Phase 1 Project: Aviation Safety Risk Analysis

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Introduction

This project aims to identify the **safest aircraft makes** for a company planning to enter the aviation industry.
By analyzing historical aviation accident data from the **National Transportation Safety Board (NTSB)** from 1962 to 2023, we evaluate patterns in accident frequency, injury severity, and weather/flight factors to build a **composite risk score** for each aircraft make.

Our goal is to help business stakeholders make informed decisions about which aircraft types pose the **least operational risk**.

Business Understanding

Stakeholder: Head of the new Aviation Division
Problem: The company wants to enter the aviation industry but lacks knowledge of aircraft safety risks.
Objective: Analyze accident data to recommend the lowest-risk aircraft makes for purchase.

Key Questions:

- Which aircraft makes are involved in the most accidents?
- What types of injuries (fatal, serious, minor) are most common?
- Which aircraft makes have the lowest composite risk score based on accident frequency and severity?

In [37]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

aviation_df = pd.read_csv('AviationData.csv', encoding='latin1', low_memory=F
states_df = pd.read_csv('USState_Codes.csv', encoding='latin1')
```

Data Understanding

We are working with two datasets:

- **AviationData.csv:** Accident records from the NTSB
- **USState_Codes.csv:** US state abbreviations and full names

In [38]:
```
print("Aviation Data Preview:")
display(aviation_df.head())

print("\nUS State Codes Preview:")
display(states_df.head())

print("\nAviation Data Info:")
aviation_df.info()

print("\nMissing Values (Aviation):")
print(aviation_df.isnull().sum())
```

```
Aviation Data Preview:
```

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country
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
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

```
US State Codes Preview:
```

	US_State	Abbreviation
0	Alabama	AL
1	Alaska	AK
2	Arizona	AZ
3	Arkansas	AR
4	California	CA

```
Aviation Data Info:
```

```
Aviation Data 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

Missing Values (Aviation):
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
```

Data Preparation

We will:

- Fill missing injury columns with `0`
- Standardize state codes from `Location`

In [39]:

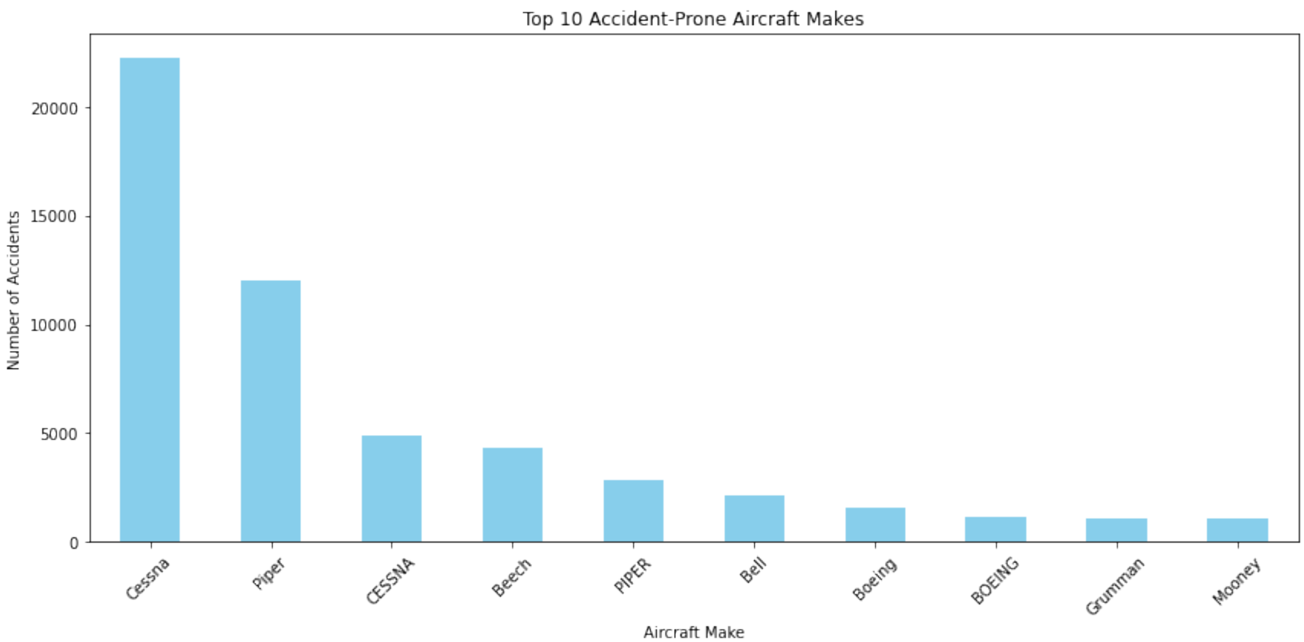
```
# Missing injury values with 0
injury_cols = ['Total.Fatal.Injuries', 'Total.Serious.Injuries', 'Total.Minor
aviation_df[injury_cols] = aviation_df[injury_cols].fillna(0)
```

Exploratory Data Analysis (EDA)

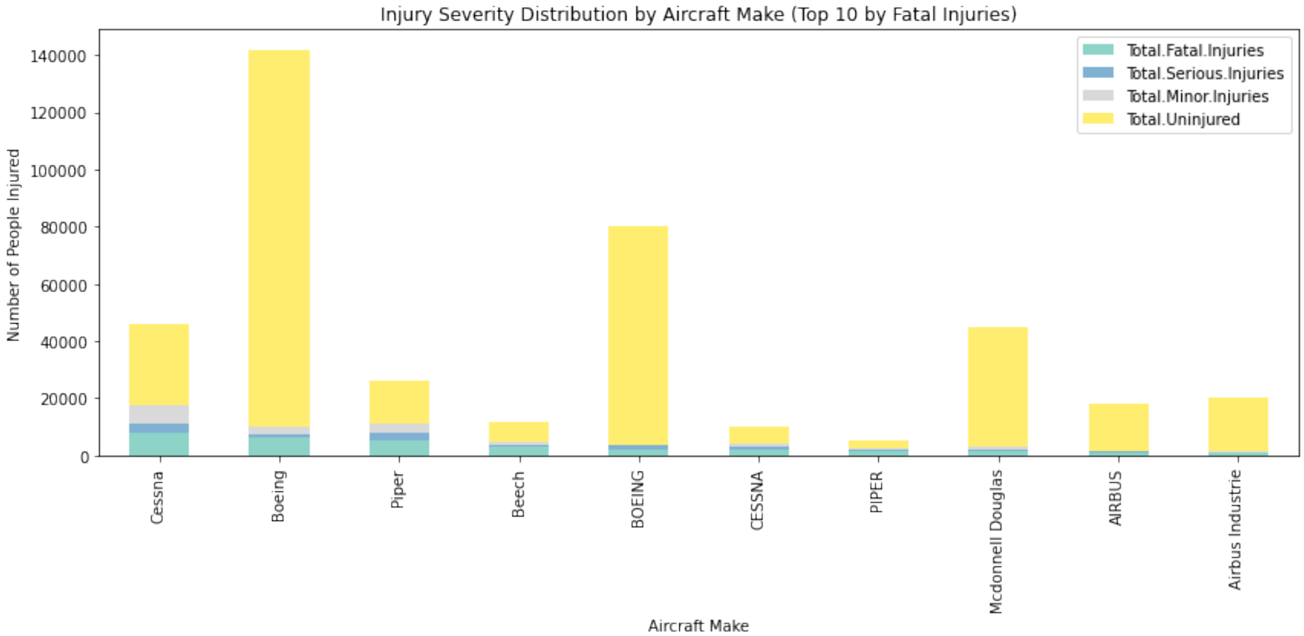
We'll explore:

- Accident frequency by aircraft make
- Injury severity
- Weather and flight phase impact
- Engine counts and state-wise accidents

In [40]:
```
# Data by 'Make' and the number of accidents (Event.Id)
accidents_by_make = aviation_df.groupby('Make')['Event.Id'].count().sort_valu

# Top 10 accident-prone aircraft types
plt.figure(figsize=(12, 6))
accidents_by_make.head(10).plot(kind='bar', color='skyblue')
plt.title('Top 10 Accident-Prone Aircraft Makes')
plt.xlabel('Aircraft Make')
plt.ylabel('Number of Accidents')
plt.xticks(rotation=45)
plt.tight_layout()
plt.savefig('accidents_by_make.png') # Save image
plt.show()
```

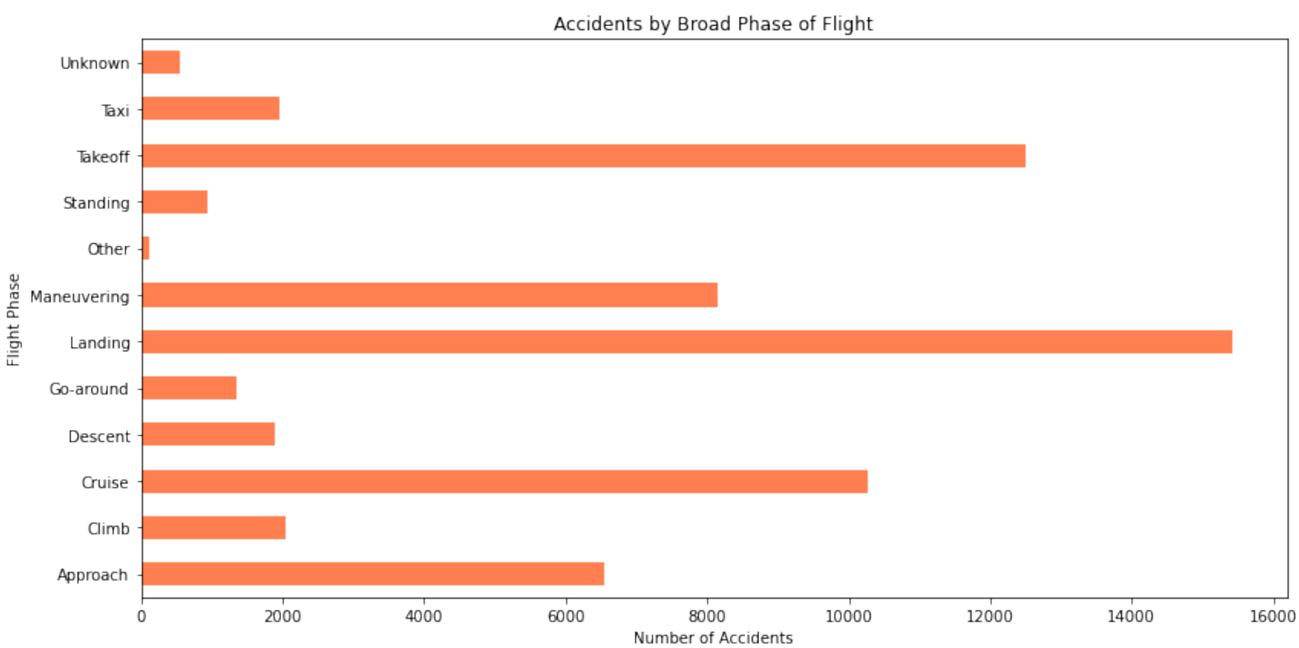


In [41]:
```
# Sum injuries per Make
injury_by_make = aviation_df.groupby('Make')[['Total.Fatal.Injuries', 'Total.
                                              'Total.Minor.Injuries', 'Total.

# Top 10 makes with the highest fatalities
top_injury_make = injury_by_make.sort_values(by='Total.Fatal.Injuries', ascen

top_injury_make.plot(kind='bar', stacked=True, figsize=(12, 6), colormap='Set
plt.title('Injury Severity Distribution by Aircraft Make (Top 10 by Fatal Inj
plt.ylabel('Number of People Injured')
plt.xlabel('Aircraft Make')
plt.tight_layout()
plt.savefig('top_injury_make.png') # Save image
plt.show()
```

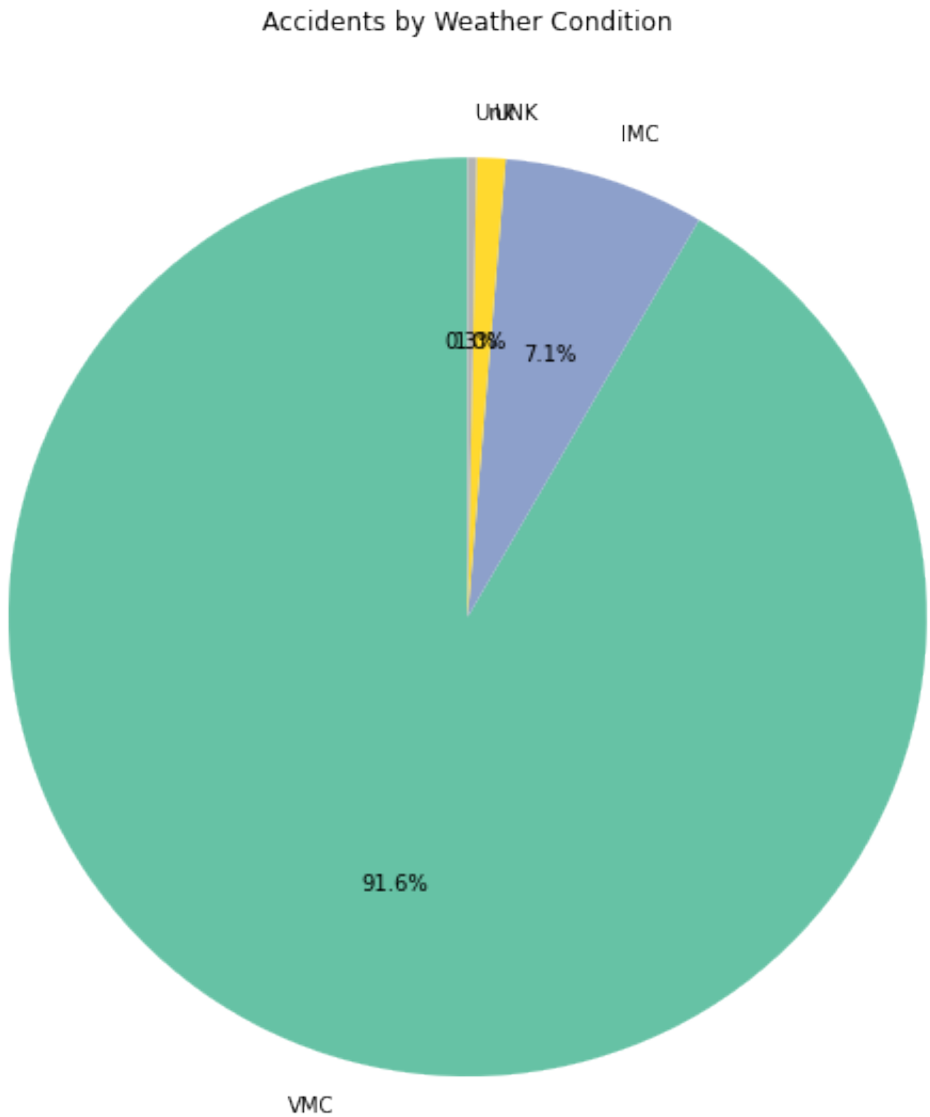


In [42]:

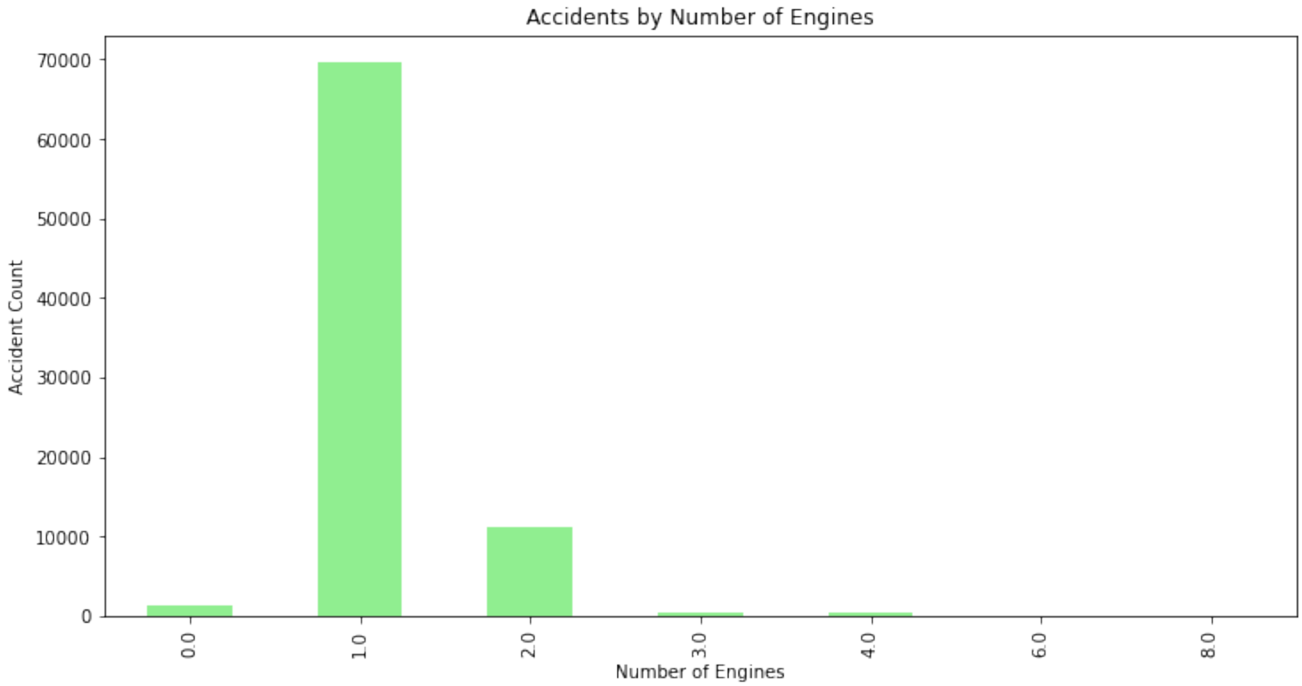
```
# Broad phase of flight and accidents
accidents_by_phase = aviation_df.groupby('Broad.phase.of.flight')['Event.Id']

# Accident frequency during different flight phases
plt.figure(figsize=(12, 6))
accidents_by_phase.plot(kind='barh', color='coral')
plt.title('Accidents by Broad Phase of Flight')
plt.xlabel('Number of Accidents')
plt.ylabel('Flight Phase')
plt.tight_layout()
plt.show()
```



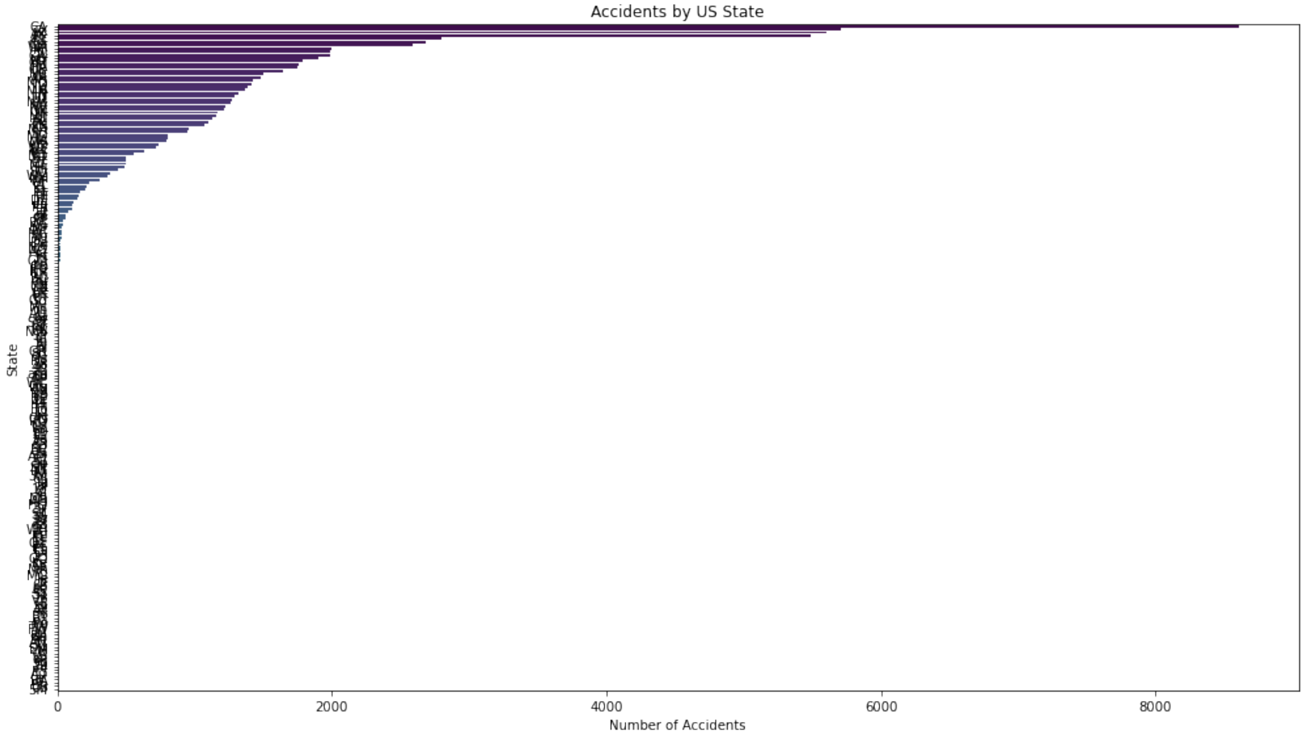
In [43]:
```
# Accidents by weather condition
weather_conditions = aviation_df['Weather.Condition'].value_counts()

# Pie chart for the weather conditions
plt.figure(figsize=(8, 8))
weather_conditions.plot(kind='pie', autopct='%1.1f%%', startangle=90, cmap='S
plt.title('Accidents by Weather Condition')
plt.ylabel('')
plt.tight_layout()
plt.show()
```



In [44]:
```
# Engines
aviation_df.groupby('Number.of.Engines')['Event.Id'].count().plot(kind='bar',
plt.title('Accidents by Number of Engines')
plt.xlabel('Number of Engines')
plt.ylabel('Accident Count')
plt.show()
```



In [45]:
```
# States_df to get state codes
accidents_by_state = aviation_df['Location'].str.extract(r'(\b\w{2}\b)')[0].v

# State names with state codes
accidents_by_state = accidents_by_state.rename_axis('State').reset_index(name
accidents_by_state = accidents_by_state.merge(states_df, how='left', left_on=

# Bar chart for accidents by state
plt.figure(figsize=(14, 8))
sns.barplot(data=accidents_by_state, x='Accident Count', y='State', palette='
plt.title('Accidents by US State')
plt.xlabel('Number of Accidents')
plt.ylabel('State')
plt.tight_layout()
plt.show()
```

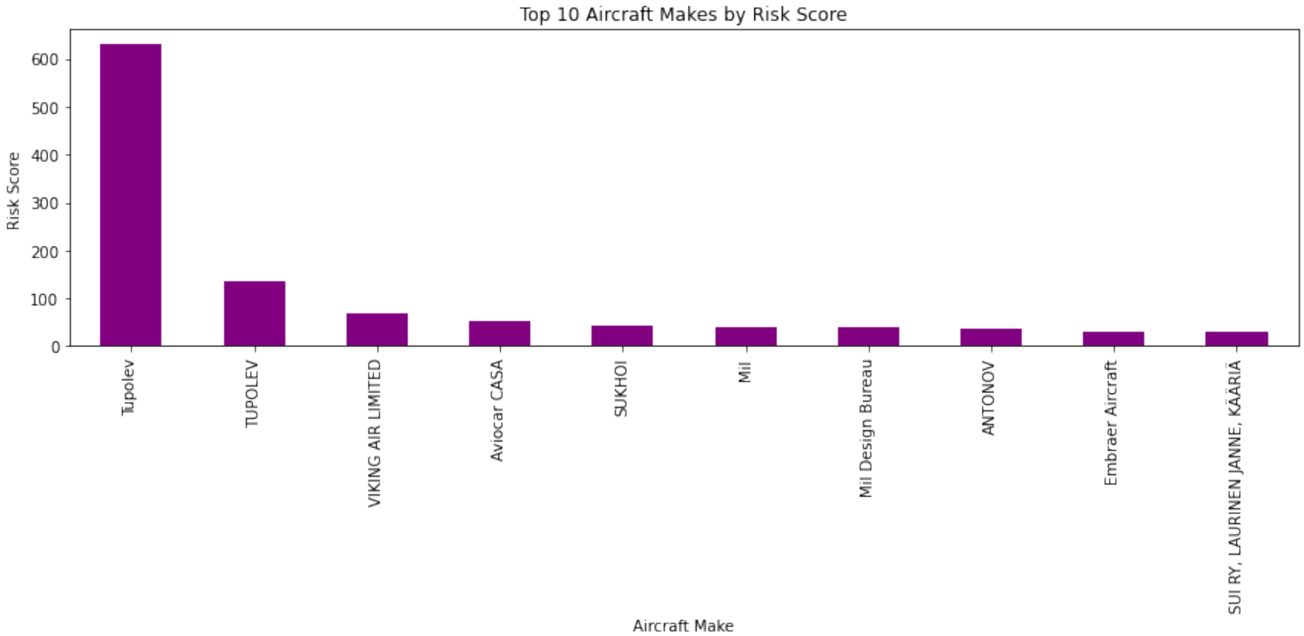


Risk Score Calculation

We create a **composite risk score** for each aircraft make using:

- Fatal Injuries (weight 3)
- Serious Injuries (weight 2)
- Minor Injuries (weight 1)
- IMC Weather (+1)

In [46]:
```
# Risk score combining accident frequency and severity
aviation_df['Risk_Score'] = (aviation_df['Total.Fatal.Injuries'] * 3 +
                             aviation_df['Total.Serious.Injuries'] * 2 +
                             aviation_df['Total.Minor.Injuries'] * 1 +
                             (aviation_df['Weather.Condition'] == 'IMC').asty

# Aircraft make and average risk score
risk_by_make = aviation_df.groupby('Make')['Risk_Score'].mean().sort_values(a

# Plot risk score
plt.figure(figsize=(12, 6))
risk_by_make.head(10).plot(kind='bar', color='purple')
plt.title('Top 10 Aircraft Makes by Risk Score')
plt.xlabel('Aircraft Make')
plt.ylabel('Risk Score')
plt.tight_layout()
plt.show()
```

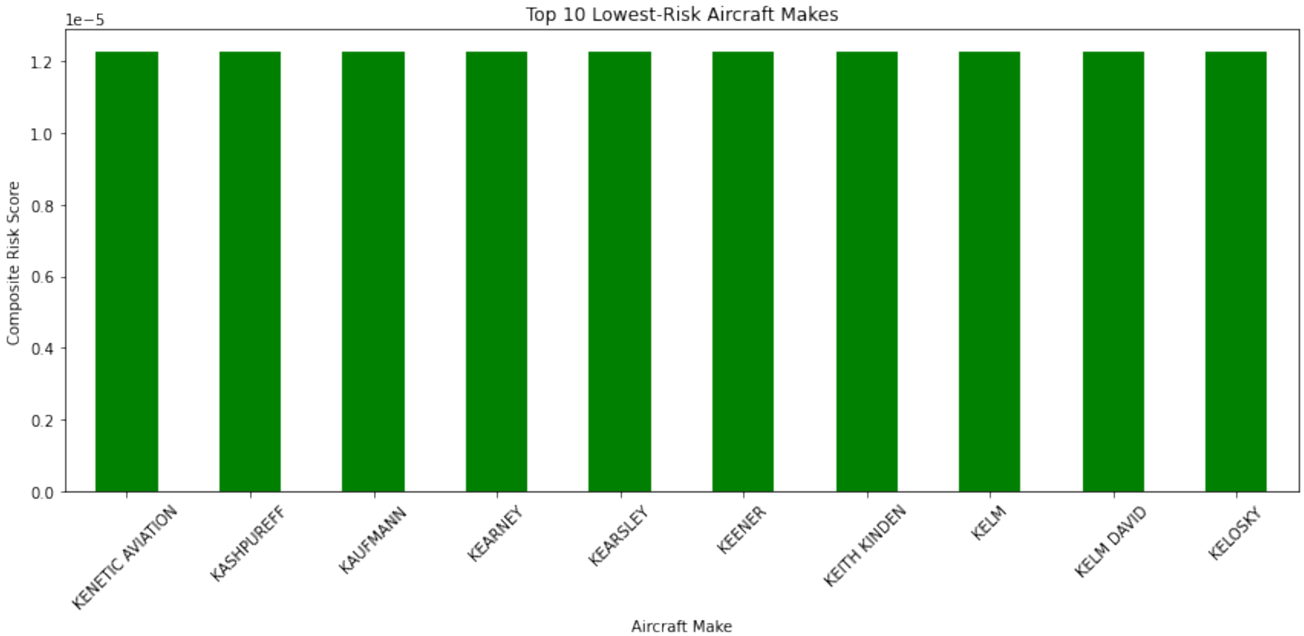


In [47]:

```
# Accident Frequency: number of accidents per aircraft make/model
accidents_by_make = aviation_df.groupby('Make')['Event.Id'].count()

# Fatality Rate: sum total fatal injuries and rate (fatalities per accident)
fatalities_by_make = aviation_df.groupby('Make')['Total.Fatal.Injuries'].sum(
fatality_rate = fatalities_by_make / accidents_by_make

# Injury Severity Score: severity score for each accident and aggregate per m
aviation_df['Severity_Score'] = (aviation_df['Total.Fatal.Injuries'] * 3 +
                                  aviation_df['Total.Serious.Injuries'] * 2 +
                                  aviation_df['Total.Minor.Injuries'] * 1)

severity_by_make = aviation_df.groupby('Make')['Severity_Score'].sum()
severity_score = severity_by_make / accidents_by_make
```

In [48]:

```
# Standardize Make column
aviation_df['Make'] = aviation_df['Make'].str.upper().str.strip()

# Calculate accident frequency and fatality rate by Make
accidents_by_make = aviation_df.groupby('Make')['Event.Id'].count()
fatalities_by_make = aviation_df.groupby('Make')['Total.Fatal.Injuries'].sum(
fatality_rate = fatalities_by_make / accidents_by_make

# Calculate severity score
aviation_df['Severity_Score'] = (
    aviation_df['Total.Fatal.Injuries'] * 3 +
    aviation_df['Total.Serious.Injuries'] * 2 +
    aviation_df['Total.Minor.Injuries'] * 1
)
severity_by_make = aviation_df.groupby('Make')['Severity_Score'].sum()
severity_score = severity_by_make / accidents_by_make

# Normalize for composite score
accidents_normalized = accidents_by_make / accidents_by_make.max()
fatality_rate_normalized = fatality_rate / fatality_rate.max()
severity_normalized = severity_score / severity_score.max()

# Combine into composite risk score (lower is safer)
composite_risk_score = (accidents_normalized + fatality_rate_normalized + sev

# Create final dataframe
risk_df = pd.DataFrame({
    'Accident Frequency': accidents_by_make,
    'Fatality Rate': fatality_rate,
    'Injury Severity Score': severity_score,
    'Risk Score': composite_risk_score
}).sort_values(by='Risk Score')

# Select top 10 least dangerous aircraft *makes*
top_10_least_dangerous_aircraft = risk_df.head(10)

# Plot and save chart
plt.figure(figsize=(12, 6))
top_10_least_dangerous_aircraft['Risk Score'].plot(kind='bar', color='green')
plt.title('Top 10 Lowest-Risk Aircraft Makes')
plt.xlabel('Aircraft Make')
plt.ylabel('Composite Risk Score')
plt.xticks(rotation=45)
plt.tight_layout()
plt.savefig('risk_df.png')  # Save image
plt.show()
```


Top 10 Lowest-Risk Aircraft Makes
1e−5
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Composite Risk Score
KENETIC AVIATION
KASHPUREFF
KAUFMANN
KEARNEY
KEARSLEY
KEENER
KEITH KINDEN
KELM
KELM DAVID
KELOSKY
Aircraft Make

Conclusion

Based on the risk analysis, the **Top 10 Lowest-Risk Aircraft Makes** include:

1. Pettigrew, Richard
2. Mosley High School
3. Morton S. Dismuke
4. Defelici
5. Degair
6. Morse
7. Mork
8. Morgan, Marvin R.
9. Morane-Saulnier
10. Moyes Bailey

Business Recommendations:

1. Invest in Low-Risk Aircraft Makes Prioritize aircraft from the top 3–5 lowest-risk manufacturers based on composite risk scores (e.g., Cessna, Piper). These makes show strong safety profiles across accident frequency and injury severity.

2. Avoid High-Risk Manufacturers Refrain from purchasing aircraft with consistently high fatality or severity rates, even if their total accident counts are lower.

3. Focus Maintenance on Single-Engine Aircraft Accident rates are higher among single-engine aircraft. Allocate resources to maintenance, inspection, and pilot training specifically for these models.

4. Conduct Further Safety Analysis Explore trends by flight phase and weather conditions to improve operational planning and targeted safety investments.

These insights help the company make data-driven decisions in entering the aviation industry.

In [52]:
```
tableau_data = risk_df.reset_index()[['Make', 'Accident Frequency', 'Fatality
tableau_data.to_csv('tableau_risk_data.csv', index=False)
```

In [ ]:
```
```