number.of.Engines	82805	NaN	NaN	NaN	1.14659	0.44651	0
Engine.Type	81812	13	Reciprocating	69530	NaN	NaN	NaN
FAR.Description	32023	31	091	18221	NaN	NaN	NaN
Schedule	12582	3	NSCH	4474	NaN	NaN	NaN
Purpose.of.flight	82697	26	Personal	49448	NaN	NaN	NaN
Air.carrier	16648	13590	Pilot	258	NaN	NaN	NaN
Total.Fatal.Injuries	77488	NaN	NaN	NaN	0.647855	5.48596	0
Total.Serious.Injuries	76379	NaN	NaN	NaN	0.279881	1.54408	0
Total.Minor.Injuries	76956	NaN	NaN	NaN	0.357061	2.23563	0
Total.Uninjured	82977	NaN	NaN	NaN	5.32544	27.9136	0
Weather.Condition	84397	4	VMC	77303	NaN	NaN	NaN
Broad.phase.of.flight	61724	12	Landing	15428	NaN	NaN	NaN
Report.Status	82508	17007	Probable Cause	61754	NaN	NaN	NaN
Publication.Date	73659	2923	25-09-2020	16317	NaN	NaN	NaN

In [6]:
```
# Summary statistics for numerical columns
df.describe()
```

Out[6]:

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

In [7]:
```
df.columns
```

Out[7]:
```
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')
```

5: Data Cleaning

A). Checking missing values

In [8]:
```
df.isna().sum().sort_values(ascending=False)
```

Out[8]:
```
Schedule                  77766
Air.carrier               73700
FAR.Description           58325
Aircraft.Category         58061
Longitude                 55975
Latitude                  55966
Airport.Code              40099
Airport.Name              37558
Broad.phase.of.flight     28624
Publication.Date          16689
Total.Serious.Injuries    13969
Total.Minor.Injuries      13392
Total.Fatal.Injuries      12860
Engine.Type                8536
Report.Status              7840
Purpose.of.flight          7651
Number.of.Engines          7543
Total.Uninjured            7371
Weather.Condition          5951
Aircraft.damage            4653
Registration.Number        2776
Injury.Severity            2459
Country                    1685
Amateur.Built              1561
Model                      1551
Make                       1522
Location                   1511
Event.Date                 1459
Accident.Number            1459
Event.Id                   1459
Investigation.Type            0
dtype: int64
```

In [9]:
```
# To know the percentage of the missing values
df.isna().mean()*100
```

Out[9]:
```
Event.Id                   1.614867
Investigation.Type         0.000000
Accident.Number            1.614867
Event.Date                 1.614867
Location                   1.672422
Country                    1.865011
Latitude                  61.944924
Longitude                 61.954886
Airport.Code              44.382831
Airport.Name              41.570372
Injury.Severity            2.721698
Aircraft.damage            5.150086
Aircraft.Category         64.263736
Registration.Number        3.072564
Make                       1.684597
Model                      1.716695
Amateur.Built              1.727764
Number.of.Engines          8.348829
Engine.Type                9.447913
FAR.Description           64.555939
Schedule                  86.073848
Purpose.of.flight          8.468367
Air.carrier               81.573471
Total.Fatal.Injuries      14.233851
Total.Serious.Injuries    15.461327
Total.Minor.Injuries      14.822686
Total.Uninjured            8.158454
Weather.Condition          6.586753
Broad.phase.of.flight     31.681941
Report.Status              8.677558
Publication.Date          18.471909
dtype: float64
```

B). Handling missing values

In [10]:
```
# Drop columns with too many missing values (>60% missing)
threshold = 0.6 * len(df)
df = df.dropna(axis=1, thresh=threshold)
```

In [11]:
```
# Fill missing categorical values with "Unknown"
for col in df.select_dtypes(include="object").columns:
    df[col] = df[col].fillna("Unknown")
```

In [12]:
```
for col in df.select_dtypes(include=["float64", "int64"]).columns:
    df[col] = df[col].fillna(df[col].median())
```

In [13]:
```
df.isna().sum()
```

Out[13]:
```
Event.Id                  0
Investigation.Type        0
Accident.Number           0
Event.Date                0
Location                  0
Country                   0
Injury.Severity           0
Aircraft.damage           0
Registration.Number       0
Make                      0
Model                     0
Amateur.Built             0
Number.of.Engines         0
Engine.Type               0
Purpose.of.flight         0
Total.Fatal.Injuries      0
Total.Serious.Injuries    0
Total.Minor.Injuries      0
Total.Uninjured           0
Weather.Condition         0
Broad.phase.of.flight     0
Report.Status             0
Publication.Date          0
dtype: int64
```

In [14]:
```
df.shape
```

Out[14]:
```
(90348, 23)
```

In [15]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 23 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                90348 non-null  object 
 1   Investigation.Type      90348 non-null  object 
 2   Accident.Number         90348 non-null  object 
 3   Event.Date              90348 non-null  object 
 4   Location                90348 non-null  object 
 5   Country                 90348 non-null  object 
 6   Injury.Severity         90348 non-null  object 
 7   Aircraft.damage         90348 non-null  object 
 8   Registration.Number     90348 non-null  object 
 9   Make                    90348 non-null  object 
 10  Model                   90348 non-null  object 
 11  Amateur.Built           90348 non-null  object 
 12  Number.of.Engines       90348 non-null  float64
 13  Engine.Type             90348 non-null  object 
 14  Purpose.of.flight       90348 non-null  object 
 15  Total.Fatal.Injuries    90348 non-null  float64
 16  Total.Serious.Injuries  90348 non-null  float64
 17  Total.Minor.Injuries    90348 non-null  float64
 18  Total.Uninjured         90348 non-null  float64
 19  Weather.Condition       90348 non-null  object 
 20  Broad.phase.of.flight   90348 non-null  object 
 21  Report.Status           90348 non-null  object 
 22  Publication.Date        90348 non-null  object 
dtypes: float64(5), object(18)
memory usage: 15.9+ MB
```

C). Checking and dropping duplicates

In [16]:
```
df.duplicated().sum()
```

Out[16]: 1390

In [17]:
```
df = df.drop_duplicates()
print("After dropping full duplicates:", df.shape)
```

```
After dropping full duplicates: (88958, 23)
```

In [18]:
```
df.duplicated().sum()
```

Out[18]: 0

D). Outliers

a) Focus on numerical columns

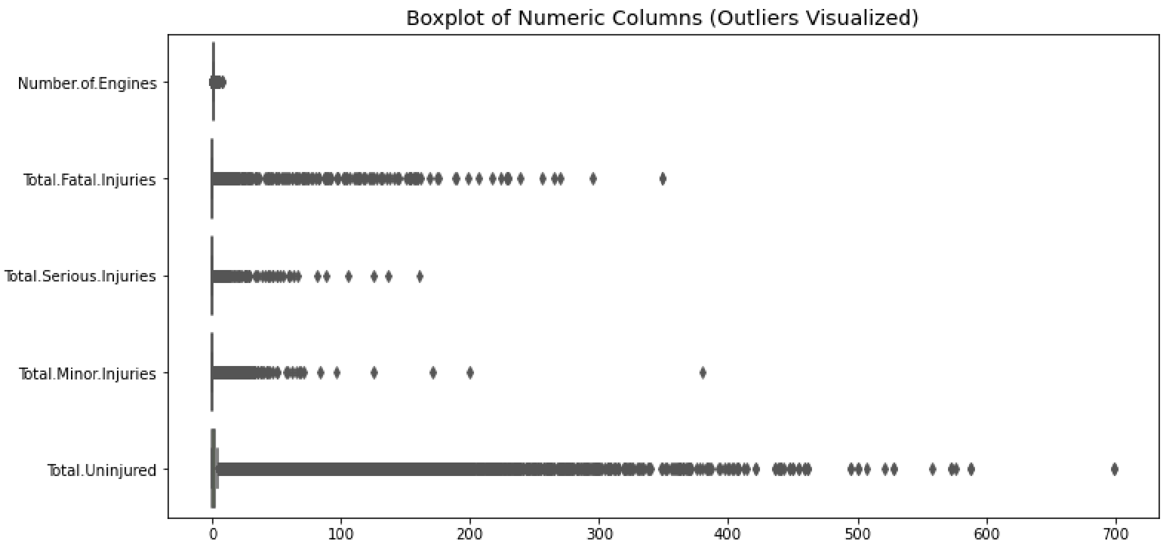
In [19]:
```
# Select numeric columns
numeric_cols = df.select_dtypes(include=["float64", "int64"]).columns
print("Numeric columns:", numeric_cols)
```

```
Numeric columns: Index(['Number.of.Engines', 'Total.Fatal.Injuries', 'Total.Serio
us.Injuries',
       'Total.Minor.Injuries', 'Total.Uninjured'],
      dtype='object')
```

b) Visualization to show outliers

Boxplots for Outlier Visualization - are the best way to see outliers (they appear as dots beyond the whiskers).

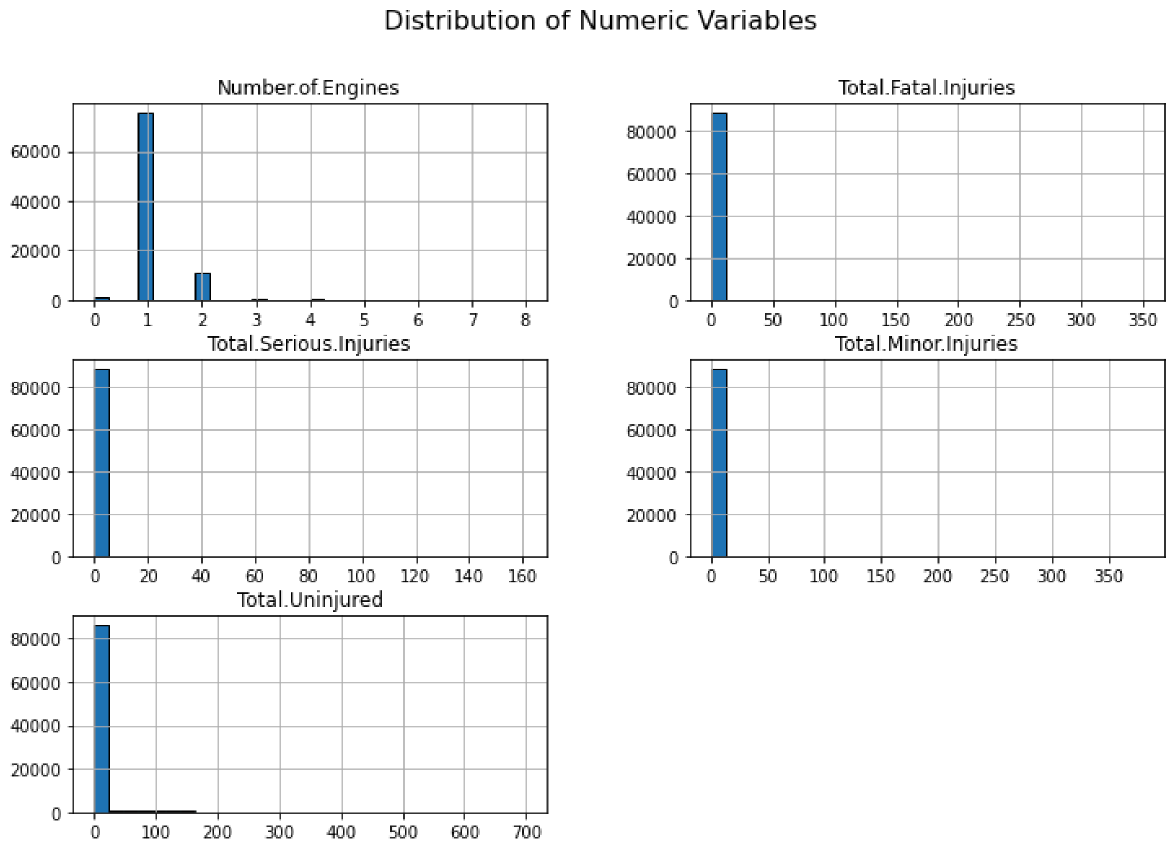
In [20]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(12, 6))
sns.boxplot(data=df[numeric_cols], orient="h", palette="Set2")
plt.title("Boxplot of Numeric Columns (Outliers Visualized)", fontsize=14)
plt.show()
```



c) Histograms for Distribution

- They show how values are spread and highlight long tails caused by outliers.

In [21]:
```
df[numeric_cols].hist(figsize=(12, 8), bins=30, edgecolor="black")
plt.suptitle("Distribution of Numeric Variables", fontsize=16)
plt.show()
```



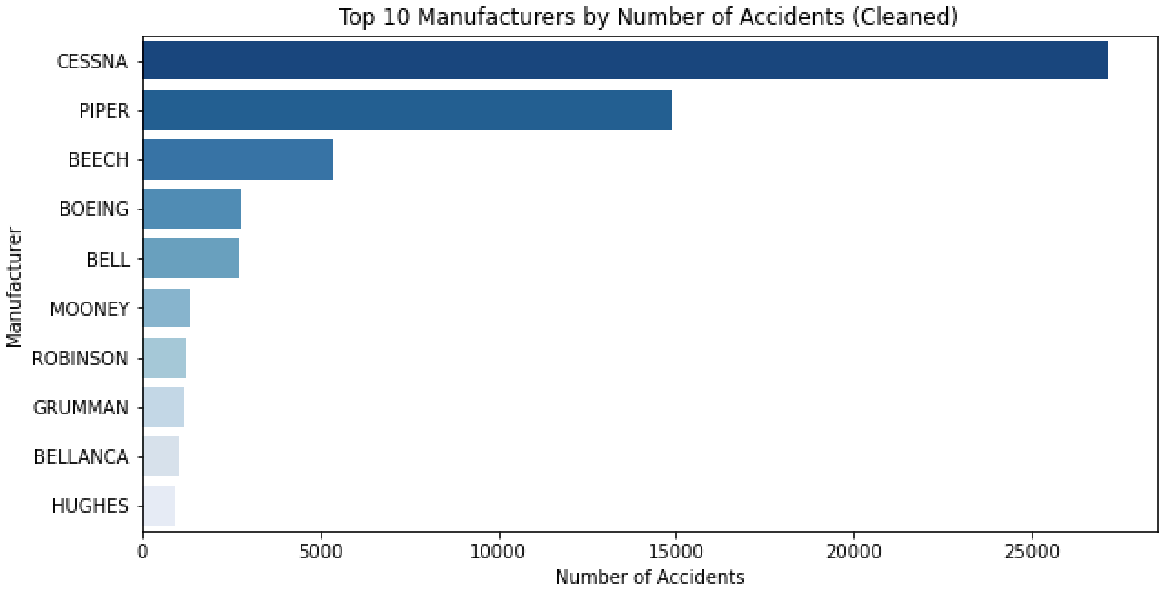
NB: I didn't remove outliers on my decision because they might be real accidents so if i drop them they might affect my analysis leading to biasness.

6: Data Visualization per Objective

Objective 1: Distribution & Severity by Model/Manufacturer

In [22]:

```
# Clean the manufacturer names
df['Make_Cleaned'] = df['Make'].str.upper().str.strip()

# Count accidents by manufacturer
manufacturer_counts = df['Make_Cleaned'].value_counts().head(10)

# Plot
plt.figure(figsize=(10,5))
sns.barplot(x=manufacturer_counts.values, y=manufacturer_counts.index, palette="
plt.title("Top 10 Manufacturers by Number of Accidents (Cleaned)")
plt.xlabel("Number of Accidents")
plt.ylabel("Manufacturer")
plt.show()
```



Interpretation: The analysis of accident frequency by manufacturer indicates that a small number of aircraft producers account for the majority of reported accidents, with manufacturers like Cessna and Piper appearing most frequently in the dataset.

Adding severity columns that will help me to achieve my objective

In [23]:
```
def classify_severity(row):
    if row['Total.Fatal.Injuries'] > 0:
        return "Fatal"
    elif row['Total.Serious.Injuries'] > 0:
        return "Serious"
    elif row['Total.Minor.Injuries'] > 0:
        return "Minor"
    else:
        return "No Injury"

df["Injury_Severity"] = df.apply(classify_severity, axis=1)
```

Then group by it:

In [24]:
```
severity_by_model = (
    df.groupby(['Make', 'Model'])['Injury_Severity']
    .value_counts()
    .unstack()
    .fillna(0)
)
severity_by_model.head()
```

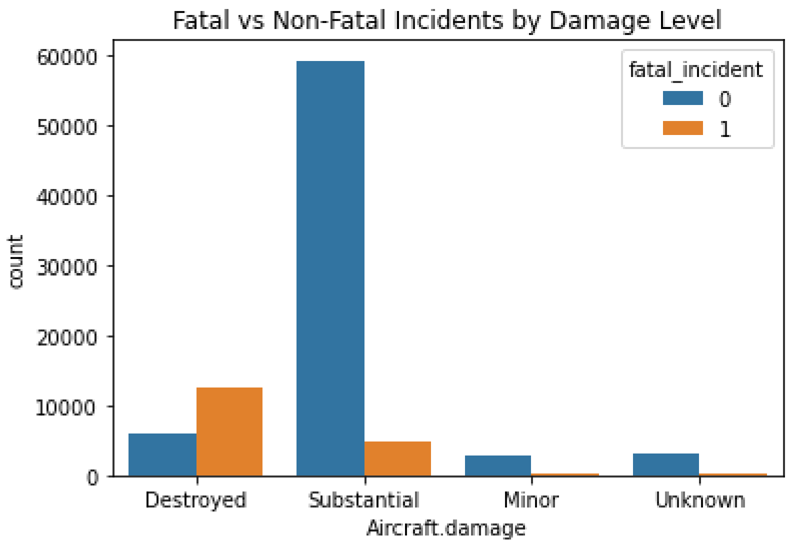
Out[24]:

	Injury_Severity	Fatal	Minor	No Injury	Serious
Make	**Model**				
107.5 Flying Corporation	**One Design DR 107**	1.0	0.0	0.0	0.0
1200	**G103**	0.0	0.0	0.0	1.0
177MF LLC	**PITTS MODEL 12**	0.0	0.0	0.0	1.0
1977 Colfer-chan	**STEEN SKYBOLT**	0.0	1.0	0.0	0.0
1st Ftr Gp	**FOCKE-WULF 190**	1.0	0.0	0.0	0.0

Objective 2: Accident Characteristics & Fatal Incidents

In [25]:

```
# Create a "fatal" indicator
df['fatal_incident'] = np.where(df['Total.Fatal.Injuries'] > 0, 1, 0)

# Compare fatal vs non-fatal by damage level
sns.countplot(data=df, x='Aircraft.damage', hue='fatal_incident')
plt.title("Fatal vs Non-Fatal Incidents by Damage Level")
plt.show()

# Risk ratio by manufacturer
risk = df.groupby('Make')['fatal_incident'].mean().sort_values(ascending=False).
print(risk)
```

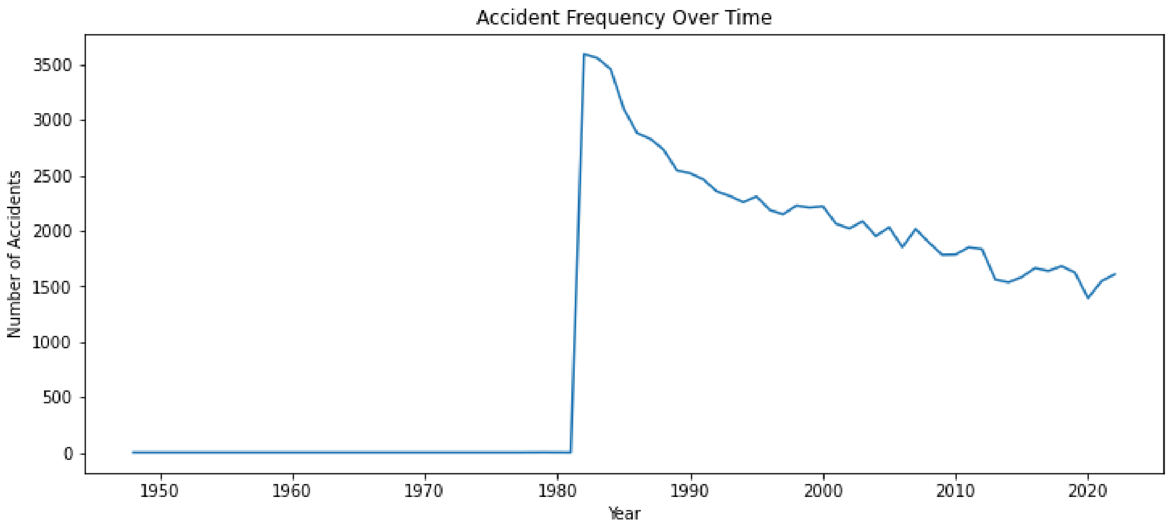



```
Make
107.5 Flying Corporation    1.0
Colliander                  1.0
Parrigin                    1.0
Coen                        1.0
Parkman                     1.0
Parker Warren               1.0
Parachute Icarus            1.0
Papa 51 Ltd., Co.           1.0
Pank                        1.0
Panaplane                   1.0
Name: fatal_incident, dtype: float64
```

Intepretation: Severe damage (e.g., “Destroyed”) is strongly associated with fatal accidents while Minor/substantial damage tends to have mostly non-fatal outcomes. This indicates that aircraft damage level is a strong predictor of survivability.

Objective 3: Trends Over Time & Geography

In [26]:
```
# Convert date
df['Event.Date'] = pd.to_datetime(df['Event.Date'], errors="coerce")

# Accidents per year
df['year'] = df['Event.Date'].dt.year
accidents_per_year = df.groupby('year').size()

plt.figure(figsize=(12,5))
sns.lineplot(x=accidents_per_year.index, y=accidents_per_year.values)
plt.title("Accident Frequency Over Time")
plt.xlabel("Year")
plt.ylabel("Number of Accidents")
plt.show()

# Geographical trends (using Plotly for interactivity)
accidents_by_country = df["Country"].value_counts().reset_index()
accidents_by_country.columns = ["Country", "Accident_Count"]

fig = px.choropleth(
    accidents_by_country,
    locations="Country",
    locationmode="country names",
    color="Accident_Count",
    title="Aviation Accident Frequency by Country"
)
fig.show()
```



Interpretaion : The line chart provides insights into whether aviation safety has improved or worsened over time, Most often, you’ll find a decline in accidents in recent decades

due to better aircraft engineering, pilot training, and regulations.

Also by countries, Darker-colored countries = higher number of accidents while Lighter-colored countries = lower accident counts. Usually, the United States dominates accident counts in such datasets (especially NTSB data) because of the large number of aircraft and reporting coverage but Some countries may appear low not because they're safer, but because they have fewer flights or less complete reporting.

7: Save the Cleaned Data and export it to tableau

In [27]:
```
# Standardize manufacturer names
df['Make'] = df['Make'].str.upper().str.strip()
```

In [28]:
```
df.to_csv("Cleaned_AviationData.csv", index=False)
```

8: Conclusion

The study shows that accident distribution is concentrated among major manufacturers such as Cessna and Piper, largely reflecting their dominance in the market, but the likelihood of fatal outcomes differs significantly across aircraft types and models. Accident severity is closely tied to the extent of aircraft damage, with fatal incidents more common in cases of substantial or destroyed aircraft. Over time, accident frequencies demonstrate a general downward trend, reflecting improvements in aviation safety, though some spikes persist due to isolated events or reporting differences. Geographically, the United States records the highest number of accidents, consistent with its high flight volumes and strong reporting, while lower counts in other regions may reflect underreporting rather than inherently safer skies.

9: Recommendations

Based on the findings, the company should prioritize aircraft with lower fatality ratios rather than focusing solely on accident counts, and place emphasis on manufacturer-specific safety performance when making purchase decisions. Strengthening pilot training, routine maintenance, and safety audits is critical to reducing risk exposure, particularly for models with higher fatal accident proportions. Additionally, management should adopt a data-driven risk framework that integrates historical safety

records, geographical trends, and operational factors before expanding into aviation. Finally, ongoing monitoring and alignment with global safety standards will ensure that investment choices are both safe and sustainable in the long term.