Aircraft Risk Analysis for Business Expansion

Introduction

We will analyse historical aviation accident data to identify aircraft models with the lowest risk profile. Using a dataset pulled from the National Transportation Safety Board (NTSB) covering aviation accidents from 1962 to 2022, we will assess key factors contributing to aircraft incidents and determine which aircraft types are safest for a new aviation division.

Approach

To achieve this, we will:

- Clean and preprocess the dataset, handling missing values and ensuring data integrity.
- Analyze risk factors such as accident frequency, severity, aircraft type, and operational conditions.
- Develop visual insights tto showcase insights and facilitate data-driven decision-making.

1. Data preprocessing

Importing the libraries and loading the files

In [1]:
```
#Import Standard Libraries and Packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Loading the csv file then printing the first 5 rows
# Read the CSV file into a DataFrame
AviationData= pd.read_csv('AviationData.csv', encoding='latin1') # add en

# Create a working copy of the DataFrame
aviation_df = AviationData.copy()

# Display the first few rows of the working copy
aviation_df.head()
```

```
/var/folders/xz/p8mfkld52573c5bbm0h9ssh00000gn/T/ipykernel_42953/265116943
4.py:3: DtypeWarning: Columns (6,7,28) have mixed types. Specify dtype opt
ion on import or set low_memory=False.
  AviationData= pd.read_csv('AviationData.csv', encoding='latin1') # add e
ngine
```

Out[2]:

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

5 rows × 31 columns

Getting to know the data

In [3]:

```
# looking at the number of rows and columns

aviation_df.shape
```

Out[3]:

```
(88889, 31)
```

In [4]:

```
# looking at column names

aviation_df.columns
```

Out[4]:

```
Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Dat
e',
       '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.Descrip
tion',
       'Schedule', 'Purpose.of.flight', 'Air.carrier', 'Total.Fatal.Inju
ries',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjure
d',
       'Weather.Condition', 'Broad.phase.of.flight', 'Report.Status',
       'Publication.Date'],
      dtype='object')
```

In [5]:

```
# looking at data types and rows with missing values
aviation_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            50132 non-null  object 
 9   Airport.Name            52704 non-null  object 
 10  Injury.Severity         87889 non-null  object 
 11  Aircraft.damage         85695 non-null  object 
 12  Aircraft.Category       32287 non-null  object 
 13  Registration.Number     87507 non-null  object 
 14  Make                    88826 non-null  object 
 15  Model                   88797 non-null  object 
 16  Amateur.Built           88787 non-null  object 
 17  Number.of.Engines       82805 non-null  float64
 18  Engine.Type             81793 non-null  object 
 19  FAR.Description         32023 non-null  object 
 20  Schedule                12582 non-null  object 
 21  Purpose.of.flight       82697 non-null  object 
 22  Air.carrier             16648 non-null  object 
 23  Total.Fatal.Injuries    77488 non-null  float64
 24  Total.Serious.Injuries  76379 non-null  float64
 25  Total.Minor.Injuries    76956 non-null  float64
 26  Total.Uninjured         82977 non-null  float64
 27  Weather.Condition       84397 non-null  object 
 28  Broad.phase.of.flight   61724 non-null  object 
 29  Report.Status           82505 non-null  object 
 30  Publication.Date        75118 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

In [6]:
```python
# descriptive statistics summary
aviation_df.describe()
```

Out[6]:

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Inju
count	82805.000000	77488.000000	76379.000000	76956.000
mean	1.146585	0.647855	0.279881	0.357
std	0.446510	5.485960	1.544084	2.235
min	0.000000	0.000000	0.000000	0.000
25%	1.000000	0.000000	0.000000	0.000
50%	1.000000	0.000000	0.000000	0.000
75%	1.000000	0.000000	0.000000	0.000
max	8.000000	349.000000	161.000000	380.000

In [7]:
```
# displaying last 5 rows of the dataset

aviation_df.tail()
```

Out[7]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Locati
88884	20221227106491	Accident	ERA23LA093	2022-12-26	Annapol M
88885	20221227106494	Accident	ERA23LA095	2022-12-26	Hamptc N
88886	20221227106497	Accident	WPR23LA075	2022-12-26	Paysc /
88887	20221227106498	Accident	WPR23LA076	2022-12-26	Morga U
88888	20221230106513	Accident	ERA23LA097	2022-12-29	Ather (

5 rows × 31 columns

2. Data Cleaning

We will:

- Identify missing values across all columns.
- Remove unnecessary rows or columns that are not relevant to our analysis.
- Impute missing data using appropriate techniques to maintain dataset integrity.

In [8]:
```
# assessing the percentage of missing data

aviation_df.isna().mean()*100
```

Out[8]:
```
Event.Id                   0.000000
Investigation.Type         0.000000
Accident.Number            0.000000
Event.Date                 0.000000
Location                   0.058500
Country                    0.254250
Latitude                  61.320298
Longitude                 61.330423
Airport.Code              43.601570
Airport.Name              40.708074
Injury.Severity            1.124999
Aircraft.damage            3.593246
Aircraft.Category         63.677170
Registration.Number        1.554748
Make                       0.070875
Model                      0.103500
Amateur.Built              0.114750
Number.of.Engines          6.844491
Engine.Type                7.982990
FAR.Description           63.974170
Schedule                  85.845268
Purpose.of.flight          6.965991
Air.carrier               81.271023
Total.Fatal.Injuries      12.826109
Total.Serious.Injuries    14.073732
Total.Minor.Injuries      13.424608
Total.Uninjured            6.650992
Weather.Condition          5.053494
Broad.phase.of.flight     30.560587
Report.Status              7.181991
Publication.Date          15.492356
dtype: float64
```

In [9]:
```
# Dropping columns were more than 25% of the data is missing
dropped_columns= ['Latitude', 'Longitude', 'Airport.Code', 'Airport.Name'

aviation_df.drop(columns= dropped_columns, inplace= True)
```

In [10]:
```
# confirming the change
aviation_df.columns
```

Out[10]:
```
Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Dat
e',
       'Location', 'Country', 'Injury.Severity', 'Aircraft.damage',
       'Registration.Number', 'Make', 'Model', 'Amateur.Built',
       'Number.of.Engines', 'Engine.Type', 'Purpose.of.flight',
       'Total.Fatal.Injuries', 'Total.Serious.Injuries',
       'Total.Minor.Injuries', 'Total.Uninjured', 'Weather.Condition',
       'Report.Status', 'Publication.Date'],
      dtype='object')
```

In [11]:
```
# dropping additonal comments that will not be useful to my analysis
dropped_columns2= ['Accident.Number', 'Registration.Number', 'Amateur.Bui

aviation_df.drop(columns= dropped_columns2, inplace= True)
```

In [12]:
```
# confirming the changes
aviation_df.columns
```

Out[12]:
```
Index(['Event.Id', 'Investigation.Type', 'Event.Date', 'Location', 'Coun
try',
       'Injury.Severity', 'Aircraft.damage', 'Make', 'Model',
       'Number.of.Engines', 'Engine.Type', 'Purpose.of.flight',
       'Total.Fatal.Injuries', 'Total.Serious.Injuries',
       'Total.Minor.Injuries', 'Total.Uninjured', 'Weather.Condition'],
      dtype='object')
```

In [13]:
```
#inspecting missing data of remaining columns

aviation_df.isna().mean()*100
```

Out[13]:
```
Event.Id                   0.000000
Investigation.Type         0.000000
Event.Date                 0.000000
Location                   0.058500
Country                    0.254250
Injury.Severity            1.124999
Aircraft.damage            3.593246
Make                       0.070875
Model                      0.103500
Number.of.Engines          6.844491
Engine.Type                7.982990
Purpose.of.flight          6.965991
Total.Fatal.Injuries      12.826109
Total.Serious.Injuries    14.073732
Total.Minor.Injuries      13.424608
Total.Uninjured            6.650992
Weather.Condition          5.053494
dtype: float64
```

In [14]:
```
#explicitly marking missing values

aviation_df.fillna({
    'Country': 'Unknown',
    'Location': 'Unknown',
    'Aircraft.damage': 'Unknown',
    'Injury.Severity': 'Not Reported',
    'Make' : 'Unknown',
    'Model' : 'Unknown'
}, inplace=True)


# completing fatalities based on the correlation to aircraft damage

aviation_df['Total.Fatal.Injuries'] = aviation_df.groupby('Aircraft.damag

# completing columns with median values

aviation_df.fillna({'Number.of.Engines': aviation_df['Number.of.Engines']
```

In [15]:
```
# reassessing the dataset

aviation_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 17 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                88889 non-null  object
 1   Investigation.Type      88889 non-null  object
 2   Event.Date              88889 non-null  object
 3   Location                88889 non-null  object
 4   Country                 88889 non-null  object
 5   Injury.Severity         88889 non-null  object
 6   Aircraft.damage         88889 non-null  object
 7   Make                    88889 non-null  object
 8   Model                   88889 non-null  object
 9   Number.of.Engines       88889 non-null  float64
 10  Engine.Type             81793 non-null  object
 11  Purpose.of.flight       82697 non-null  object
 12  Total.Fatal.Injuries    88889 non-null  float64
 13  Total.Serious.Injuries  76379 non-null  float64
 14  Total.Minor.Injuries    76956 non-null  float64
 15  Total.Uninjured         82977 non-null  float64
 16  Weather.Condition       84397 non-null  object
dtypes: float64(5), object(12)
memory usage: 11.5+ MB
```

In [16]:

```
# changing date type to the appropriate format

aviation_df['Event.Date'] = pd.to_datetime(aviation_df['Event.Date'], for
aviation_df['Event.Date']
```

Out[16]:

```
0       1948-10-24
1       1962-07-19
2       1974-08-30
3       1977-06-19
4       1979-08-02
           ...
88884   2022-12-26
88885   2022-12-26
88886   2022-12-26
88887   2022-12-26
88888   2022-12-29
Name: Event.Date, Length: 88889, dtype: datetime64[ns]
```

In [17]:

```
#reinspecting mising data in columns

aviation_df.isna().mean()*100
```

Out[17]:
```
Event.Id                  0.000000
Investigation.Type        0.000000
Event.Date                0.000000
Location                  0.000000
Country                   0.000000
Injury.Severity           0.000000
Aircraft.damage           0.000000
Make                      0.000000
Model                     0.000000
Number.of.Engines         0.000000
Engine.Type               7.982990
Purpose.of.flight         6.965991
Total.Fatal.Injuries      0.000000
Total.Serious.Injuries   14.073732
Total.Minor.Injuries     13.424608
Total.Uninjured           6.650992
Weather.Condition         5.053494
dtype: float64
```

In [18]:
```
#looking at the unique values in the Engine.Type column
aviation_df['Engine.Type'].unique()
```

Out[18]:
```
array(['Reciprocating', nan, 'Turbo Fan', 'Turbo Shaft', 'Unknown',
       'Turbo Prop', 'Turbo Jet', 'Electric', 'Hybrid Rocket',
       'Geared Turbofan', 'LR', 'NONE', 'UNK'], dtype=object)
```

In [19]:
```
# Replace specific values in the 'Engine.Type' column with 'Unknown'
# Fill any remaining missing (NaN) values in the 'Engine.Type' column wit
aviation_df['Engine.Type'] = aviation_df['Engine.Type'].replace(
    {'None': 'Unknown', 'UNK': 'Unknown', 'NONE': 'Unknown'}
).fillna('Unknown')
```

For the weather conditions we have:

- VMC - we will change this to indicate that this is good weather (clear skies, good visibility, and minimal cloud cover)
- IMC - we will change this to indicate that this is bad weather (fog, heavy rain, snow, low clouds, or any conditions that reduce visibility below VMC limits)
- UNK - weather conditions were unknown

In [20]:
```
aviation_df['Weather.Condition'].unique()
```

Out[20]:
```
array(['UNK', 'IMC', 'VMC', nan, 'Unk'], dtype=object)
```

In [21]:
```
# cleaning up the values in the Weather.Conditions column

# Standardize and clean Weather.Condition values
aviation_df['Weather.Condition'] = aviation_df['Weather.Condition'].repla
    'Unk': 'Unknown',
    'UNK': 'Unknown',
    'VMC': 'VMC (GOOD)',
    'IMC': 'IMC (BAD)'
}).fillna('Unknown')

# Display unique values after cleaning
aviation_df['Weather.Condition'].unique()
```

Out[21]: array(['Unknown', 'IMC (BAD)', 'VMC (GOOD)'], dtype=object)

Although there are some columns of missing data, I do not see them being a hinderance to my data analysis

3. Data Analysis and Visualisation

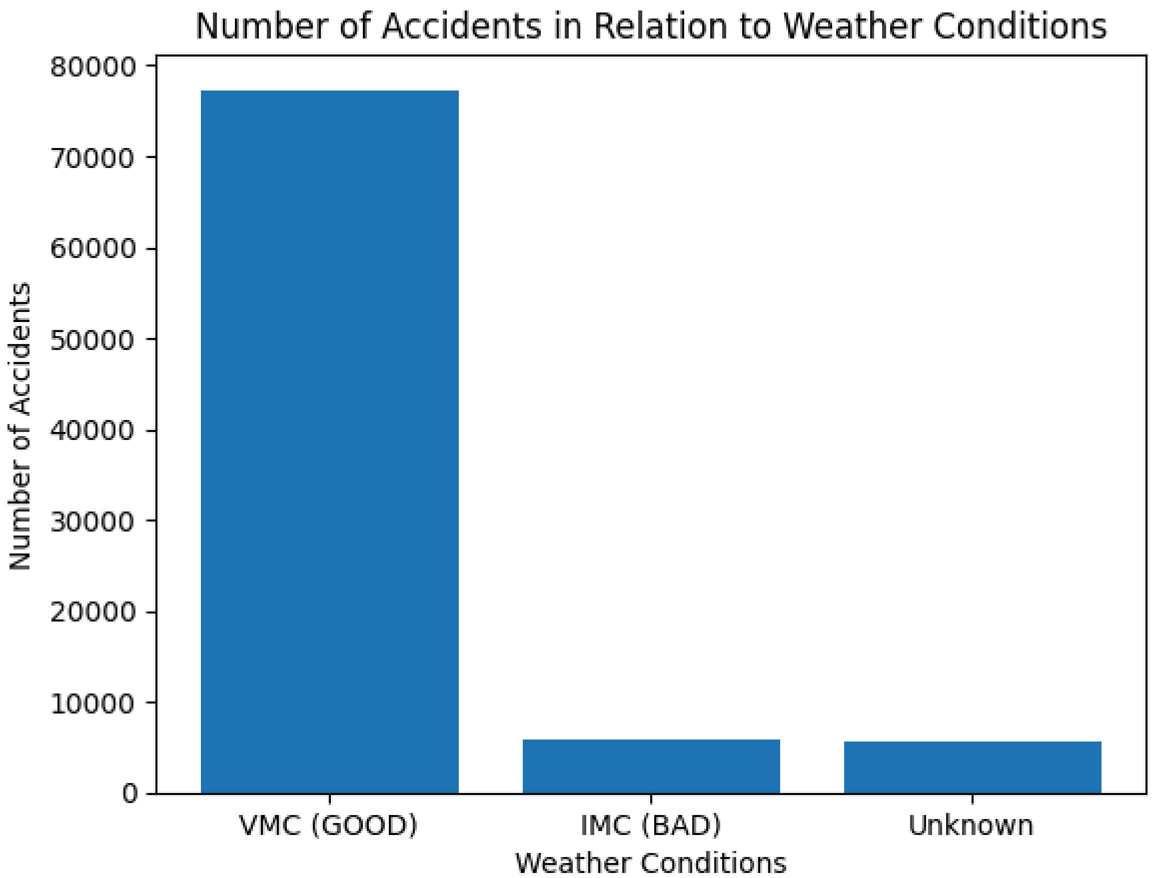
For the number of accidents over the years, we will plot a line graph starting 1982 because the years before did not have significant data to analyse.

In [22]:
```
# Let's have a look at the line plot of US aviation accidents over years

aviation_df['Year'] = aviation_df['Event.Date'].dt.year
aviation_df_filtered = aviation_df[aviation_df['Year'] >= 1982]

accidents_by_year = aviation_df_filtered['Year'].value_counts().sort_inde

plt.figure(figsize=(8, 4))
plt.plot(accidents_by_year.index, accidents_by_year.values, linestyle='-'
plt.title('Number of Aviation Accidents over the Years')
plt.xlabel('Year')
plt.ylabel('Number of Accidents')
plt.grid(True)
plt.xticks(rotation=45)
plt.show()
```

As per the finding the rate of accidents has reduced indicating better safety in aircrafts over the years.

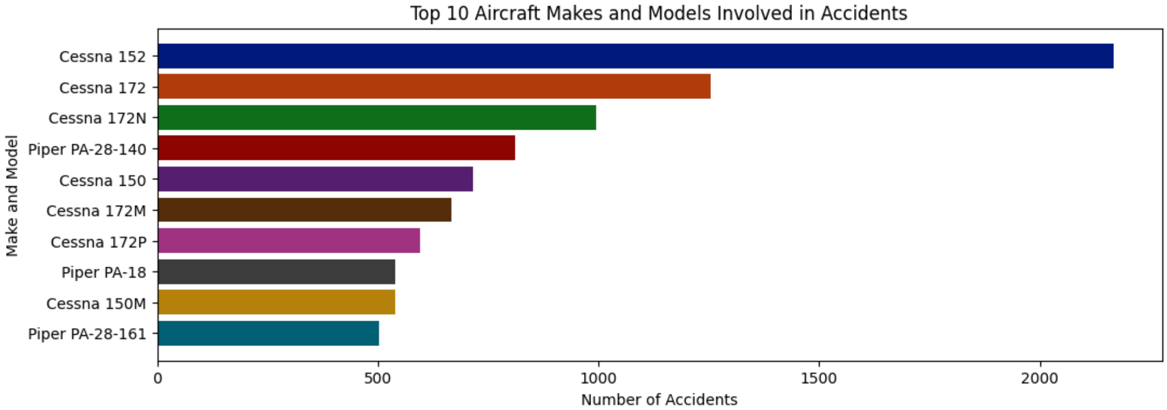
In [23]:
```
bar_chart_title = "Number of Accidents in Relation to Weather Conditions"

fig, ax = plt.subplots()

x = aviation_df['Weather.Condition'].value_counts().index  # Unique weath
y = aviation_df['Weather.Condition'].value_counts().values  # Count of ea
```

```
ax.bar(x, y)

ax.set_ylabel('Number of Accidents')
ax.set_xlabel('Weather Conditions')
ax.set_title(bar_chart_title)

plt.show()
```



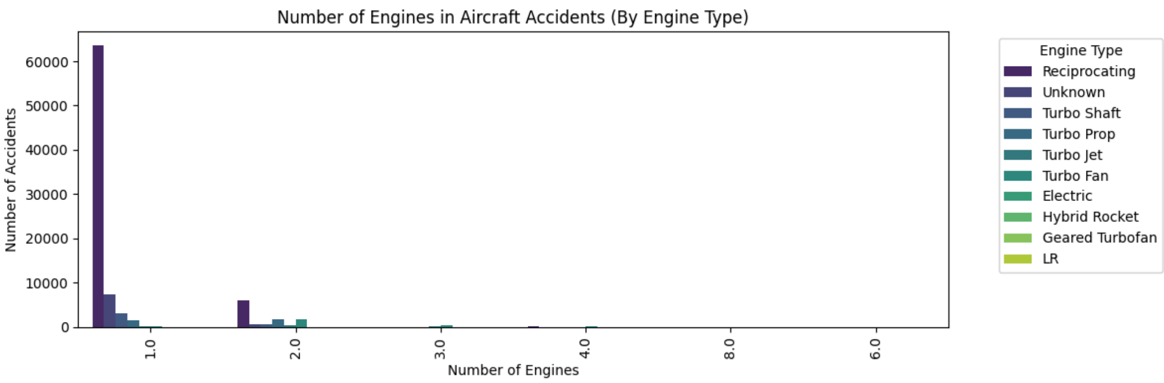
Bad weather conditions were not a major contributing factor to the number of accidents.

In [24]:
```
fig, ax = plt.subplots(figsize=(12, 4))

# looking at the relationship between Makes, Models and engine types with
make_model_accidents = aviation_df.groupby(['Make', 'Model']).size().rese
make_model_accidents = make_model_accidents.sort_values(by='AccidentCount

top_10_make_model = make_model_accidents.head(10)
colors = sns.color_palette("dark", len(top_10_make_model))
ax.barh(top_10_make_model['Make'] + ' ' + top_10_make_model['Model'], top
ax.set_xlabel('Number of Accidents')
ax.set_ylabel('Make and Model')
ax.set_title('Top 10 Aircraft Makes and Models Involved in Accidents')
ax.invert_yaxis()
```



Cessna152, Cessna172, Cessna172N invoved in more accidents. This might be due to the populariy and accessibility of these models but more investigation must be conducted.

In [25]:
```
# Plotting a bar graph to determine the number and types of engines that
aviation_df['Number.of.Engines'] = aviation_df['Number.of.Engines'].repla

fig, ax = plt.subplots(figsize=(12, 4))

sns.countplot(data=aviation_df,
              x='Number.of.Engines',
              hue='Engine.Type',  # Grouping by Engine Type
              order=aviation_df['Number.of.Engines'].value_counts().index
              palette='viridis',
              ax=ax)

ax.set_title('Number of Engines in Aircraft Accidents (By Engine Type)')
ax.set_ylabel('Number of Accidents')
ax.set_xlabel('Number of Engines')
ax.tick_params(axis='x', rotation=90)
ax.legend(title="Engine Type", bbox_to_anchor=(1.05, 1), loc='upper left'

# Adjust layout and display
plt.tight_layout()
plt.show()
```

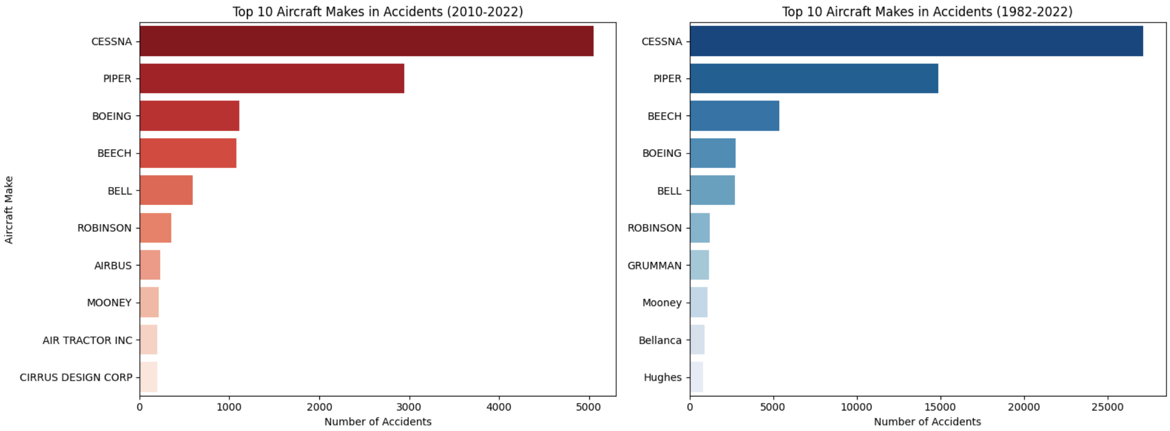


The fewer the engines the higher the number of accidents. This could possibly be due to the fact that they are more accessible for personal use or are more readily available but ould need to be explored farther.

In [26]:
```
# Ensuring consistent capitalization
aviation_df['Make'] = aviation_df['Make'].replace({
```

```
    'Cessna': 'CESSNA',
    'Piper': 'PIPER',
    'Boeing': 'BOEING',
    'Beech': 'BEECH',
    'Grumman': 'GRUMMAN',
    'Robinson': 'ROBINSON',
    'Bell': 'BELL'
})

# Filter dataset for both time periods
aviation_recent = aviation_df[(aviation_df['Year'] >= 2010) & (aviation_d
aviation_historical = aviation_df[(aviation_df['Year'] >= 1982) & (aviati

# Get the top 10 makes for both time periods
top_10_recent = aviation_recent['Make'].value_counts().head(10).reset_ind
top_10_recent.columns = ['Make', 'AccidentCount']

top_10_historical = aviation_historical['Make'].value_counts().head(10).r
top_10_historical.columns = ['Make', 'AccidentCount']

# Set up side-by-side bar plots
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Plot for 2010-2022
sns.barplot(ax=axes[0], x=top_10_recent['AccidentCount'], y=top_10_recent
axes[0].set_title('Top 10 Aircraft Makes in Accidents (2010-2022)')
axes[0].set_xlabel('Number of Accidents')
axes[0].set_ylabel('Aircraft Make')

# Plot for 1982-2022
sns.barplot(ax=axes[1], x=top_10_historical['AccidentCount'], y=top_10_hi
axes[1].set_title('Top 10 Aircraft Makes in Accidents (1982-2022)')
axes[1].set_xlabel('Number of Accidents')
axes[1].set_ylabel('')

# Adjust layout and show the plots
plt.tight_layout()
plt.show()
```

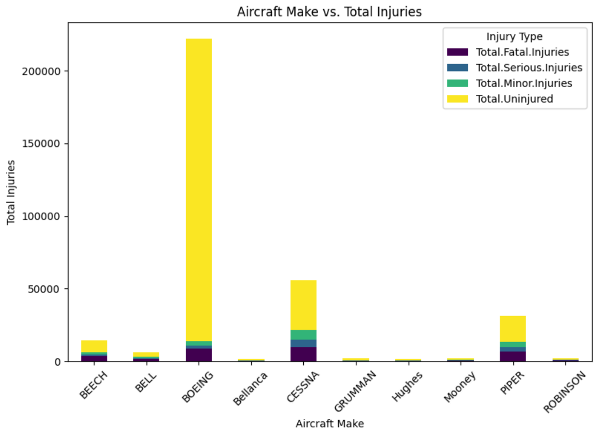
```
/var/folders/xz/p8mfkld52573c5bbm0h9ssh00000gn/T/ipykernel_42953/320504044
5.py:27: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for
the same effect.

  sns.barplot(ax=axes[0], x=top_10_recent['AccidentCount'], y=top_10_recen
t['Make'], palette='Reds_r')
/var/folders/xz/p8mfkld52573c5bbm0h9ssh00000gn/T/ipykernel_42953/320504044
5.py:33: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remove
d in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for
the same effect.

  sns.barplot(ax=axes[1], x=top_10_historical['AccidentCount'], y=top_10_h
istorical['Make'], palette='Blues_r')
```

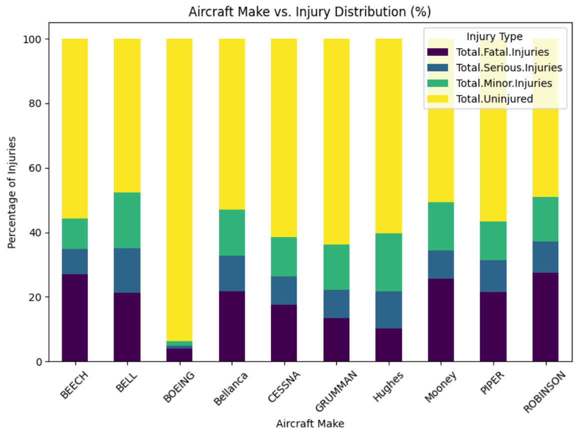


The top 5 aircrafts makes with the most accidents have remained the same since 1982-2022 and over the last 12 years. In the bottom 5 for recent times we see a change in the more frequesnt makes listed.

In [27]:

```
# Get top 10 aircraft makes with most incidents
top_10_makes = aviation_df['Make'].value_counts().head(10).index
filtered_df = aviation_df[aviation_df['Make'].isin(top_10_makes)]

# Define injury-related columns
injury_cols = ['Total.Fatal.Injuries', 'Total.Serious.Injuries', 'Total.M
injuries_by_make = filtered_df.groupby('Make')[injury_cols].sum()

# Convert to percentages for a 100% stacked bar chart
injuries_by_make_pct = injuries_by_make.div(injuries_by_make.sum(axis=1),

# Set figure size
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Absolute values plot
injuries_by_make.plot(kind='bar', stacked=True, colormap='viridis', ax=ax
axes[0].set_ylabel('Total Injuries')
axes[0].set_xlabel('Aircraft Make')
axes[0].set_title('Aircraft Make vs. Total Injuries')
axes[0].legend(title='Injury Type')
axes[0].tick_params(axis='x', rotation=45)

# Percentage (100% stacked) plot
injuries_by_make_pct.plot(kind='bar', stacked=True, colormap='viridis', a
axes[1].set_ylabel('Percentage of Injuries')
axes[1].set_xlabel('Aircraft Make')
axes[1].set_title('Aircraft Make vs. Injury Distribution (%)')
axes[1].legend(title='Injury Type')
axes[1].tick_params(axis='x', rotation=45)

plt.tight_layout()
plt.show()
```



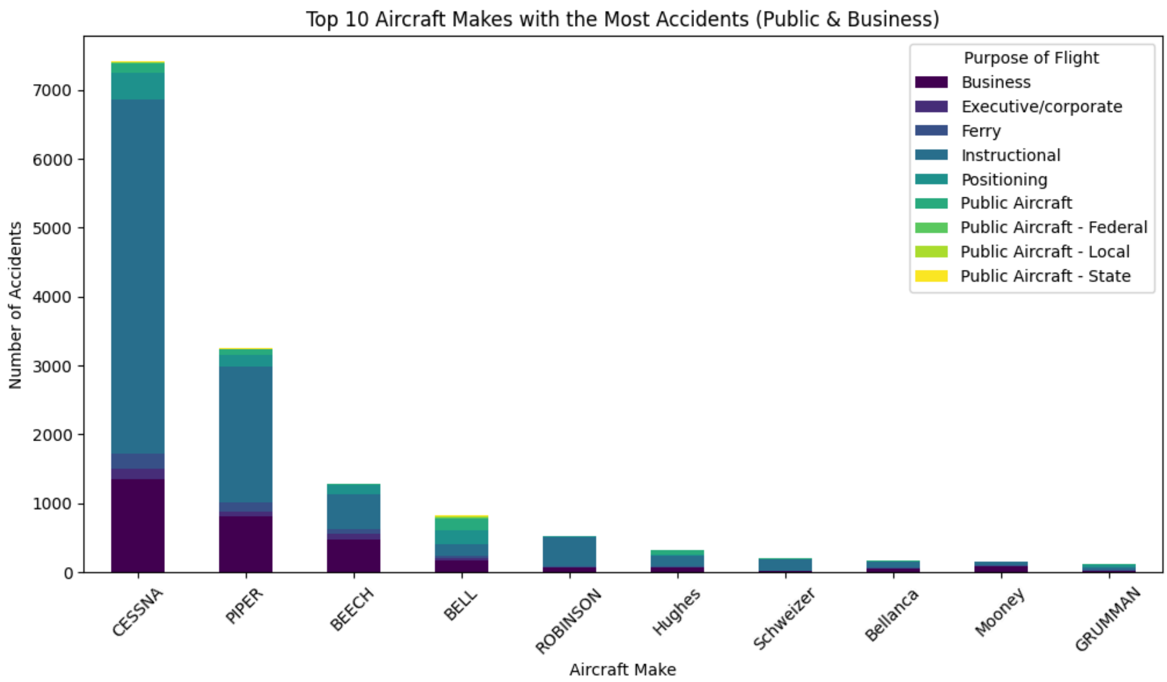


Looking at the top 10 makes Boeing stood out in regards to the number of uninjured passengers against the number of incidients implying more safety with this make.

In [28]:
```
aviation_df['Purpose.of.flight'].unique()
```

Out[28]:
```
array(['Personal', nan, 'Business', 'Instructional', 'Unknown', 'Ferry',
       'Executive/corporate', 'Aerial Observation', 'Aerial Applicatio
n',
       'Public Aircraft', 'Skydiving', 'Other Work Use', 'Positioning',
       'Flight Test', '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 [29]:
```
# Define categories related to public and business flight purposes
public_purposes = ['Public Aircraft', 'Public Aircraft - Federal', 'Publi
business_purposes = ['Business', 'Executive/corporate', 'Instructional',

# Filter the dataset to include only relevant flight purposes
filtered_df = aviation_df[aviation_df['Purpose.of.flight'].isin(public_pu

# Count the number of accidents per aircraft make for these categories
accidents_by_make = filtered_df.groupby(['Make', 'Purpose.of.flight']).si

# Select the top 10 aircraft makes with the most accidents
top_10_makes = accidents_by_make.sum(axis=1).nlargest(10).index
top_10_accidents = accidents_by_make.loc[top_10_makes]

# Plot the results
fig, ax = plt.subplots(figsize=(12, 6))
top_10_accidents.plot(kind='bar', stacked=True, colormap='viridis', ax=ax

# Formatting
ax.set_ylabel('Number of Accidents')
ax.set_xlabel('Aircraft Make')
ax.set_title('Top 10 Aircraft Makes with the Most Accidents (Public & Bus
ax.legend(title='Purpose of Flight')
plt.xticks(rotation=45)
plt.show()
```



In [31]:
```
# creating a cleaned version of the dataset

aviation_df.to_csv('AviationData_cleaned.csv', index=False)
```

Conclusion

Analysis of the dataset reveals a steady decline in aviation accidents over the years, likely indicating improvements in safety measures across the industry.

Key insights include:

- Weather Conditions: Bad weather contributed to less than 10% of recorded accidents, suggesting that most incidents were due to other factors.
- Flight Purpose: Among different flight purposes, instructional flights posed the highest risk, while executive/corporate flights had significantly lower accident rates.
- Engine Type & Risk: Aircraft with reciprocating engines recorded the highest number of accidents Additionally, planes with fewer engines (especially between one and two) had a higher accident rate.
- Aircraft Manufacturers: While Boeing appeared in the top 10 for most accidents, it outperformed other manufacturers in terms of passenger survival rates. Conversely, Cessna emerged as the riskiest aircraft make, recording the highest number of accidents.

We would need to look at the total flights done by the brands that stand out to get more of a comparative analysis of successful flights and those with accidents to get a better understandong of the proportion and probaility and expand the geographical focus.