1.0 Project Title: Risk Assessment for the Operations Of Private and Commercial Aircrafts

Author: Patrice Okoiti

1.1 Data Understanding

The selected Dataset [https://www.kaggle.com/datasets/khsamaha/aviation-accident-database-synopses (https://www.kaggle.com/datasets/khsamaha/aviation-accident-database-synopses)](https://www.kaggle.com/datasets/khsamaha/aviation-accident-database-synopses) for this analysis is from the National Transportation Safety Board, available on Kaggle, detailing the civil aviation accidents and selected incidents in the United States and international waters between 1962 and 2023. It details aircraft accidents, including information on accident, aircraft specifications, weather conditions, and injury severity which are relevant to our analysis.

1.1.1 column description

Columns	Description
Event Id, Accident Number, Event Date, Location, Country, Latitude, Longitude, Airport Code, Airport Name	Unique identifiers for each accident and its location.
Make, Model, Aircraft Category, Amateur Built, Number of Engines, Engine Type	Details about the aircraft involved in the accident.
Injury Severity, Aircraft Damage, Weather Condition, Broad Phase of Flight	Risk factors contributing to the accident.
FAR Description, Schedule, Purpose of Flight, Air Carrier	Type of operations and flight purpose.
Total Fatal Injuries, Total Serious Injuries, Total Minor Injuries, Total Uninjured	Casualties per accident.

1.2 Business Problem

Umoja Logistics is diversifying their portfolio by venturing into the aviation industry. The aim is to purchase and operate aircraft for commercial and private enterprises. However, aviation involves significant safety risks, including accidents and operational hazards. The goal of this project is to analyze historical aircraft accident data to identify low-risk aircraft models and key risk factors that could impact operations.

1.2.1 Objectives

1. Identify the safest type of aircraft
2. Identify risk factors contributing to aircraft accidents
3. Evaluate flight risks based on operations

In [1]:
```
# First step is to import the important libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

1.3 Data Mining

This involves reading and loading our data on to our notebook based on the file format.

In [2]:
```
# Next step is data loading
df =pd.read_csv('Data/AviationData.csv', encoding='latin-1', low_memory=False)

# Display the fisrt 5 rows of the dataframe
df.head()
```

Out[2]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	L
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	

5 rows × 31 columns

1.4 Data Preparation

This involves inspecting our dataset to identify the shape, name of columns, datatype of each column and any columns with missing values

In [3]:
```
# Inspect the dataframe
df.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
```

From the above information, we can deduce that our dataframe has a shape of 88889 rows and 31 columns. The dataframe has 5 numerical columns and 26 categorical column. All the 5 numerical columns have float datatype. Of the 31 columns only the first 4 have complete entries, meaning 27 columns have missing values.

In [4]:
```
# Get summary statistics of the data
df.describe()
```

Out[4]:

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Total.Unin
count	82805.000000	77488.000000	76379.000000	76956.000000	82977.0
mean	1.146585	0.647855	0.279881	0.357061	5.3
std	0.446510	5.485960	1.544084	2.235625	27.9
min	0.000000	0.000000	0.000000	0.000000	0.0
25%	1.000000	0.000000	0.000000	0.000000	0.0
50%	1.000000	0.000000	0.000000	0.000000	1.0
75%	1.000000	0.000000	0.000000	0.000000	2.0
max	8.000000	349.000000	161.000000	380.000000	699.0

The above information is a statistical summary of the numerical column of the dataframe.

1.5 Data Cleaning

This step is validation of the dataset. It involves identifying and handling missing values and duplicates so as to get a clean dataset.

In [5]:
```
# First step is to create a copy of the original dataset
df_clean = df.copy() # Henceforth we will use the copy to clean our dataset

# Identify duplicates from the created copy of dataset
df_clean.duplicated().value_counts()
```

Out[5]:
```
False    88889
dtype: int64
```

From the above output we can deduce that our dataset does not contain any duplicates.

In [6]:
```
# Next we display a breakdown of missing values in our dataset
df_clean.isna().sum()
```

Out[6]:
```
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
dtype: int64
```

In [7]:
```
# Next we replace our missing values
for col in df_clean.columns:
    if str(df_clean[col].dtype) == 'object':
        df_clean[col].fillna('Unknown', inplace=True)
    else:
        df_clean[col].fillna(0, inplace=True)
df_clean.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                88889 non-null  object 
 5   Country                 88889 non-null  object 
 6   Latitude                88889 non-null  object 
 7   Longitude               88889 non-null  object 
 8   Airport.Code            88889 non-null  object 
 9   Airport.Name            88889 non-null  object 
 10  Injury.Severity         88889 non-null  object 
 11  Aircraft.damage         88889 non-null  object 
 12  Aircraft.Category       88889 non-null  object 
 13  Registration.Number     88889 non-null  object 
 14  Make                    88889 non-null  object 
 15  Model                   88889 non-null  object 
 16  Amateur.Built           88889 non-null  object 
 17  Number.of.Engines       88889 non-null  float64
 18  Engine.Type             88889 non-null  object 
 19  FAR.Description         88889 non-null  object 
 20  Schedule                88889 non-null  object 
 21  Purpose.of.flight       88889 non-null  object 
 22  Air.carrier             88889 non-null  object 
 23  Total.Fatal.Injuries    88889 non-null  float64
 24  Total.Serious.Injuries  88889 non-null  float64
 25  Total.Minor.Injuries    88889 non-null  float64
 26  Total.Uninjured         88889 non-null  float64
 27  Weather.Condition       88889 non-null  object 
 28  Broad.phase.of.flight   88889 non-null  object 
 29  Report.Status           88889 non-null  object 
 30  Publication.Date        88889 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

The above output involved creating a 'for' loop that iterates through our dataset columns and fill the missing values with the set values based on the datatype. Replacing the missing values helps avoid unexpected arrors and completeness of the dataset for analysis.Filling of the missing values in categorical column with placeholder 'Unknown' and numerical column with zero allows me to maintain consistency of dataset without dropping valuable records, hence avoiding bias.

In [8]:
```
# Convert our date column to datetime
df_clean['Event.Date'] = pd.to_datetime(df_clean['Event.Date'])

# Create a year column on our dataset
df_clean['Year'] = df_clean['Event.Date'].dt.year.astype(int)

# Filter for the 21st century only
df_clean = df_clean[df_clean['Year'] >= 2000]
```

The above code filters out the possibly discontinued and outdated aircrafts and leaves us with only aircrafts active in the 21st century.

In [9]:
```
# Identify the unique operational purpose of each flight
df_clean['Purpose.of.flight'].unique()
```

Out[9]:
```
array(['Positioning', 'Personal', 'Instructional', 'Unknown',
       'Aerial Observation', 'Ferry', 'Public Aircraft', 'Business',
       'Aerial Application', 'Executive/corporate', 'Other Work Use',
       'Flight Test', 'Skydiving', 'Air Race/show', 'Air Drop',
       'Public Aircraft - Federal', 'Glider Tow',
       'Public Aircraft - Local', 'External Load',
       'Public Aircraft - State', 'Banner Tow', 'Firefighting',
       'Air Race show', 'PUBS', 'ASHO', 'PUBL'], dtype=object)
```

In [10]:
```python
# Create a list that distuinguishes between private and commercial purposes
private = ['Personal', 'Executive/corporate', 'Business', 'Ferry']
commercial = ['Aerial Application', 'Aerial Observation', 'Public Aircraft']

# Create a column that describes operations category
flight_purpose = []

for purpose in df_clean['Purpose.of.flight']:
    if purpose in private:
        flight_purpose.append('Private')
    elif purpose in commercial:
        flight_purpose.append('Commercial')
    else:
        flight_purpose.append('Other')

df_clean['Category of Operation'] = flight_purpose

# Filter our dataset to include only private and commercial used planes
df_clean = df_clean[(df_clean['Category of Operation'] == 'Private') |
                       (df_clean['Category of Operation'] == 'Commercial')]

# Displays first 5 rows
df_clean.head()
```

Out[10]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country
47676	20001212X20327	Accident	ATL00FA019	2000-01-01	MONTEAGLE, TN	United States
47677	20001212X20383	Accident	LAX00LA063	2000-01-02	VICTORVILLE, CA	United States
47679	20001212X20364	Accident	FTW00LA067	2000-01-02	CORNING, AR	United States
47680	20001212X20358	Accident	FTW00LA057	2000-01-02	ODESSA, TX	United States
47681	20001212X20344	Accident	DEN00FA037	2000-01-02	TELLURIDE, CO	United States

5 rows × 33 columns

The above code filters out all aircrafts that were not utilized for private and commercial flight use.

In [11]:
```
# Format the text of categorical columns for consistency
df_clean['Weather.Condition'] = df_clean['Weather.Condition'].str.title()

# Edit the initials of weather to the full names
df_clean['Weather.Condition'] = df_clean['Weather.Condition'].apply(
    lambda x: 'Visual Meteorological Conditions'
    if x == 'Vmc'
    else 'Instrument Meteorological Conditions'
    if x == 'Imc'
    else "Unknown"
    if x == 'Unk'
    else x)

# Format the text of categorical columns for consistency
df_clean['Make'] = df_clean['Make'].str.title()
df_clean['Model'] = df_clean['Model'].str.upper()

# Create a new column that combines make and model
df_clean['Make_and_Model'] = df_clean['Make'] + ' ' + df_clean['Model']
```

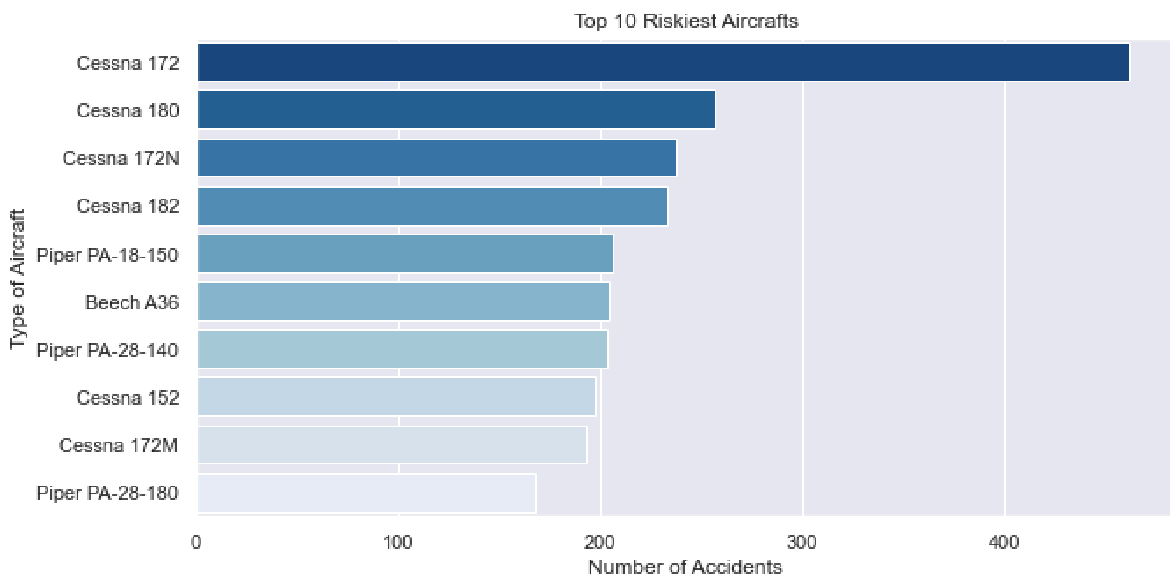
The above code edits the texts of the relevant columns to ensure consistency since python is case sensitive.

1.6 Data Evaluation

1.6.1 Objective 1

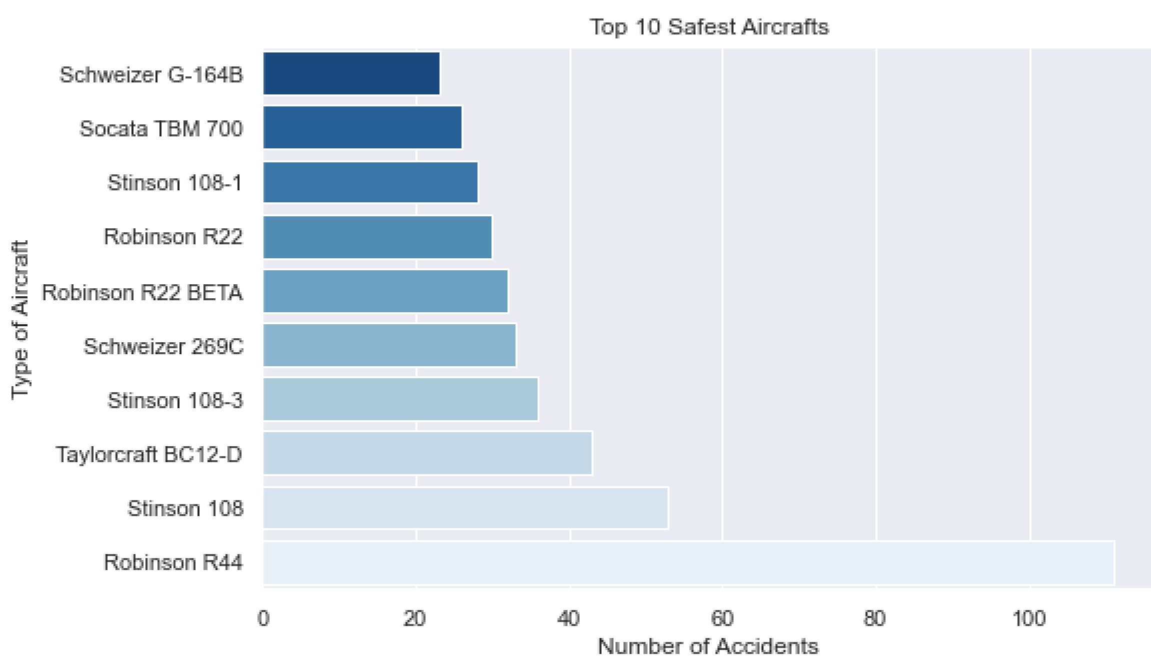
The first objective is to identify safest aircraft. This involves analyzing the number of accidents based on aircraft 'Make' and 'Model' to determine the aircraft with the lowest risk of accidents.

In [13]:
```
# Identify riskiest aircfrafts based on number of accidents
riskiest_aircraft = df_clean['Make_and_Model'].value_counts().head(10)

# Display visualization
fig, ax = plt.subplots(figsize=(10,5))
sns.set_theme(style='darkgrid')

sns.barplot(y=riskiest_aircraft.index,
            x=riskiest_aircraft.values,
            palette='Blues_r')
ax.set(title='Top 10 Riskiest Aircrafts',
       xlabel='Number of Accidents',
       ylabel='Type of Aircraft')

#show plot
plt.show

#save the visualization and ensure full image displayed
plt.savefig('Images/Risky-aircrafts.jpg', dpi=300, bbox_inches='tight')
```



The plot shows the the top 10 riskiest aircrafts based on the most accidents between 2000 and 2023.

In [14]:
```
# Identify safest aircrafts based on the lowest number of accidents

# For accuracy lets assume each aircraft has atleast 1 accident per year
safest_aircraft = (df_clean.groupby('Make_and_Model')
                   .size()  # Count occurrences
                   .loc[lambda x: x > 22]# Filter for counts > 22
                   .tail(10))

# sorts counts from least to most
safest_aircraft = safest_aircraft.sort_values(ascending=True)


# Visualize the safest aicrafts
fig, ax = plt.subplots(figsize=(8,5))
sns.set_theme(style='darkgrid')

sns.barplot(y=safest_aircraft.index,
            x=safest_aircraft.values,
            palette='Blues_r')
ax.set(title='Top 10 Safest Aircrafts',
       xlabel='Number of Accidents',
       ylabel= 'Type of Aircraft',
       )

# show plot
plt.show()

#save the image and ensure full image displayed
fig.savefig('Images/Safest-aircrafts.jpg', dpi=300, bbox_inches='tight')
```



The above output shows the safest aircraft based on the number of accidents encountered between 2000 and 2023. It is based on the assumption the most active aircrafts have atleast 1 accident per year for the period, hence on average the least number of accidents should be 23.

1.6.2 Objective 2

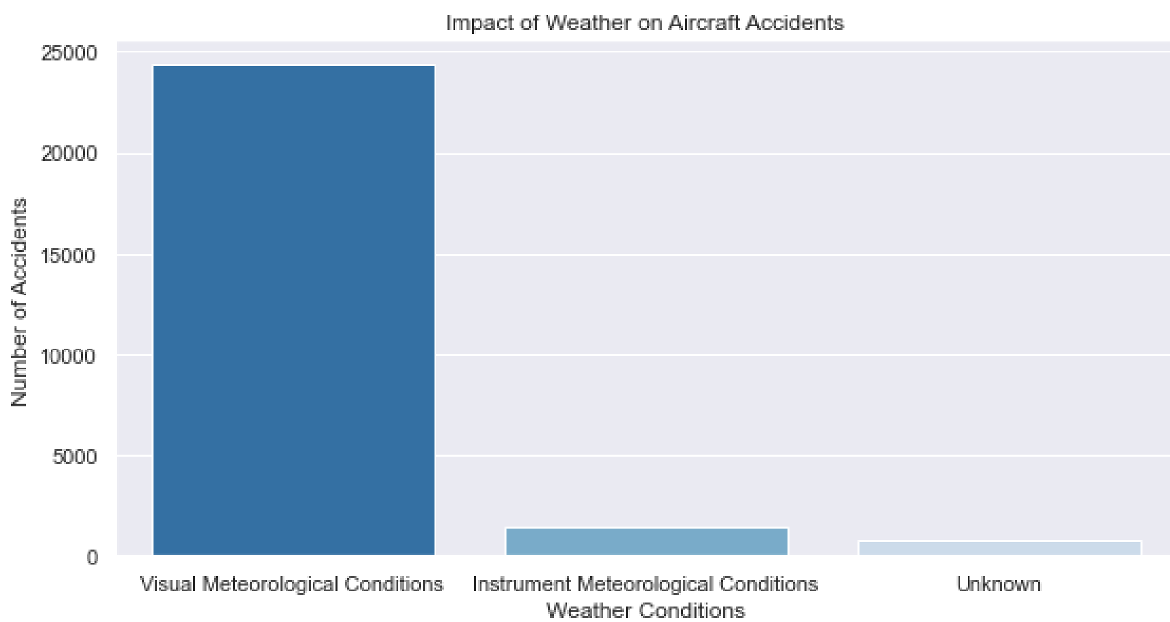
The second objective involves identifying the risk factors contributing to accidents by analyzing the weather conditions and the broad phase of the aircraft, for example landing or taking off, during the accident.

In [15]:
```
# Number of accidents per aircraft per year
yearly_accidents = df_clean.groupby('Year')['Make_and_Model'].count()
yearly_accidents

# visualize number of accidents over the years for the past 23years
fig, ax = plt.subplots(figsize=(10,5))
sns.set_theme(style='darkgrid')

sns.lineplot(x=yearly_accidents.index,
             y=yearly_accidents.values,
             marker='o')
ax.set(title="Aircraft Accident Trend Overtime",
       xlabel='Years',
       ylabel='Number of Accidents',
       ylim=(500,2000))

# show plot
plt.show()

# save the image and ensure image fuly displayed
plt.savefig('Images/Accident-trend.jpg', dpi=300, bbox_inches='tight')
```


```
<Figure size 432x288 with 0 Axes>
```

From the above output it can be seen that the overall accidents risk associated with the aircrafts is at a steady decline over the years.

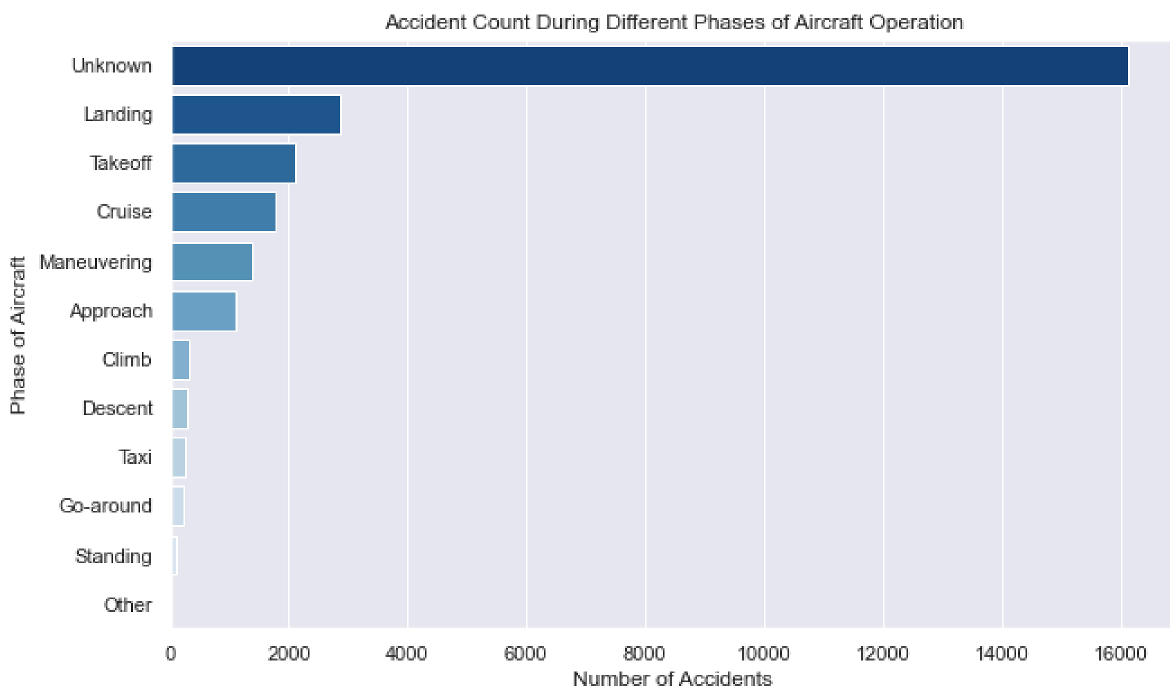
In [16]:
```
# Weather as risk factor in aircraft accidents
weather_risk = df_clean['Weather.Condition'].value_counts()

# Visualize weather as a risk factor
fig, ax = plt.subplots(figsize=(10,5))
sns.set_theme(style='darkgrid')

sns.barplot(y=weather_risk.values,
            x=weather_risk.index,
            palette='Blues_r')
ax.set(title='Impact of Weather on Aircraft Accidents',
       ylabel= 'Number of Accidents',
       xlabel = 'Weather Conditions')

# show plot
plt.show()

#save the image and ensure image fully dispalyed
plt.savefig('Images/Weather-impact.jpg', dpi=300, bbox_inches='tight')
```




```
<Figure size 432x288 with 0 Axes>
```

From above output it can be seen that most accidents happened during Visual Meteorological Conditions, meaning that they happened when the weather conditions allowed the pilots to fly with visual references to the ground and other aircrafts without solely relying on instruments. This rules out weather conditions as primary cause of aircraft accidents.

In [17]:
```
# Identify the phase the aircraft when most accident occur
aircraft_phase = df_clean['Broad.phase.of.flight'].value_counts()

#Visualize every phase by accidents
fig, ax = plt.subplots(figsize=(10,6))
sns.set_theme(style='darkgrid')

sns.barplot(y=aircraft_phase.index,
            x=aircraft_phase.values,
            palette='Blues_r')
ax.set(title='Accident Count During Different Phases of Aircraft Operation',
       ylabel= 'Phase of Aircraft',
       xlabel = 'Number of Accidents')

# show plot
plt.show()

#save the image and ensure image fully displayed
plt.savefig('Images/Flight-phase.jpg', dpi=300, bbox_inches='tight')
```



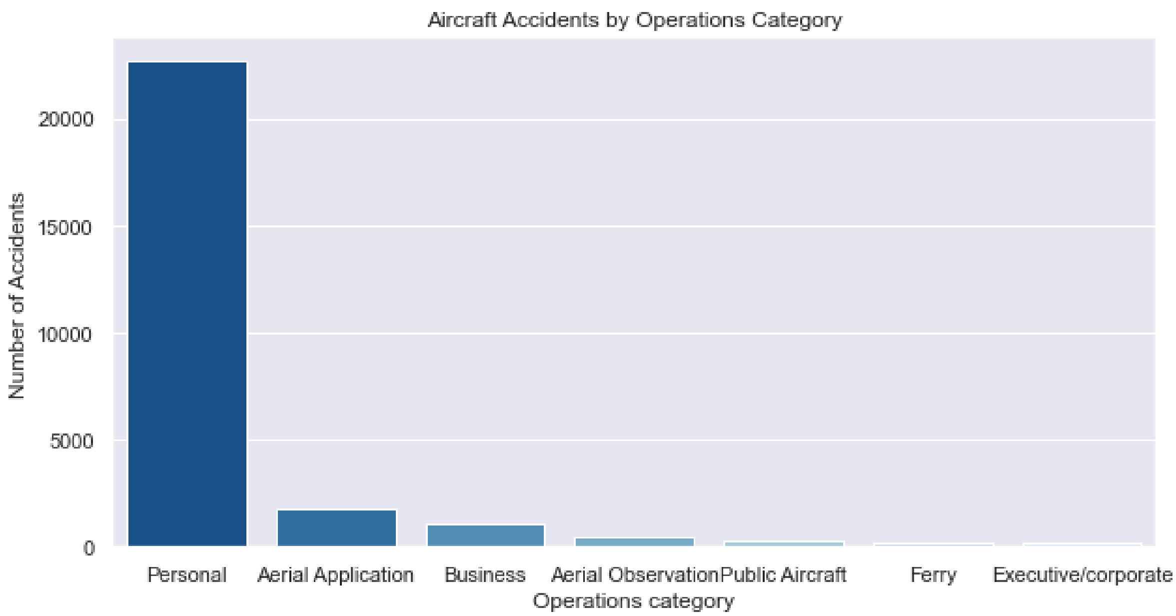

```
<Figure size 432x288 with 0 Axes>
```

From the above output it can be clearly seen that phase of accidents for most of accidents remain clearly unknown. But We can also clearly deduce that a significant number of accidents happened during landing, taking off and during cruising, hence we should view these 3 phases as major risk factors associated with aircraft accidents.

1.6.3 Objective 3

The final objective is to evaluate operational risk factors of the aircraft. This involves analysing the number of accidents as per operations category of aircraft, that is, private and commercial.

In [18]:
```
# Evaluate operational risk
operational_category = df_clean['Purpose.of.flight'].value_counts()

# Visualize opeartional risk
fig, ax = plt.subplots(figsize=(10,5))
sns.set_theme(style='darkgrid')

sns.barplot(x=operational_category.index,
            y=operational_category.values,
            palette='Blues_r')
ax.set(title='Aircraft Accidents by Operations Category',
       xlabel='Operations category',
       ylabel='Number of Accidents')

# show plot
plt.show()

#save the image and ensure image fully displayed
plt.savefig('Images/Operations-risk.jpg', dpi=300, bbox_inches='tight')
```




```
<Figure size 432x288 with 0 Axes>
```

The above output clearly shows that operating private flights is riskier compared to commercial fights due to the number of accidents by private flights.

In [19]:
```
# Next we save our cleaned data which will be useful during creation Dashboard
df_clean.to_csv('Data/CleanAviationData.csv')
```

1.7 Conclusion

From the analysis of the Aviation Data it be can concluded that:

- The aircrafts with the high number of accidents may be due to high levels of usage

- Adverse weather conditions is a significant risk factor in aircraft accidents but it has not been the primary risk factor in the 21st Century.
- The phase the aircraft is in when accidents occur remains majorly unknown, but a significant number of accidents often occur during landing, taking off and cruising making them significant risk factors.
- Prioritizing operations of commercial flights is more viable as compared to private flights