aviation-accident-analysis

March 30, 2025

1 Phase 1 Final Project:

2 Aviation Accident Analysis To Identifying the Safest Aircraft Makes and Models for Business Expansion

2.1 Problem Statement

As our company is prioritizing to expand into the aviation industry, we need to make informed decisions about aircraft acquisitions. However, we lack sufficient knowledge about the risks associated with different aircraft makes and models for commercial and private operations. This analysis aims to identify the safest aircraft makes and models with the lowest accident rates, ensuring data-driven purchasing decisions.

2.2 Project Objectives

We aim to achieve the following: - Analyze trends in aviation accidents over time. - Identify common causes of aviation accidents. - Examine accident distribution by aircraft make and model. - Recommend the safest aircraft makes and models for purchase.

2.3 Expected Outcomes:

- Insights into aviation accident trends and contributing factors.
- A comparative analysis of accident rates across different aircraft makes and models.
- Data-driven recommendations for acquiring the safest aircraft for business expansion.

First we will load our data, clean it, analyze it, give insights and provide recommendations.

2.4 1. Importing Libraries

[14]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set_style('whitegrid')
plt.style.use('ggplot')
```

2.5 2. Loading the Datasets

[16]:
```
#loading our datasets, use encoding to handle encoding errors
df1 = pd.read_csv("AviationData.csv",  encoding ='latin1', low_memory=False)
df2 = pd.read_csv("USState_Codes.csv")
```

2.6 3. Data Understanding

[18]:
```
#previewing first 5 rows of df1 dataset
df1.head()
```

[18]:
```
         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]
```

[19]:
```
##previewing first 5 rows of df2 dataset
df2.head()
```

[19]:
```
     US_State Abbreviation
0     Alabama           AL
1      Alaska           AK
2     Arizona           AZ
3    Arkansas           AR
4  California           CA
```

The datasets have been successfully loaded. The aviation dataset contains 31 columns, including accident details, locations, and fatalities. The state codes dataset provides abbreviations for U.S. states, which we will merge with the aviation dataset.

[21]:
```
#checking the summary of our dataset
df1.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            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   75118 non-null object
dtypes: float64(5), object(26)
memory usage: 21.0+ MB

2.7 4. Data Cleaning and Preparation

lets clean the data, merge state names, and proceed with analysis

[24]:
```python
# Extract state abbreviations from the 'Location' column
df1['State_Abbreviation'] = df1['Location'].str.extract(r',\s*([A-Z]{2})$')

# Merge with state codes to get full state names
df1 = df1.merge(df2, left_on='State_Abbreviation', right_on='Abbreviation',␣
 ↪how='left')

# Drop redundant abbreviation column
df1.drop(columns=['Abbreviation'], inplace=True)

# Rename the column for clarity
df1.rename(columns={'US_State': 'State'}, inplace=True)

# Check the updates
df1[['Location', 'State_Abbreviation', 'State']].head(5)
```

[24]:
```
          Location State_Abbreviation       State
0  MOOSE CREEK, ID                 ID       Idaho
1   BRIDGEPORT, CA                 CA  California
2    Saltville, VA                 VA    Virginia
3       EUREKA, CA                 CA  California
4       Canton, OH                 OH        Ohio
```

[25]:
```python
df1.head()
```

[25]:
```
         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  … Total.Fatal.Injuries Total.Serious.Injuries  \
0          NaN  …                  2.0                    0.0
1          NaN  …                  4.0                    0.0
2          NaN  …                  3.0                    NaN
3          NaN  …                  2.0                    0.0
4          NaN  …                  1.0                    2.0

  Total.Minor.Injuries Total.Uninjured Weather.Condition  \
0                  0.0             0.0               UNK
1                  0.0             0.0               UNK
2                  NaN             NaN               IMC
3                  0.0             0.0               IMC
4                  NaN             0.0               VMC

  Broad.phase.of.flight   Report.Status  Publication.Date State_Abbreviation  \
0                Cruise  Probable Cause               NaN                 ID
1               Unknown  Probable Cause        19-09-1996                 CA
2                Cruise  Probable Cause        26-02-2007                 VA
3                Cruise  Probable Cause        12-09-2000                 CA
4              Approach  Probable Cause        16-04-1980                 OH

        State
0       Idaho
1  California
2    Virginia
3  California
4        Ohio

[5 rows x 33 columns]
```

The dataset now includes full state names instead of abbreviations, making it more readable.

[27]:
```
# Checking for missing values
df1.isnull().sum()
```

[27]:
```
Event.Id                      0
Investigation.Type            0
Accident.Number               0
Event.Date                    0
Location                     52
Country                     226
Latitude                  54507
Longitude                 54516
Airport.Code              38640
```

```
Airport.Name               36099
Injury.Severity             1000
Aircraft.damage             3194
Aircraft.Category          56602
Registration.Number         1317
Make                          63
Model                         92
Amateur.Built                102
Number.of.Engines           6084
Engine.Type                 7077
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               6381
Publication.Date           13771
State_Abbreviation          6463
State                       6727
dtype: int64
```

We can clearly ascertain that there are missing values in our df1 dataset that need to be handled. We will focus only on the columns that align directly with our business problem and objectives.

2.7.1 Handling Missing Data

Lets Drop columns with excessive missing values and Drop rows with missing critical information

[31]:
```
# create a copy of our dataset
df1_copy = df1.copy()
```

[32]:
```
#dropping columns with excessive missing values, that are unlikely to␣
↪contribute meaningful insights to our analysis.
df1_copy.drop(columns=['Latitude', 'Longitude', 'Schedule', 'Air.carrier', 'FAR.
↪Description', 'Airport.Code','Broad.phase.of.flight','Airport.Name'],␣
↪inplace=True)
```

[33]:
```
# drop rows with missing values
df1_copy.dropna(inplace = True)
```

[34]:
```
#confirming the changes
df1_copy.shape
```

[34]: (19695, 25)

[35]:
```
#lets check for duplicates and drop them if any
df1_copy.duplicated().sum()
```

[35]: 0

The dataset is free from duplicates

[37]:
```
#check for datatypes and modify any inconsistent dtypes
df1_copy.dtypes
```

[37]:
```
Event.Id                   object
Investigation.Type         object
Accident.Number            object
Event.Date                 object
Location                   object
Country                    object
Injury.Severity            object
Aircraft.damage            object
Aircraft.Category          object
Registration.Number        object
Make                       object
Model                      object
Amateur.Built              object
Number.of.Engines         float64
Engine.Type                object
Purpose.of.flight          object
Total.Fatal.Injuries      float64
Total.Serious.Injuries    float64
Total.Minor.Injuries      float64
Total.Uninjured           float64
Weather.Condition          object
Report.Status              object
Publication.Date           object
State_Abbreviation         object
State                      object
dtype: object
```

[38]:
```
# Convert 'Event.Date' , 'Publication.Date' to datetime format and Amateur.
↪Built to boolean
df1_copy['Event.Date'] = pd.to_datetime(df1_copy['Event.Date'], errors='coerce')
df1_copy['Publication.Date'] = pd.to_datetime(df1_copy['Publication.Date'],␣
↪errors='coerce')
df1_copy["Amateur.Built"] = df1_copy["Amateur.Built"].str.strip().str.lower().
↪map({"yes": True, "no": False})
```

```
df1_copy.dtypes
```

[38]:
```
Event.Id                          object
Investigation.Type                object
Accident.Number                   object
Event.Date                datetime64[ns]
Location                          object
Country                           object
Injury.Severity                   object
Aircraft.damage                   object
Aircraft.Category                 object
Registration.Number               object
Make                              object
Model                             object
Amateur.Built                       bool
Number.of.Engines                float64
Engine.Type                       object
Purpose.of.flight                 object
Total.Fatal.Injuries             float64
Total.Serious.Injuries           float64
Total.Minor.Injuries             float64
Total.Uninjured                  float64
Weather.Condition                 object
Report.Status                     object
Publication.Date          datetime64[ns]
State_Abbreviation                object
State                             object
dtype: object
```

[39]:
```
# Display cleaned dataset
df1_copy.head()
```

[39]:
```
          Event.Id Investigation.Type Accident.Number Event.Date  \
7   20020909X01562           Accident      SEA82DA022 1982-01-01
8   20020909X01561           Accident      NYC82DA015 1982-01-01
12  20020917X02148           Accident      FTW82FRJ07 1982-01-02
13  20020917X02134           Accident      FTW82FRA14 1982-01-02
14  20020917X02119           Accident      FTW82FPJ10 1982-01-02

            Location        Country Injury.Severity Aircraft.damage  \
7        PULLMAN, WA  United States       Non-Fatal     Substantial
8   EAST HANOVER, NJ  United States       Non-Fatal     Substantial
12         HOMER, LA  United States       Non-Fatal       Destroyed
13        HEARNE, TX  United States        Fatal(1)       Destroyed
14     CHICKASHA, OK  United States        Fatal(1)       Destroyed

   Aircraft.Category Registration.Number  … Purpose.of.flight  \
```

```
7           Airplane              N2482N  …         Personal
8           Airplane              N7967Q  …         Business
12          Airplane              N14779  …         Personal
13          Airplane              N758SK  …         Personal
14          Airplane              N4876K  …         Personal

   Total.Fatal.Injuries  Total.Serious.Injuries  Total.Minor.Injuries  \
7                   0.0                     0.0                   0.0
8                   0.0                     0.0                   0.0
12                  0.0                     0.0                   1.0
13                  1.0                     0.0                   0.0
14                  1.0                     0.0                   0.0

   Total.Uninjured Weather.Condition   Report.Status  Publication.Date  \
7              2.0               VMC  Probable Cause        1982-01-01
8              2.0               IMC  Probable Cause        1982-01-01
12             0.0               IMC  Probable Cause        1983-02-01
13             0.0               IMC  Probable Cause        1983-02-01
14             0.0               IMC  Probable Cause        1983-02-01

    State_Abbreviation       State
7                   WA  Washington
8                   NJ  New Jersey
12                  LA   Louisiana
13                  TX       Texas
14                  OK    Oklahoma

[5 rows x 25 columns]
```

2.8 5. Data Analysis and visualization

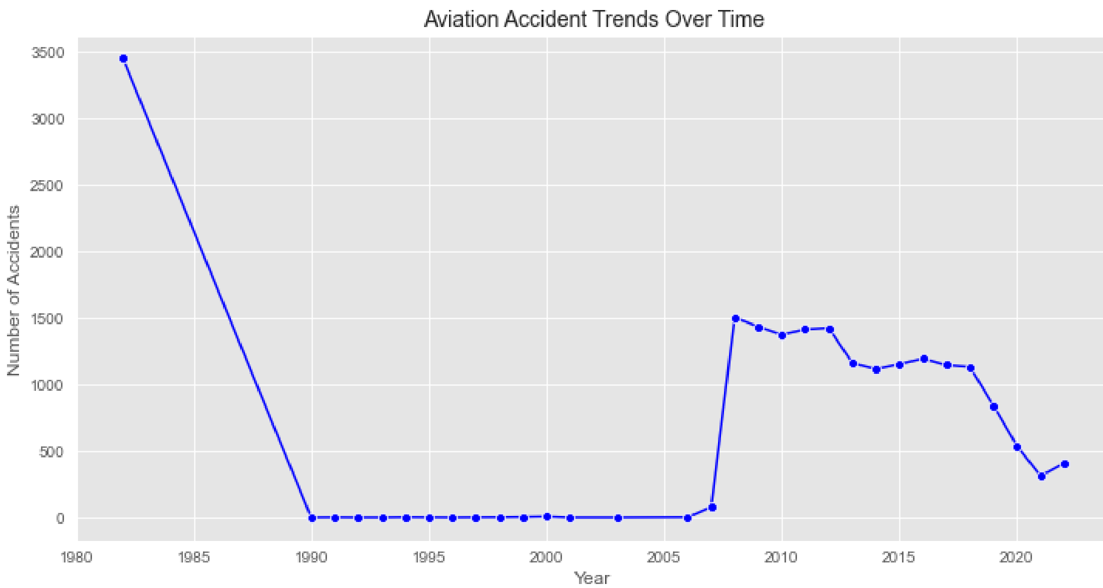
2.8.1 i. Trends in aviation accidents over time

We'll group the data by year and plot a line chart to observe trends.

[42]:

```
# Extract year from Event.Date
df1_copy["Year"] = df1_copy["Event.Date"].dt.year

# Count accidents per year
accidents_per_year = df1_copy.groupby("Year").size()

# Plot the trend
plt.figure(figsize=(12, 6))
sns.lineplot(x=accidents_per_year.index, y=accidents_per_year.values,␣
 ↪marker="o", color="b")

plt.title("Aviation Accident Trends Over Time", fontsize=14)
plt.xlabel("Year", fontsize=12)
```

```
plt.ylabel("Number of Accidents", fontsize=12)
plt.grid(True)
plt.show()
```



The line chart illustrates the trend of aviation accidents from 1980 to the present. - The number of aviation accidents was extremely high around 1980, reaching over 3,500 incidents. There was a dramatic drop in accidents by the late 1980s, suggesting significant improvements in aviation safety, regulatory measures, or changes in reporting practices. - From the 1990s to early 2000s, the number of recorded accidents remained extremely low. - A sharp increase in accidents occurred in the mid-2000s, reaching over 1,500 incidents per year. Possible reasons include changes in aviation traffic, an increase in aircraft operations, or more comprehensive accident reporting. - After peaking, the accident rate fluctuates but remains relatively high until around 2020. A noticeable decline in accidents is observed in recent years, possibly due to advancements in aircraft safety, stricter regulations, or the impact of reduced air travel (e.g., due to the COVID-19 pandemic).

Insights for Business Decision-Making

- The overall trend suggests aviation safety has improved significantly since the 1980s.
- Recent declines in accidents indicate safer aircraft and better risk management, making this an opportune time for new investments in aviation.

2.8.2 ii. Common causes of accidents

Accidents by number of engines lets create a pivot table Summarizing accidents by engine count.

[46]:
```
# Pivot table summarizing accidents by number of engines
engine_pivot = df1_copy.groupby("Number.of.Engines")["Event.Id"].count().
 ↪reset_index()
```

```
engine_pivot.rename(columns={"Event.Id": "Accident Count"}, inplace=True)
engine_pivot
```

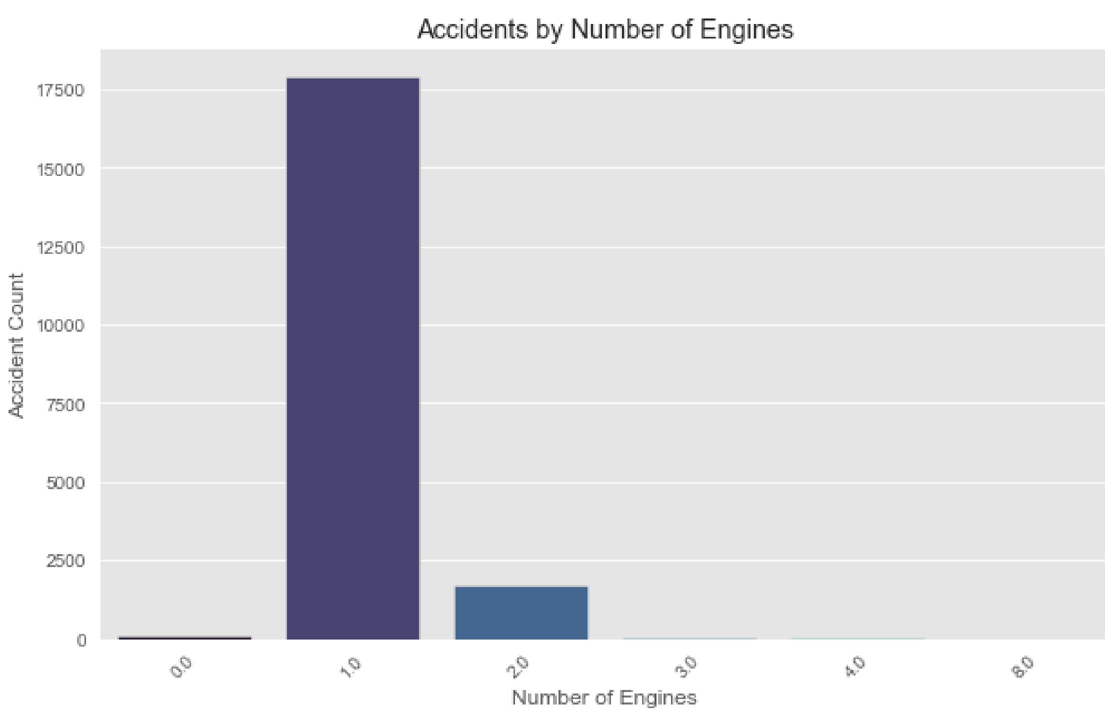
[46]:

	Number.of.Engines	Accident Count
0	0.0	83
1	1.0	17899
2	2.0	1681
3	3.0	16
4	4.0	14
5	8.0	2

Number of accidents reduces by increased number of engines

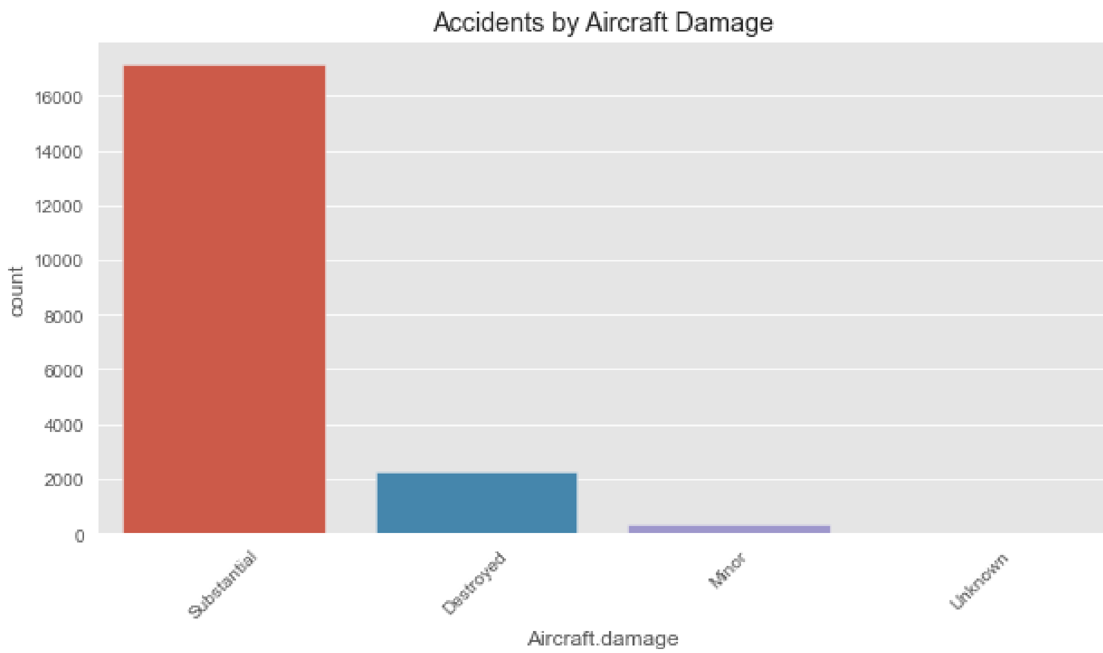
[48]:

```
# Plot accidents by number of engines
plt.figure(figsize=(10, 6))
sns.barplot(data=engine_pivot, x="Number.of.Engines", y="Accident Count",␣
↪palette="mako")

# Formatting
plt.title("Accidents by Number of Engines")
plt.xlabel("Number of Engines")
plt.ylabel("Accident Count")
plt.xticks(rotation=45)
plt.show()
```



Accidents by Aircraft Damage

[50]:
```
plt.figure(figsize=(10, 5))

sns.countplot(data=df1_copy, x="Aircraft.damage")
plt.title("Accidents by Aircraft Damage")
plt.xticks(rotation=45)
plt.show()
```

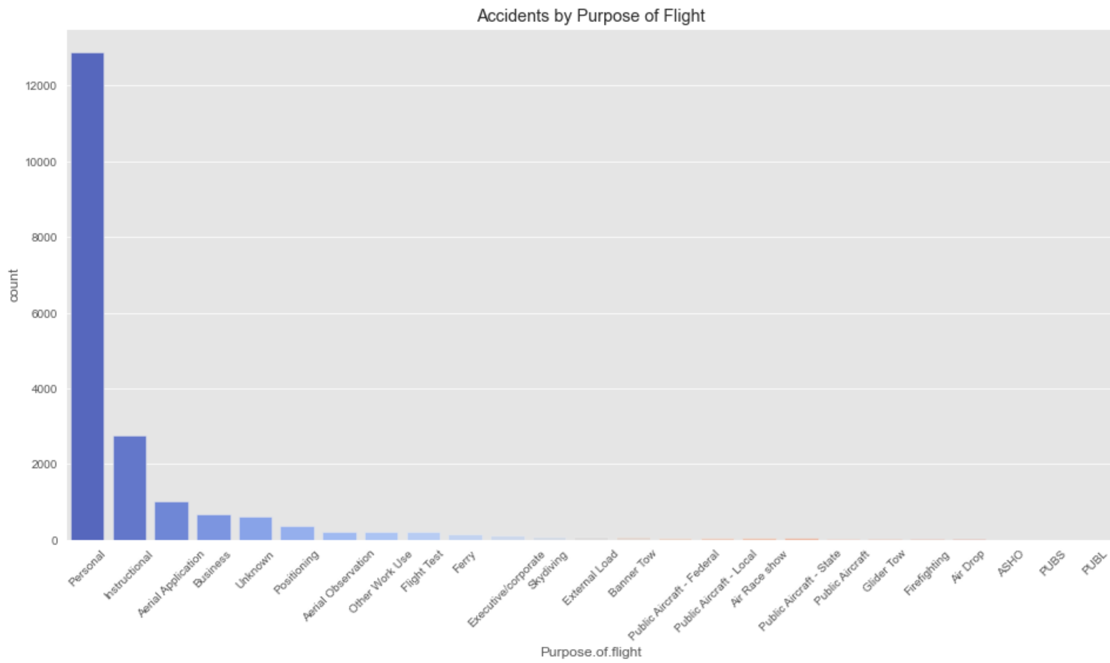


The bar chart shows the distribution of aviation accidents based on the extent of aircraft damage. - "Substantial" damage is the most common category, with the highest number of incidents. - "Destroyed" aircraft comes second but with significantly fewer occurrences. - "Minor" and "Unknown" damage categories have the least incidents.

This suggests that while many accidents result in severe damage, total destruction is relatively rare.

Accidents by Purpose of Flight

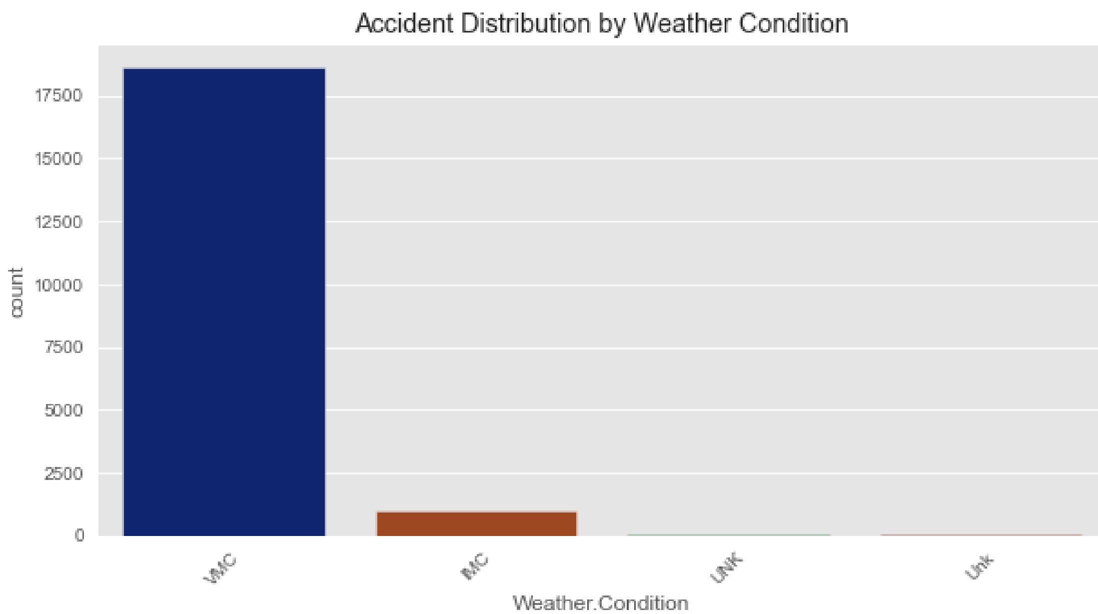
[53]:
```
plt.figure(figsize=(16, 8))

# Sorting by count
sorted_purpose = df1_copy["Purpose.of.flight"].value_counts().index

sns.countplot(data=df1_copy, x="Purpose.of.flight", palette="coolwarm",␣
↪order=sorted_purpose)
plt.title("Accidents by Purpose of Flight")
plt.xticks(rotation=45)
plt.show()
```



The Personal category has the highest number of accidents by a significant margin, followed by Instructional and Aerial Application flights. Business, Unknown, and Positioning flights also show notable accident counts, while other flight purposes, such as Air Race Show, Firefighting, and Public Aircraft operations, have minimal occurrences. This suggests that personal flights are the most prone to accidents, likely due to factors such as pilot experience, aircraft maintenance, or operational conditions.

Accidents by Weather Condition

[120]:
```
plt.figure(figsize=(10, 5))
sns.countplot(data=df1_copy, x="Weather.Condition", palette="dark")
plt.title("Accident Distribution by Weather Condition")
plt.xticks(rotation=45)
plt.show()
```



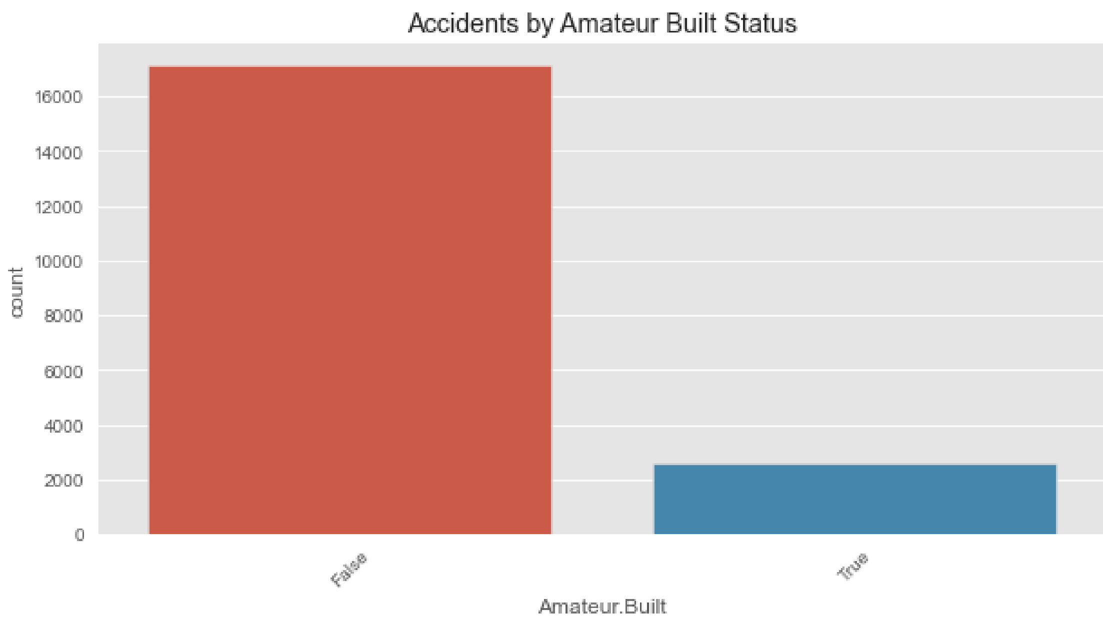
The bar chart visualizes the distribution of aviation accidents based on weather conditions. The key observations include:

- IMC (Instrument Meteorological Conditions) has the highest number of accidents, significantly dominating the dataset.
- VMC (Visual Meteorological Conditions) shows a much smaller number of accidents compared to IMC.
- UNK (Unknown) and LNK (Likely Unknown) have very few recorded accidents, indicating incomplete or unclear data.

This suggests that most accidents occur under Instrument Meteorological Conditions, likely due to poor visibility and reliance on instruments rather than visual cues.

Accidents by Amateur Built Status

[59]:
```
plt.figure(figsize=(10, 5))
sns.countplot(data=df1_copy, x="Amateur.Built")
plt.title("Accidents by Amateur Built Status")
plt.xticks(rotation=45)
plt.show()
```



This bar chart displays the distribution of aviation accidents based on whether the aircraft was amateur-built or not.

- "False" (Not Amateur-Built) has the highest number of accidents, significantly outweighing the "True" category.
- "True" (Amateur-Built) has a noticeably lower count of accidents, but they still occur.

This suggests that most aviation accidents involve factory-built aircraft rather than amateur-built ones. However, the number of accidents in the amateur-built category is still significant, indicating that these aircraft may have unique risk factors.

2.8.3 iii. Accident distribution by aircraft make and model.

To examine this we will group the data by aircraft make and model, counting the number of accidents, sort the results to highlight the most least accident-prone aircraft and visualize our findings.

[63]:
```
# Grouping by Make and Model to count accidents
accident_distribution = df1_copy.groupby(["Make", "Model"]).size().
 ↪reset_index(name="Accident Count")
accident_distribution.head()
```

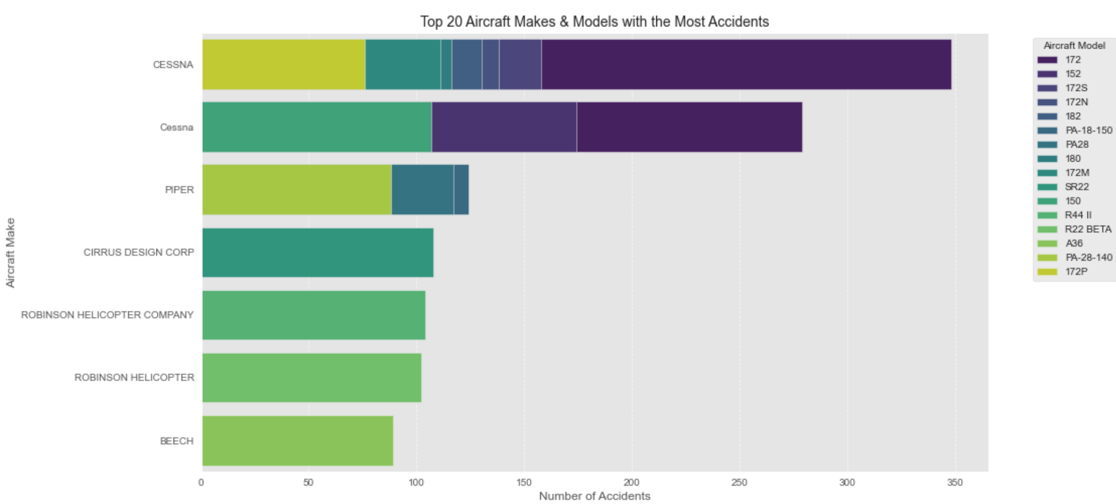
[63]:
```
                 Make                Model  Accident Count
0           177MF LLC       PITTS MODEL 12               1
1  2007 Savage Air LLC             EPIC LT               1
2          2021FX3 LLC            CCX-2000               1
3          781569 INC               FX 210               1
4  AARDEMA ROBERT JOHN  1 AARDEMA RAG WNG SP               1
```

[64]:
```
# Sorting by highest number of accidents
accident_distribution = accident_distribution.sort_values(by="Accident Count",␣
↪ascending=False).head(20)
accident_distribution.head(10)
```

[64]:

	Make	Model	Accident Count
1494	CESSNA	172	348
2005	Cessna	172	279
1995	Cessna	152	174
1517	CESSNA	172S	158
1486	CESSNA	152	157
1513	CESSNA	172N	138
1540	CESSNA	182	130
4807	PIPER	PA-18-150	124
4921	PIPER	PA28	117
1529	CESSNA	180	116

[65]:
```
# Plotting the distribution
plt.figure(figsize=(14, 8))
sns.barplot(data=accident_distribution, y="Make", x="Accident Count",␣
↪hue="Model", dodge=False, palette="viridis")
plt.title("Top 20 Aircraft Makes & Models with the Most Accidents", fontsize=14)
plt.xlabel("Number of Accidents")
plt.ylabel("Aircraft Make")
plt.legend(title="Aircraft Model", bbox_to_anchor=(1.05, 1), loc="upper left")
plt.grid(axis="x", linestyle="--", alpha=0.7)
plt.show()
```



Insights:

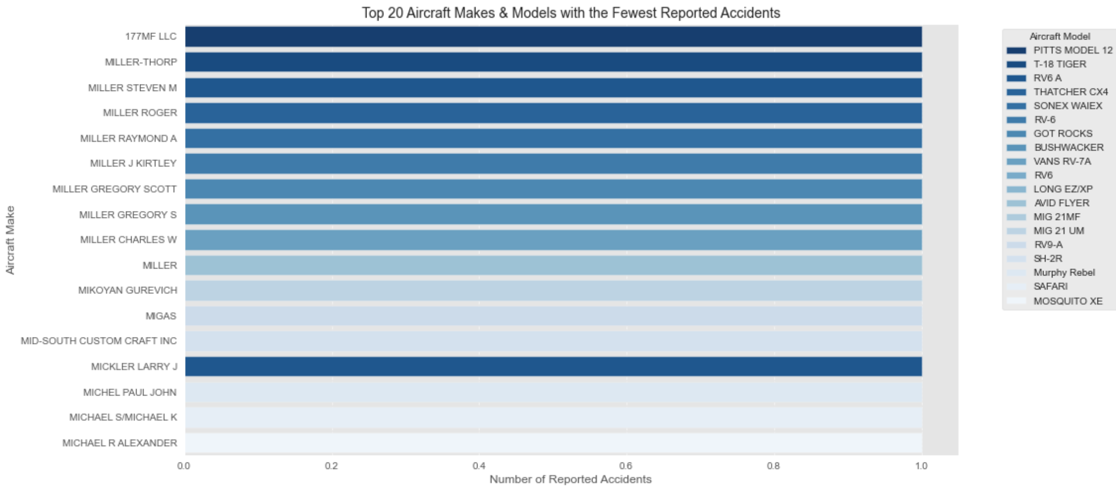
- Cessna dominates accident counts, indicating that it is either the most commonly used aircraft and has higher accident rates.
- Robinson Helicopters (R22 & R44 models) also appear frequently, suggesting potential safety concerns or high usage.
- The distribution suggests that certain models within a brand (e.g., Cessna 172, Piper PA-28) significantly contribute to accident numbers.

Business Recommendations:

- Avoid using high-accident aircraft models like the Cessna 172 and Piper PA-28 for business expansion.
- Investigate why Cessna has so many accidents (e.g., pilot error, aircraft age, mechanical failure).
- Consider alternative aircraft with fewer recorded accidents for lower-risk operations.

Aircraft makes & models with the least accidents

[68]:
```
# Get aircraft makes & models with the least accidents
safest_aircraft = df1_copy.groupby(["Make", "Model"]).size().
 ↪reset_index(name="Accident Count")

# Filter to the lowest accident counts
safest_aircraft = safest_aircraft.sort_values(by="Accident Count",␣
 ↪ascending=True).head(20)

# Plot
plt.figure(figsize=(14, 8))
sns.barplot(data=safest_aircraft, y="Make", x="Accident Count", hue="Model",␣
 ↪dodge=False, palette="Blues_r")
plt.title("Top 20 Aircraft Makes & Models with the Fewest Reported Accidents",␣
 ↪fontsize=14)
plt.xlabel("Number of Reported Accidents")
plt.ylabel("Aircraft Make")
plt.legend(title="Aircraft Model", bbox_to_anchor=(1.05, 1), loc="upper left")
plt.grid(axis="x", linestyle="--", alpha=0.7)
plt.show()
```



Insights:

- These aircraft have the lowest accident reports, making them potentially safer choices. Some models, like Mosquito XE and MIG aircraft, have military or specialized uses, possibly leading to fewer civilian accident reports. Some aircraft manufacturers listed might be smaller brands with fewer total flights, contributing to fewer recorded incidents.

Business Recommendations:

- Consider these aircraft models for lower-risk operations, as they have fewer reported accidents also investigate operational costs and availability, as some may be rare or not suited for business expansion.
- Cross-check safety records with usage statistics, ensuring the low accident count is due to safety and not underreporting.

[70]:
```
# Sort by least accidents
safest_aircraft = accident_distribution.sort_values(by="Accident Count",␣
↪ascending=True).head(20)
safest_aircraft.head()
```

[70]:

	Make	Model	Accident Count
1514	CESSNA	172P	76
2022	Cessna	172N	77
4839	PIPER	PA-28-140	88
725	BEECH	A36	89
5505	ROBINSON HELICOPTER	R22 BETA	102

[71]:
```
# Pivot table summarizing accidents by aircraft model
model_pivot = df1_copy.groupby("Model")["Event.Id"].count().reset_index()
model_pivot.rename(columns={"Event.Id": "Accident Count"}, inplace=True)
```

```python
# Sorting in descending order
model_pivot = model_pivot.sort_values(by="Accident Count", ascending=False)

# Display the top models with the most accidents
model_pivot.head(10)
```

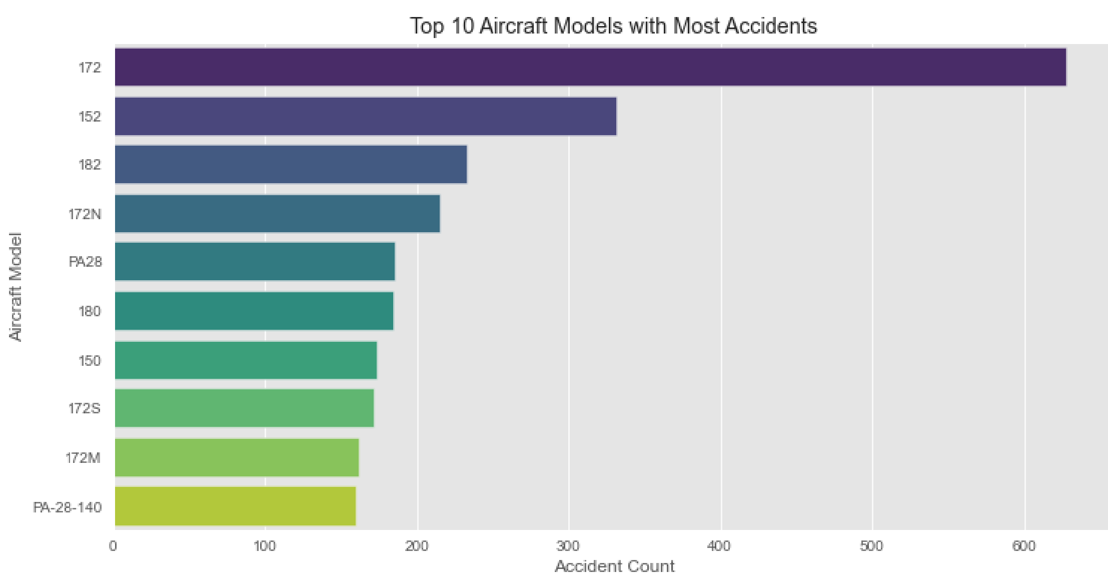
[71]:

	Model	Accident Count
115	172	628
82	152	331
175	182	233
138	172N	215
2976	PA28	186
160	180	185
65	150	174
144	172S	172
137	172M	162
2860	PA-28-140	160

visualization of the top 10 aircraft models with the most accidents:

[73]:

```python
plt.figure(figsize=(12, 6))
sns.barplot(data=model_pivot.head(10), x="Accident Count", y="Model",
 ↪palette="viridis")
plt.title("Top 10 Aircraft Models with Most Accidents")
plt.xlabel("Accident Count")
plt.ylabel("Aircraft Model")
plt.show()
```



Analyzing Accident Distribution by Aircraft Manufacturer (Make) We can analyze the accident distribution by aircraft manufacturers to see which brands have the highest number of accidents.

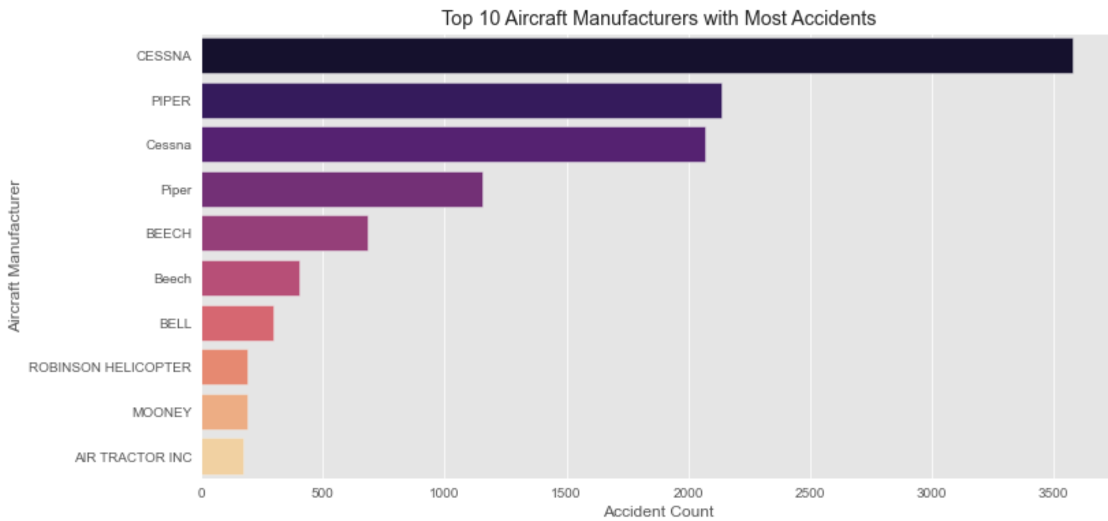
[75]:
```
# Pivot table summarizing accidents by aircraft make (manufacturer)
make_pivot = df1_copy.groupby("Make")["Event.Id"].count().reset_index()
make_pivot.rename(columns={"Event.Id": "Accident Count"}, inplace=True)

# Sorting in descending order
make_pivot = make_pivot.sort_values(by="Accident Count", ascending=False)

# Display the top manufacturers with the most accidents
make_pivot.head(10)
```

[75]:

	Make	Accident Count
591	CESSNA	3578
2357	PIPER	2137
742	Cessna	2071
2422	Piper	1156
302	BEECH	686
486	Beech	401
310	BELL	298
2565	ROBINSON HELICOPTER	192
2066	MOONEY	188
50	AIR TRACTOR INC	172

visualization of top 10 aircraft manufacturers with the most accidents:

[77]:
```
plt.figure(figsize=(12, 6))
sns.barplot(data=make_pivot.head(10), x="Accident Count", y="Make",␣
    ↪palette="magma")
plt.title("Top 10 Aircraft Manufacturers with Most Accidents")
plt.xlabel("Accident Count")
plt.ylabel("Aircraft Manufacturer")
plt.show()
```



2.8.4 iv. analyzing commercial vs. private aircraft accidents

First we will differentiate between Commercial and Private Use. We'll categorize the "Purpose.of.flight" into Commercial and Private groups.

- Commercial: Includes categories like "Airline", "Cargo", "Commuter", "Charter"
- Private: Includes "Personal", "Business", "Training", "Recreational"

[141]:
```
df1_copy['Purpose.of.flight'].value_counts()
```

[141]:
```
Personal                     12872
Instructional                 2751
Aerial Application            1007
Business                       671
Unknown                        609
Positioning                    361
Aerial Observation             216
Other Work Use                 208
Flight Test                    193
Ferry                          151
Executive/corporate            120
Skydiving                       94
External Load                   72
Banner Tow                      68
Public Aircraft - Federal       63
Public Aircraft - Local         54
Air Race show                   52
Public Aircraft - State         46
Public Aircraft                 33
Glider Tow                      30
```

```
Firefighting                        13
Air Drop                             6
ASHO                                 2
PUBS                                 2
PUBL                                 1
Name: Purpose.of.flight, dtype: int64
```

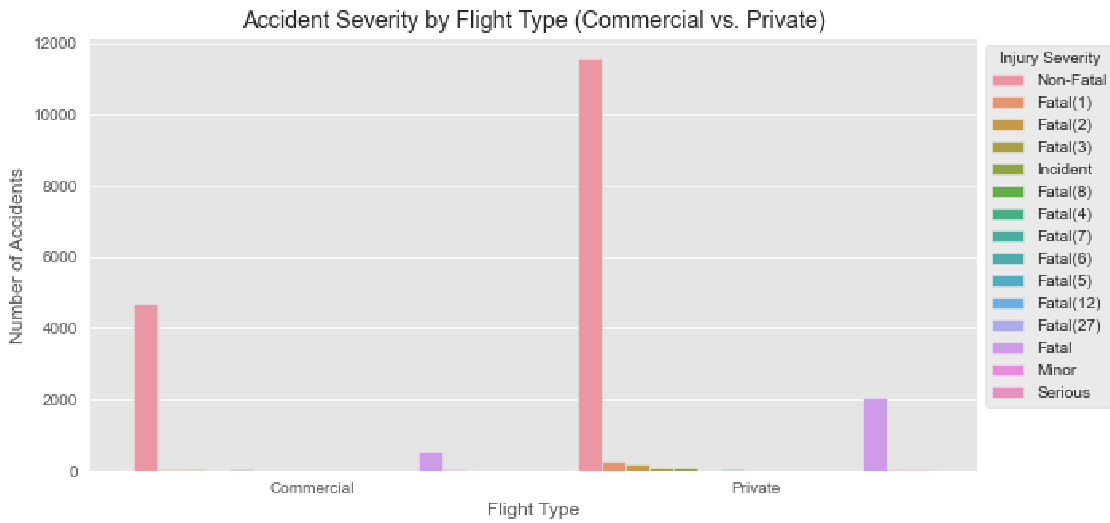
[143]:
```python
# Categorize flights into Commercial vs. Private
def categorize_flight(purpose):
    commercial_types = ["Aerial Application", "Aerial Observation", "Air Drop",␣
 ↪"Air Race show", "Banner Tow",
                        "Executive/corporate", "External Load", "Ferry",␣
 ↪"Flight Test", "Firefighting",
                        "Glider Tow", "Instructional", "Positioning", "Public␣
 ↪Aircraft",
                        "Public Aircraft - Federal", "Public Aircraft - Local",␣
 ↪"Public Aircraft - State","Skydiving"]

    private_types = ["Personal", "Business", "Unknown", "Other Work Use",␣
 ↪"ASHO", "PUBS", "PUBL"]

    if purpose in commercial_types:
        return "Commercial"
    elif purpose in private_types:
        return "Private"
    else:
        return "Other"

# Apply categorization
df1_copy["Flight_Type"] = df1_copy["Purpose.of.flight"].apply(categorize_flight)

# Count accidents per category
accident_counts = df1_copy["Flight_Type"].value_counts()
print(accident_counts)
```

```
Private       14365
Commercial     5330
Name: Flight_Type, dtype: int64
```

Secondly, lets Analyze Accident Rates for Commercial vs. Private Aircraft by comparing accident rates by total number of accidents and injury severity.

[145]:
```python
# Count accidents by Flight_Type and Injury Severity
plt.figure(figsize=(10, 5))
sns.countplot(data=df1_copy, x="Flight_Type", hue="Injury.Severity",␣
 ↪order=["Commercial", "Private"])
plt.title("Accident Severity by Flight Type (Commercial vs. Private)")
```

```
plt.xlabel("Flight Type")
plt.ylabel("Number of Accidents")
plt.legend(title="Injury Severity", bbox_to_anchor=(1,1))
plt.show()
```



Key Observation: 1. Higher Accident Count in Private Flights: - Private flights show significantly more accidents than commercial flights, especially for non-fatal incidents. - This may suggest a higher volume of private flights or a lack of strict safety regulations in private aviation. 2. Fatality Distribution: - Fatal accidents are present in both categories, but we need to check if private flights have a higher proportion of fatal accidents compared to their total number of flights. - Private aviation might have a higher fatality rate due to less experienced pilots, fewer safety checks, and maintenance gaps. 3. Commercial Accidents: - Even though commercial flights have fewer accidents, the cause of accidents might be more related to mechanical failures, airline operational risks, or bad weather conditions.

Thirdly, Lets Identify the Safest Aircraft Models for Each Category We'll filter the dataset by "Make" and "Model" with low accident counts

[168]:
```
# Set a threshold for minimum accident count
min_accidents = 10

# Identify safest commercial aircraft models with at least min_accidents
safe_commercial = df1_copy[df1_copy["Flight_Type"] == "Commercial"]["Model"].
↪value_counts()
safe_commercial = safe_commercial[safe_commercial >= min_accidents].nsmallest(5)
print("Safest Commercial Aircraft Models:")
print(safe_commercial)

# Identify safest private aircraft models with at least min_accidents
```

```python
safe_private = df1_copy[df1_copy["Flight_Type"] == "Private"]["Model"].
  ↪value_counts()
safe_private = safe_private[safe_private >= min_accidents].nsmallest(5)
print("Safest Private Aircraft Models:")
print(safe_private)
```

```
Safest Commercial Aircraft Models:
208B         10
SPORTSTAR    10
182P         10
PA-31-350    10
PA-38        10
Name: Model, dtype: int64
Safest Private Aircraft Models:
100             10
RV-9A           10
PA-32R-301      10
A-1C-200        10
SPORTCRUISER    10
Name: Model, dtype: int64
```

[174]:
```python
# Accident severity breakdown by aircraft model and flight type
severity_analysis = df1_copy.groupby(["Model", "Flight_Type"])['Injury.
  ↪Severity'].value_counts().unstack().fillna(0)
print("\nAccident Severity Analysis by Aircraft Model:")
print(severity_analysis.head(10))  # Display top 10 for readability
```

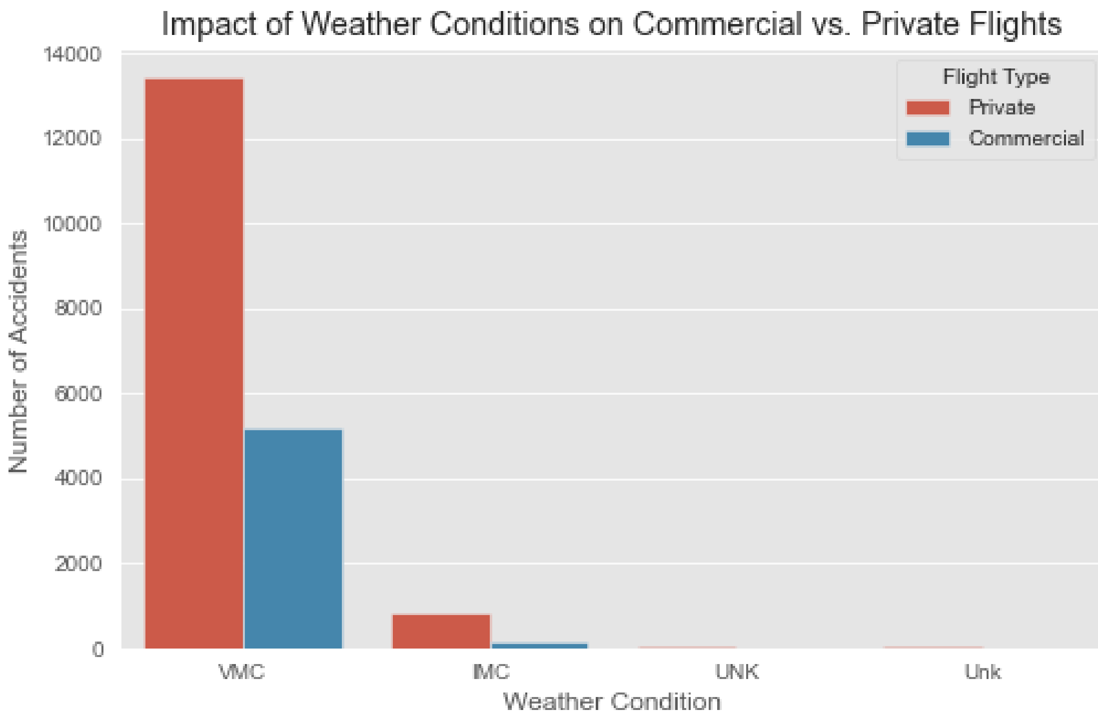
```
Accident Severity Analysis by Aircraft Model:
Injury.Severity                      Fatal  Fatal(1)  Fatal(12)  Fatal(2)  \
Model                Flight_Type
(SOLOY CONVERSION)   Commercial        0.0       0.0        0.0       0.0
0-47B                Private           0.0       0.0        0.0       0.0
0-58A                Private           0.0       0.0        0.0       0.0
0-58B                Private           0.0       0.0        0.0       0.0
0-77                 Private           0.0       0.0        0.0       0.0
1                    Private           0.0       0.0        0.0       0.0
1 AARDEMA RAG WNG SP Private           0.0       0.0        0.0       0.0
1-126E               Private           0.0       0.0        0.0       0.0
1-A                  Private           1.0       0.0        0.0       0.0
10                   Private           0.0       0.0        0.0       0.0

Injury.Severity                      Fatal(27)  Fatal(3)  Fatal(4)  Fatal(5)  \
Model                Flight_Type
(SOLOY CONVERSION)   Commercial            0.0       0.0       0.0       0.0
0-47B                Private               0.0       0.0       0.0       0.0
0-58A                Private               0.0       0.0       0.0       0.0
```

```
0-58B                 Private            0.0       0.0       0.0       0.0
0-77                  Private            0.0       0.0       0.0       0.0
1                     Private            0.0       0.0       0.0       0.0
1 AARDEMA RAG WNG SP Private            0.0       0.0       0.0       0.0
1-126E                Private            0.0       0.0       0.0       0.0
1-A                   Private            0.0       0.0       0.0       0.0
10                    Private            0.0       0.0       0.0       0.0

Injury.Severity                        Fatal(6)  Fatal(7)  Fatal(8)  Incident  \
Model                 Flight_Type
(SOLOY CONVERSION)    Commercial          0.0       0.0       0.0       0.0
0-47B                 Private             0.0       0.0       0.0       0.0
0-58A                 Private             0.0       0.0       0.0       0.0
0-58B                 Private             0.0       0.0       0.0       0.0
0-77                  Private             0.0       0.0       0.0       0.0
1                     Private             0.0       0.0       0.0       0.0
1 AARDEMA RAG WNG SP Private             0.0       0.0       0.0       0.0
1-126E                Private             0.0       0.0       0.0       0.0
1-A                   Private             0.0       0.0       0.0       0.0
10                    Private             0.0       0.0       0.0       0.0

Injury.Severity                        Minor  Non-Fatal  Serious
Model                 Flight_Type
(SOLOY CONVERSION)    Commercial         0.0        1.0      0.0
0-47B                 Private            0.0        1.0      0.0
0-58A                 Private            0.0        1.0      0.0
0-58B                 Private            0.0        1.0      0.0
0-77                  Private            0.0        1.0      0.0
1                     Private            0.0        3.0      0.0
1 AARDEMA RAG WNG SP Private            0.0        1.0      0.0
1-126E                Private            0.0        1.0      0.0
1-A                   Private            0.0        1.0      0.0
10                    Private            0.0        1.0      0.0
```

For business expansion, prioritize commercial aircraft models with zero fatal incidents and high survival rates, avoid high-risk models with multiple fatalities, and further assess private aircraft safety factors like pilot experience and maintenance.

Finaly lets compare risk factors by analyzing causes of accidents in each category

[160]:
```
# Compare Weather Conditions Impact
plt.figure(figsize=(8,5))
sns.countplot(data=df1_copy, x="Weather.Condition", hue="Flight_Type")
plt.title("Impact of Weather Conditions on Commercial vs. Private Flights")
plt.xlabel("Weather Condition")
plt.ylabel("Number of Accidents")
plt.legend(title="Flight Type")
plt.show()
```



Most accidents occur under VMC (Visual Meteorological Conditions), with private flights experiencing a significantly higher number of accidents than commercial flights. This suggests that factors other than weather—such as maintenance, or operational procedures—play a critical role in private flight safety.

For business expansion, prioritize commercial aircraft over private ones due to their lower accident rates under similar weather conditions. Additionally, if private flights are considered, implement stricter safety protocols, including enhanced pilot training and rigorous maintenance checks.

2.9 Recommendations:

To minimize operational risks and enhance business success in aviation expansion: 1. Prioritize commercial aircraft over private ones, as they exhibit lower accident rates under similar conditions. 2. If private flights are considered, enforce stricter safety protocols, including enhanced pilot training, rigorous maintenance checks, and advanced weather monitoring systems. 3. Invest in aircraft models with historically lower accident rates and operate primarily in favorable weather conditions (VMC) to reduce incident likelihood.

2.10 Conclusion:

By leveraging data-driven insights from aviation accident analysis, our business can strategically select safer aircraft models, optimize operational procedures, and mitigate risks associated with adverse weather and human factors. Implementing these recommendations will ensure cost efficiency, regulatory compliance, and long-term sustainability in the aviation sector.