Final Project Submission

Please fill out:

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- Student pace: `Part time`
- Scheduled project review date/time: `27TH OCT TO  31ST OCT 2025`
- Instructor name: `Brian Chacha`
- Blog post URL:

INTRODUCATION

Your company is expanding in to new industries to diversify its portfolio. Specifically, they are interested in purchasing and operating airplanes for commercial and private enterprises, but do not know anything about the potential risks of aircraft. You are charged with determining which aircraft are the lowest risk for the company to start this new business endeavor. You must then translate your findings into actionable insights that the head of the new aviation division can use to help decide which aircraft to purchase.

In [1]:

```
# Your code here - remember to use markdown cells for comments as well!
# Import the pandas library for data manipulation and analysis
import pandas as pd

# Import the numpy library for numerical operations and working with arrays
import numpy as np


# Import the warnings module to control or suppress warning messages
import warnings

# Suppress all warning messages to keep the output clean
warnings.filterwarnings('ignore')
```

1.1) Read Aviation_Data.csv into a pandas DataFrame named df

In [2]:

```
# Load the CSV file "Aviation_Data.csv" from the 'data' folder into a pandas DataFrame 

df = pd.read_csv("./data/Aviation_Data.csv")

# Display the first 5 rows of the DataFrame to quickly inspect the data

df.head()
```

Out[2]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude
0	20001218X45444	Accident	SEA87LA080	10/24/1948	MOOSE CREEK, ID	United States	NaN
1	20001218X45447	Accident	LAX94LA336	7/19/1962	BRIDGEPORT, CA	United States	NaN

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude
2	20061025X01555	Accident	NYC07LA005	8/30/1974	Saltville, VA	United States	36.922223
3	20001218X45448	Accident	LAX96LA321	6/19/1977	EUREKA, CA	United States	NaN
4	20041105X01764	Accident	CHI79FA064	8/2/1979	Canton, OH	United States	NaN

5 rows × 31 columns

In [3]:
```
# Display the shape (rows, columns)
df.shape

# Print the number of rows and columns in a readable format
print(f"This dataset has {df.shape[0]} rows and {df.shape[1]} columns.")
```

```
This dataset has 90348 rows and 31 columns.
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                88889 non-null  object
 1   Investigation.Type      90348 non-null  object
 2   Accident.Number         88889 non-null  object
 3   Event.Date              88889 non-null  object
 4   Location                88837 non-null  object
 5   Country                 88663 non-null  object
 6   Latitude                34382 non-null  object
 7   Longitude               34373 non-null  object
 8   Airport.Code            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        73659 non-null  object
dtypes: float64(5), object(26)
memory usage: 21.4+ MB
```

How to Find Duplicates in our Aviation Data

our data has **90,348 rows** and **31 columns**.
Sometimes the **same crash** gets entered **twice** by mistake.
We want to **find & remove** those duplicates so our analysis is clean!

In [5]:
```
duplicate_rows = df.duplicated().sum()

print(f"There are {duplicate_rows} duplicate rows in this dataset.")
```

```
There are 1390 duplicate rows in this dataset.
```

In [6]:
```
#If you don’t want to modify the original DataFrame:

cleaned_df = df.drop_duplicates()
```

How to Find Missing Values in Our Aviation Data

Our dataset(cleaned) has `88,958` rows and `31` columns. Sometimes, during data entry, some information gets left blank — like the aircraft type, location, or number of fatalities.

These missing values `(NaNs)` can affect our analysis, so we need to identify and handle them before moving forward!

We’ll check:

1. How many missing values exist in each column
2. Which columns have the most missing data
3. And decide whether to fill, drop, or keep them depending on their importance.

In [8]:
```
#Check missing data percentages:
cleaned_df.isnull().mean().sort_values(ascending=False) * 100
```

Out[8]:
```
Schedule                  85.856247
Air.carrier               81.285550
FAR.Description           64.002113
Aircraft.Category         63.705344
Longitude                 61.360417
Latitude                  61.350300
Airport.Code              43.645316
Airport.Name              40.754064
Broad.phase.of.flight     30.614447
Publication.Date          17.198004
Total.Serious.Injuries    14.140381
Total.Minor.Injuries      13.491760
Total.Fatal.Injuries      12.893725
Engine.Type                8.054363
Report.Status              7.253985
Purpose.of.flight          7.038153
Number.of.Engines          6.916747
Total.Uninjured            6.723398
```

```
Weather.Condition         5.127139
Aircraft.damage           3.668023
Registration.Number       1.631107
Injury.Severity           1.201691
Country                   0.331617
Amateur.Built             0.192226
Model                     0.180984
Make                      0.148385
Location                  0.136019
Event.Date                0.077565
Accident.Number           0.077565
Event.Id                  0.077565
Investigation.Type        0.000000
dtype: float64
```

In [9]:

```python
cleaned_df.describe()
```

Out[9]:

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Total.Uninjured
count	82805.000000	77488.000000	76379.000000	76956.000000	82977.000000
mean	1.146585	0.647855	0.279881	0.357061	5.325440
std	0.446510	5.485960	1.544084	2.235625	27.913634
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.000000	0.000000	0.000000	1.000000
75%	1.000000	0.000000	0.000000	0.000000	2.000000
max	8.000000	349.000000	161.000000	380.000000	699.000000

In [10]:

```python
#Get summary stats
cleaned_df.describe(include='all')
```

Out[10]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude
count	88889	88958	88889	88889	88837	88663	34382
unique	84468	71	88863	14782	27758	219	25589
top	2.02207E+13	Accident	DCA22LA135	6/30/1984	ANCHORAGE, AK	United States	332739N
freq	190	85015	2	25	434	82248	19
mean	NaN	NaN	NaN	NaN	NaN	NaN	NaN
std	NaN	NaN	NaN	NaN	NaN	NaN	NaN
min	NaN	NaN	NaN	NaN	NaN	NaN	NaN
25%	NaN	NaN	NaN	NaN	NaN	NaN	NaN
50%	NaN	NaN	NaN	NaN	NaN	NaN	NaN
75%	NaN	NaN	NaN	NaN	NaN	NaN	NaN
max	NaN	NaN	NaN	NaN	NaN	NaN	NaN

11 rows × 31 columns

1. Columns to **DROP** (too many blanks + not very helpful)

Column	% Missing	Why drop it?
Schedule	86%	Almost all rows are blank. It just says if the flight was on a regular schedule (like a bus). We already know from `Purpose.of.flight` if it was a normal passenger trip.
Air.carrier	82%	Mostly empty. It's just the airline name (like "Delta"). We don't need the name to understand the crash.
FAR.Description	65%	A boring legal rule number. Missing for most small planes. Doesn't help us predict injuries or damage.
Aircraft.Category	64%	Says if it's a plane, helicopter, etc. But we already have `Make` and `Model` — that's enough!
Longitude / Latitude	~62%	GPS numbers. Great for Google Maps, but more than half are missing. We still have city and airport to know *where*.
Airport.Code	44%	The short code like "LAX" or "JFK". Many crashes happen **away** from airports, so it's often blank.
Airport.Name	42%	Same as above. We can just use the city name instead.
Broad.phase.of.flight	32%	Tells you *when* in the flight it crashed (takeoff? landing?). Helpful, but too many blanks and too many options. Hard to guess the missing ones.
Publication.Date	18%	This is the day the **report** came out — not the crash day. Totally useless for understanding the accident.

In [11]:
```python
cols_to_drop = [
    'Schedule', 'Air.carrier', 'FAR.Description', 'Aircraft.Category',
    'Longitude', 'Latitude', 'Airport.Code', 'Airport.Name',
    'Broad.phase.of.flight', 'Publication.Date'
]

cleaned_df= cleaned_df.drop(columns=cols_to_drop)
```

In [12]:
```python
cleaned_df.isnull().mean().sort_values(ascending=False) * 100
```

Out[12]:
```
Total.Serious.Injuries    14.140381
Total.Minor.Injuries      13.491760
Total.Fatal.Injuries      12.893725
Engine.Type                8.054363
Report.Status              7.253985
Purpose.of.flight          7.038153
Number.of.Engines          6.916747
Total.Uninjured            6.723398
Weather.Condition          5.127139
Aircraft.damage            3.668023
Registration.Number        1.631107
Injury.Severity            1.201691
Country                    0.331617
Amateur.Built              0.192226
Model                      0.180984
```

```
Make                    0.148385
Location                0.136019
Event.Date              0.077565
Accident.Number         0.077565
Event.Id                0.077565
Investigation.Type      0.000000
dtype: float64
```

2. Columns to **KEEP** (a little blank is okay — they're super important!)

Column	% Missing	Why keep it?
Total.Serious.Injuries	15%	This tells us how many people got **really hurt**. Most crashes have 0 — so we can just fill blanks with **0**.
Total.Minor.Injuries	15%	Same idea — small cuts or bruises. Fill blanks with **0**.
Total.Fatal.Injuries	14%	**Super important!** How many people died. We *must* keep this. Fill blanks with **0**.
Engine.Type	9%	Is it a normal engine or a jet? Big difference in crashes. Easy to fill with "Unknown" if missing.
Report.Status	9%	Says if the report is "final" or "still being checked". Helps us know if the data is ready.
Purpose.of.flight	8%	Was it a normal passenger flight? Training? Crop dusting? **Tells us a lot** about the risk.
Number.of.Engines	8%	1 engine or 2+? Two engines = safer usually. Easy to guess if missing.
Total.Uninjured	8%	How many people walked away fine. Completes the story! Fill with a number if missing.
Weather.Condition	7%	Was it sunny or stormy? Weather causes many crashes. Most are "good weather" — so fill with that.
Aircraft.damage	5%	Did the plane get scratched or totally destroyed? **Main thing** we want to predict.
Registration.Number	3%	The plane's license plate (like N123AB). Helps find duplicates.
Injury.Severity	3%	Says "Fatal" or "Minor" in one word. We can make it from the injury counts if needed.
Country, Amateur.Built, Model, Make, Location, Event.Date, Accident.Number, Event.Id	≤ 2%	Almost no blanks! These are **must-haves**:

In [13]:
```python
# checking country which appears most
cleaned_df['Country'].value_counts().head()
```

Out[13]:
```
Country
United States    82248
Brazil             374
Canada             359
Mexico             358
```

```
United Kingdom      344
Name: count, dtype: int64
```

In [14]:
```
#any missing value will be replaced with mode country which is United states
cleaned_df['Country'].fillna('United States', inplace=True)
```

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

```
<class 'pandas.core.frame.DataFrame'>
Index: 88958 entries, 0 to 90347
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                88889 non-null  object 
 1   Investigation.Type      88958 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                 88958 non-null  object 
 6   Injury.Severity         87889 non-null  object 
 7   Aircraft.damage         85695 non-null  object 
 8   Registration.Number     87507 non-null  object 
 9   Make                    88826 non-null  object 
 10  Model                   88797 non-null  object 
 11  Amateur.Built           88787 non-null  object 
 12  Number.of.Engines       82805 non-null  float64
 13  Engine.Type             81793 non-null  object 
 14  Purpose.of.flight       82697 non-null  object 
 15  Total.Fatal.Injuries    77488 non-null  float64
 16  Total.Serious.Injuries  76379 non-null  float64
 17  Total.Minor.Injuries    76956 non-null  float64
 18  Total.Uninjured         82977 non-null  float64
 19  Weather.Condition       84397 non-null  object 
 20  Report.Status           82505 non-null  object 
dtypes: float64(5), object(16)
memory usage: 14.9+ MB
```

In [16]:
```
# lets get numeric column to see use mean mode or median to fill empty cells
numeric_cols = cleaned_df.select_dtypes(include=['number']).columns
print(numeric_cols.tolist())
```

```
['Number.of.Engines', 'Total.Fatal.Injuries', 'Total.Serious.Injuries', 'Total.Minor.Inj
uries', 'Total.Uninjured']
```

In [17]:
```
# Will use the number of engine using make
mode_value = cleaned_df['Number.of.Engines'].mode()[0]
median_value = cleaned_df['Number.of.Engines'].median()
mean_value = cleaned_df['Number.of.Engines'].mean()

print(f"Mode: {mode_value}, Median: {median_value}, Mean: {mean_value:.2f}")
```

```
Mode: 1.0, Median: 1.0, Mean: 1.15
```

In [18]:
```
# Replace missing or zero engine counts with 1
cleaned_df['Number.of.Engines'] = cleaned_df['Number.of.Engines'].replace(0, np.nan)
cleaned_df['Number.of.Engines'].fillna(1, inplace=True)
```

Fill missing injury counts with zero

In [19]:
```
injury_cols = ['Total.Fatal.Injuries',
               'Total.Serious.Injuries',
               'Total.Minor.Injuries',
```

```
                'Total.Uninjured']

# Replace NaN with 0
cleaned_df[injury_cols] = cleaned_df[injury_cols].fillna(0)
```

In [20]:
```
cleaned_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 88958 entries, 0 to 90347
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                88889 non-null  object 
 1   Investigation.Type      88958 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                 88958 non-null  object 
 6   Injury.Severity         87889 non-null  object 
 7   Aircraft.damage         85695 non-null  object 
 8   Registration.Number     87507 non-null  object 
 9   Make                    88826 non-null  object 
 10  Model                   88797 non-null  object 
 11  Amateur.Built           88787 non-null  object 
 12  Number.of.Engines       88958 non-null  float64
 13  Engine.Type             81793 non-null  object 
 14  Purpose.of.flight       82697 non-null  object 
 15  Total.Fatal.Injuries    88958 non-null  float64
 16  Total.Serious.Injuries  88958 non-null  float64
 17  Total.Minor.Injuries    88958 non-null  float64
 18  Total.Uninjured         88958 non-null  float64
 19  Weather.Condition       84397 non-null  object 
 20  Report.Status           82505 non-null  object 
dtypes: float64(5), object(16)
memory usage: 14.9+ MB
```

our Investigation.Type column and number has many entries of 88958 but generally the event id has 88889

In [21]:
```
cleaned_df['Investigation.Type'].value_counts()
```

Out[21]:
```
Investigation.Type
Accident      85015
Incident       3874
3/12/2020         1
8/9/2022          1
1/11/2022         1
              ...  
17-12-2021        1
16-11-2021        1
16-07-2021        1
15-12-2022        1
3/11/2020         1
Name: count, Length: 71, dtype: int64
```

cleaning event id where is null will solve the problem

our Investigation.Type column and number has many entries of 88958 but generally the event id has 88889

In [22]:
```
# cleaning event id where is null will solve the problem
cleaned_df['Event.Id'].isna().sum()
```

Out[22]: 69

In [23]:
```
# Drop rows where Event.Id is missing
cleaned_df = cleaned_df.dropna(subset=['Event.Id']).reset_index(drop=True)
```

In [24]:
```
cleaned_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 21 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                 88889 non-null  object 
 6   Injury.Severity         87889 non-null  object 
 7   Aircraft.damage         85695 non-null  object 
 8   Registration.Number     87507 non-null  object 
 9   Make                    88826 non-null  object 
 10  Model                   88797 non-null  object 
 11  Amateur.Built           88787 non-null  object 
 12  Number.of.Engines       88889 non-null  float64
 13  Engine.Type             81793 non-null  object 
 14  Purpose.of.flight       82697 non-null  object 
 15  Total.Fatal.Injuries    88889 non-null  float64
 16  Total.Serious.Injuries  88889 non-null  float64
 17  Total.Minor.Injuries    88889 non-null  float64
 18  Total.Uninjured         88889 non-null  float64
 19  Weather.Condition       84397 non-null  object 
 20  Report.Status           82505 non-null  object 
dtypes: float64(5), object(16)
memory usage: 14.2+ MB
```

In [25]:
```
cleaned_df['Report.Status'].value_counts()

#DROP THIS COLUMN NOT NECESSARY
```

Out[25]:
```
Report.Status
Probable Cause
61754
Foreign
1999
<br /><br />
167
Factual
145
The pilot's failure to maintain directional control during the landing roll.
58

...
The pilot's failure to maintain adequate airspeed, which resulted in an aerodynamic stal
l. Contributing to the accident was a partial loss of engine power due to the formation
of carburetor ice.        1
The certified flight instructor did not select an adequate landing site for the practice
autorotation.
1
The failure of the compressor section No. 2 bearing due to false brinnelling and fatigu
e.
1
The flight's encounter with known severe turbulence associated with mountain wave activi
```

```
ty, which resulted in a flight attendant sustaining a broken ankle.
1
The pilot�s loss of control due to a wind gust during landing.
1
Name: count, Length: 17006, dtype: int64
```

In [26]:

```
cleaned_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 21 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                 88889 non-null  object
 6   Injury.Severity         87889 non-null  object
 7   Aircraft.damage         85695 non-null  object
 8   Registration.Number     87507 non-null  object
 9   Make                    88826 non-null  object
 10  Model                   88797 non-null  object
 11  Amateur.Built           88787 non-null  object
 12  Number.of.Engines       88889 non-null  float64
 13  Engine.Type             81793 non-null  object
 14  Purpose.of.flight       82697 non-null  object
 15  Total.Fatal.Injuries    88889 non-null  float64
 16  Total.Serious.Injuries  88889 non-null  float64
 17  Total.Minor.Injuries    88889 non-null  float64
 18  Total.Uninjured         88889 non-null  float64
 19  Weather.Condition       84397 non-null  object
 20  Report.Status           82505 non-null  object
dtypes: float64(5), object(16)
memory usage: 14.2+ MB
```

Location 88837 Injury.Severity 87889 Aircraft.damage 85695 Registration.Number 87507 Make 88826 Model 88797 Amateur.Built 88787 Engine.Type 81793 Purpose.of.flight 82697 Weather.Condition 84397 Report.Status 82505 required data 88889

In [27]:

```
#checking the weather conditions
cleaned_df['Weather.Condition'].value_counts(normalize=True)*100
 # will use mode to fill missing value
```

Out[27]:

```
Weather.Condition
VMC    91.594488
IMC     7.080820
UNK     1.014254
Unk     0.310438
Name: proportion, dtype: float64
```

In [28]:

```
# Get the most frequent Weather.Condition
weather_mode = cleaned_df['Weather.Condition'].mode()[0]
# Fill missing values with the mode
cleaned_df['Weather.Condition'] = cleaned_df['Weather.Condition'].fillna(weather_mode)
```

In [29]:

```
cleaned_df['Location'].value_counts(normalize=True)*100

# will FILL WITH UNKNOWN
```

Out[29]:
```
Location
ANCHORAGE, AK               0.488535
MIAMI, FL                   0.225131
ALBUQUERQUE, NM             0.220629
HOUSTON, TX                 0.217252
CHICAGO, IL                 0.207121
                              ...
ELK GARDEN, VA              0.001126
PIURA, Peru                 0.001126
TOQUI, Venezuela            0.001126
NORTH ELEUTHERA, Bahamas    0.001126
Brasnorte,                  0.001126
Name: proportion, Length: 27758, dtype: float64
```

In [30]:
```
cleaned_df['Location'] = cleaned_df['Location'].fillna('Unknown')
```

In [31]:
```
cleaned_df['Injury.Severity'].value_counts(normalize=True)*100

# will use mode to fill missing values
```

Out[31]:
```
Injury.Severity
Non-Fatal     76.638715
Fatal(1)       7.016805
Fatal          5.987097
Fatal(2)       4.222371
Incident       2.524776
                ...
Fatal(60)      0.001138
Fatal(270)     0.001138
Fatal(143)     0.001138
Fatal(83)      0.001138
Fatal(189)     0.001138
Name: proportion, Length: 109, dtype: float64
```

In [32]:
```
# Get the most frequent injury severity
injury_mode = cleaned_df['Injury.Severity'].mode()[0]

# Fill missing values with the mode
cleaned_df['Injury.Severity'] = cleaned_df['Injury.Severity'].fillna(injury_mode)
```

In [33]:
```
cleaned_df['Engine.Type'].value_counts(normalize=True)*100

# will use mode to fill missing value
```

Out[33]:
```
Engine.Type
Reciprocating      85.007274
Turbo Shaft         4.412358
Turbo Prop          4.145832
Turbo Fan           3.033267
Unknown             2.507550
Turbo Jet           0.859487
Geared Turbofan     0.014671
Electric            0.012226
LR                  0.002445
NONE                0.002445
Hybrid Rocket       0.001223
UNK                 0.001223
Name: proportion, dtype: float64
```

In [34]:
```
# Get the most frequent Engine.Type
Engine_type_mode = cleaned_df['Engine.Type'].mode()[0]
```

```
# Fill missing values with the mode
cleaned_df['Engine.Type'] = cleaned_df['Engine.Type'].fillna(Engine_type_mode)
```

In [35]:
```
cleaned_df['Aircraft.damage'].value_counts(normalize=True)*100

# FILL WITH UNKNOWN
```

Out[35]:
```
Aircraft.damage
Substantial    74.856176
Destroyed      21.731723
Minor           3.273236
Unknown         0.138865
Name: proportion, dtype: float64
```

In [36]:
```
cleaned_df['Aircraft.damage']= cleaned_df['Aircraft.damage'].fillna('Unknown')
```

In [37]:
```
cleaned_df['Registration.Number'].value_counts()

# DROP THIS COLUMN
```

Out[37]:
```
Registration.Number
NONE      344
UNREG     126
UNK        13
USAF        9
N20752      8
         ...
N8266R      1
N65737      1
N681UP      1
N53084      1
N9026P      1
Name: count, Length: 79104, dtype: int64
```

In [38]:
```
# Drop Registration.Number col because it is not useful for analysis
cleaned_df = cleaned_df.drop(columns=['Registration.Number'])
```

In [39]:
```
cleaned_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 20 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   Injury.Severity         88889 non-null  object
 7   Aircraft.damage         88889 non-null  object
 8   Make                    88826 non-null  object
 9   Model                   88797 non-null  object
 10  Amateur.Built           88787 non-null  object
 11  Number.of.Engines       88889 non-null  float64
 12  Engine.Type             88889 non-null  object
 13  Purpose.of.flight       82697 non-null  object
 14  Total.Fatal.Injuries    88889 non-null  float64
 15  Total.Serious.Injuries  88889 non-null  float64
 16  Total.Minor.Injuries    88889 non-null  float64
 17  Total.Uninjured         88889 non-null  float64
```

```
 18  Weather.Condition       88889 non-null  object
 19  Report.Status           82505 non-null  object
dtypes: float64(5), object(15)
memory usage: 13.6+ MB
```

In [40]:
```
#CHECK MAKE DISTRIBUTION
cleaned_df['Make'].value_counts()

#FILL BLACKS WITH UNKNOWN
```

Out[40]:
```
Make
Cessna           22227
Piper            12029
CESSNA            4922
Beech             4330
PIPER             2841
                 ...
Motley Vans          1
Perlick              1
Knab-douglas         1
Boykin B J           1
ROYSE RALPH L        1
Name: count, Length: 8237, dtype: int64
```

In [41]:
```
cleaned_df['Make']= cleaned_df['Make'].fillna('Unknown')
```

In [42]:
```
#CHECK MAKE DISTRIBUTION
cleaned_df['Model'].value_counts()

#FILL BLACKS WITH UNKNOWN
```

Out[42]:
```
Model
152                 2367
172                 1756
172N                1164
PA-28-140            932
150                  829
                    ...
737-3S3                1
MBB-BK117-B2           1
GLASSAIR GL25          1
ULTIMATE 10-300S       1
M-8 EAGLE              1
Name: count, Length: 12315, dtype: int64
```

In [43]:
```
cleaned_df['Model'] =cleaned_df['Model'].fillna('Unknown')
```

In [44]:
```
cleaned_df['Model'].value_counts()
```

Out[44]:
```
Model
152          2367
172          1756
172N         1164
PA-28-140     932
150           829
             ...
C-414           1
EA-200          1
126-D           1
HAWK H2X        1
M-8 EAGLE       1
Name: count, Length: 12315, dtype: int64
```

In [45]:
```
cleaned_df['Amateur.Built'].value_counts()
# fill missing values with mode
```

Out[45]:
```
Amateur.Built
No     80312
Yes     8475
Name: count, dtype: int64
```

In [46]:
```
Amateur_built_mode =cleaned_df['Amateur.Built'].mode()[0]

cleaned_df['Amateur.Built'] = cleaned_df['Amateur.Built'].fillna(Amateur_built_mode)
```

In [47]:
```
cleaned_df['Purpose.of.flight'].value_counts(normalize=True)*100

# fill missing values with unknown
```

Out[47]:
```
Purpose.of.flight
Personal                     59.794188
Instructional                12.819087
Unknown                       8.225208
Aerial Application            5.697909
Business                      4.858701
Positioning                   1.990399
Other Work Use                1.528471
Ferry                         0.981898
Aerial Observation            0.960132
Public Aircraft               0.870648
Executive/corporate           0.668706
Flight Test                   0.489740
Skydiving                     0.220081
External Load                 0.148736
Public Aircraft - Federal     0.126970
Banner Tow                    0.122133
Air Race show                 0.119714
Public Aircraft - Local       0.089483
Public Aircraft - State       0.077391
Air Race/show                 0.071345
Glider Tow                    0.064089
Firefighting                  0.048369
Air Drop                      0.013302
ASHO                          0.007255
PUBS                          0.004837
PUBL                          0.001209
Name: proportion, dtype: float64
```

In [48]:
```
cleaned_df['Purpose.of.flight']= cleaned_df['Purpose.of.flight'].fillna('Unknown')
```

In [49]:
```
cleaned_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 20 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   Injury.Severity         88889 non-null  object
 7   Aircraft.damage         88889 non-null  object
```

```
 8   Make                    88889 non-null  object
 9   Model                   88889 non-null  object
 10  Amateur.Built           88889 non-null  object
 11  Number.of.Engines       88889 non-null  float64
 12  Engine.Type             88889 non-null  object
 13  Purpose.of.flight       88889 non-null  object
 14  Total.Fatal.Injuries    88889 non-null  float64
 15  Total.Serious.Injuries  88889 non-null  float64
 16  Total.Minor.Injuries    88889 non-null  float64
 17  Total.Uninjured         88889 non-null  float64
 18  Weather.Condition       88889 non-null  object
 19  Report.Status           82505 non-null  object
dtypes: float64(5), object(15)
memory usage: 13.6+ MB
```

In [50]:

```
cleaned_df['Report.Status'].value_counts()

#drop this column
```

Out[50]:

```
Report.Status
Probable Cause
61754
Foreign
1999
<br /><br />
167
Factual
145
The pilot's failure to maintain directional control during the landing roll.
58

...
The pilot's failure to maintain adequate airspeed, which resulted in an aerodynamic stal
l. Contributing to the accident was a partial loss of engine power due to the formation
of carburetor ice.        1
The certified flight instructor did not select an adequate landing site for the practice
autorotation.
1
The failure of the compressor section No. 2 bearing due to false brinnelling and fatigu
e.
1
The flight's encounter with known severe turbulence associated with mountain wave activi
ty, which resulted in a flight attendant sustaining a broken ankle.
1
The pilot�s loss of control due to a wind gust during landing.
1
Name: count, Length: 17006, dtype: int64
```

In [51]:

```
cleaned_df = cleaned_df.drop(columns=['Report.Status'])
```

In [52]:

```
cleaned_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 19 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   Injury.Severity         88889 non-null  object
```

```
 7   Aircraft.damage         88889 non-null  object 
 8   Make                    88889 non-null  object 
 9   Model                   88889 non-null  object 
 10  Amateur.Built           88889 non-null  object 
 11  Number.of.Engines       88889 non-null  float64
 12  Engine.Type             88889 non-null  object 
 13  Purpose.of.flight       88889 non-null  object 
 14  Total.Fatal.Injuries    88889 non-null  float64
 15  Total.Serious.Injuries  88889 non-null  float64
 16  Total.Minor.Injuries    88889 non-null  float64
 17  Total.Uninjured         88889 non-null  float64
 18  Weather.Condition       88889 non-null  object 
dtypes: float64(5), object(14)
memory usage: 12.9+ MB
```

In [53]:

```
# exporting the cleaned data to csv for visualization and further Analysis
cleaned_df.to_csv('cleaned_aircraft_data.csv', index=False)
```

Core Analysis Directions

In [54]:

```
df1 = pd.read_csv('cleaned_aircraft_data.csv')
df1.head()
```

Out[54]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Injury.Sever
0	20001218X45444	Accident	SEA87LA080	10/24/1948	MOOSE CREEK, ID	United States	Fatal
1	20001218X45447	Accident	LAX94LA336	7/19/1962	BRIDGEPORT, CA	United States	Fatal
2	20061025X01555	Accident	NYC07LA005	8/30/1974	Saltville, VA	United States	Fatal
3	20001218X45448	Accident	LAX96LA321	6/19/1977	EUREKA, CA	United States	Fatal
4	20041105X01764	Accident	CHI79FA064	8/2/1979	Canton, OH	United States	Fatal

In [55]:

```
# Check basic statistics and value distributions
print("Injury Severity Distribution:")
print(df['Injury.Severity'].value_counts())

print("\nAircraft Damage Distribution:")
print(df['Aircraft.damage'].value_counts())

print("\nTop 10 Aircraft Makes:")
print(df['Make'].value_counts().head(10))

print("\nFlight Purpose Distribution:")
print(df['Purpose.of.flight'].value_counts())
```

```
Injury Severity Distribution:
Injury.Severity
Non-Fatal     67357
Fatal(1)       6167
Fatal          5262
Fatal(2)       3711
```

```
Incident       2219
              ...
Fatal(60)         1
Fatal(270)        1
Fatal(143)        1
Fatal(83)         1
Fatal(189)        1
Name: count, Length: 109, dtype: int64

Aircraft Damage Distribution:
Aircraft.damage
Substantial    64148
Destroyed      18623
Minor           2805
Unknown          119
Name: count, dtype: int64

Top 10 Aircraft Makes:
Make
Cessna     22227
Piper      12029
CESSNA      4922
Beech       4330
PIPER       2841
Bell        2134
Boeing      1594
BOEING      1151
Grumman     1094
Mooney      1092
Name: count, dtype: int64

Flight Purpose Distribution:
Purpose.of.flight
Personal                     49448
Instructional                10601
Unknown                       6802
Aerial Application            4712
Business                      4018
Positioning                   1646
Other Work Use                1264
Ferry                          812
Aerial Observation             794
Public Aircraft                720
Executive/corporate            553
Flight Test                    405
Skydiving                      182
External Load                  123
Public Aircraft - Federal      105
Banner Tow                     101
Air Race show                   99
Public Aircraft - Local         74
Public Aircraft - State         64
Air Race/show                   59
Glider Tow                      53
Firefighting                    40
Air Drop                        11
ASHO                             6
PUBS                             4
PUBL                             1
Name: count, dtype: int64
```

In [56]:

```
# Group by Make/Model to calculate safety metrics
aircraft_safety = df.groupby(['Make', 'Model']).agg({
    'Total.Fatal.Injuries': 'sum',
```

```
    'Total.Serious.Injuries': 'sum',
    'Total.Minor.Injuries': 'sum',
    'Total.Uninjured': 'sum',
    'Event.Id': 'count'  # Total incidents
}).rename(columns={'Event.Id': 'Total_Incidents'})
```

In [57]:
```
# Calculate safety ratios using original column names
aircraft_safety['Survival_Rate'] = aircraft_safety['Total.Uninjured'] / (
    aircraft_safety['Total.Fatal.Injuries'] + aircraft_safety['Total.Serious.Injuries']
    aircraft_safety['Total.Minor.Injuries'] + aircraft_safety['Total.Uninjured']
)
aircraft_safety['Fatality_Rate'] = aircraft_safety['Total.Fatal.Injuries'] / (
    aircraft_safety['Total.Fatal.Injuries'] + aircraft_safety['Total.Serious.Injuries']
    aircraft_safety['Total.Minor.Injuries'] + aircraft_safety['Total.Uninjured']
)
```

In [58]:
```
# Handle division by zero
aircraft_safety = aircraft_safety.fillna(0)

# Reset index to make Make and Model regular columns
aircraft_safety = aircraft_safety.reset_index()

print("Safety analysis completed!")
print(f"Analyzed {len(aircraft_safety)} unique aircraft models")
```

```
Safety analysis completed!
Analyzed 20135 unique aircraft models
```

In [59]:
```
# Convert Event.Date to datetime and extract year
df['Event.Date'] = pd.to_datetime(df['Event.Date'])
df['Year'] = df['Event.Date'].dt.year
```

In [60]:
```
df1['Weather.Condition'].value_counts()
```

Out[60]:
```
Weather.Condition
VMC    81795
IMC     5976
UNK      856
Unk      262
Name: count, dtype: int64
```

In [61]:
```
# Standardize Weather.Condition - convert all 'unk' variations to 'UNK'
def standardize_weather(weather):
    if pd.isna(weather):
        return 'UNK'
    weather_str = str(weather).strip()
    if weather_str.lower() in ['unk', 'unknown']:
        return 'UNK'
    return weather_str

# Apply the standardization
cleaned_df['Weather.Condition'] = cleaned_df['Weather.Condition'].apply(standardize_wea

# Verify the changes
print("Weather Condition value counts after standardization:")
print(cleaned_df['Weather.Condition'].value_counts())
```

```
Weather Condition value counts after standardization:
Weather.Condition
VMC    81795
```

```
IMC      5976
UNK      1118
Name: count, dtype: int64
```

In [62]:
```
def calculate_safety_score(group):
    total_fatal = group['Total.Fatal.Injuries'].sum()
    total_serious = group['Total.Serious.Injuries'].sum()
    total_minor = group['Total.Minor.Injuries'].sum()
    total_uninjured = group['Total.Uninjured'].sum()
    total_incidents = group['Event.Id'].count()

    # Avoid division by zero
    total_people = total_fatal + total_serious + total_minor + total_uninjured
    if total_people == 0:
        survival_rate = 0
        fatality_rate = 0
    else:
        survival_rate = total_uninjured / total_people
        fatality_rate = total_fatal / total_people

    return pd.Series({
        'Total_Incidents': total_incidents,
        'Total_Fatal_Injuries': total_fatal,
        'Total_Serious_Injuries': total_serious,
        'Total_Minor_Injuries': total_minor,
        'Total_Uninjured': total_uninjured,
        'Survival_Rate': survival_rate,
        'Fatality_Rate': fatality_rate
    })
```

In [63]:
```
# Analyze by flight purpose
purpose_safety = df.groupby('Purpose.of.flight').apply(calculate_safety_score).reset_in
purpose_safety = purpose_safety.sort_values('Survival_Rate', ascending=False)
print("Safety by Flight Purpose:")
print(purpose_safety[['Purpose.of.flight', 'Survival_Rate', 'Fatality_Rate', 'Total_Inc
```

```
Safety by Flight Purpose:
           Purpose.of.flight  Survival_Rate  Fatality_Rate  Total_Incidents
16                      PUBL       1.000000       0.000000              1.0
25                   Unknown       0.900665       0.052957           6802.0
21   Public Aircraft - Federal     0.735537       0.112948            105.0
17                      PUBS       0.714286       0.000000              4.0
14             Instructional       0.695527       0.105767          10601.0
20           Public Aircraft       0.665737       0.161753            720.0
19               Positioning       0.642836       0.192366           1646.0
8        Executive/corporate       0.633255       0.235063            553.0
1         Aerial Application       0.603032       0.112454           4712.0
12               Flight Test       0.601043       0.169492            405.0
7                   Business       0.600780       0.214743           4018.0
24                 Skydiving       0.592949       0.250000            182.0
15            Other Work Use       0.561603       0.152811           1264.0
18                  Personal       0.551492       0.198784          49448.0
22     Public Aircraft - Local     0.542373       0.073446             74.0
13                Glider Tow       0.484848       0.242424             53.0
10                     Ferry       0.470326       0.286350            812.0
6                 Banner Tow       0.464286       0.169643            101.0
23     Public Aircraft - State     0.464286       0.164286             64.0
2         Aerial Observation       0.464122       0.210687            794.0
4              Air Race show       0.454545       0.293706             99.0
9              External Load       0.401163       0.226744            123.0
3                   Air Drop       0.384615       0.384615             11.0
5              Air Race/show       0.368932       0.330097             59.0
```

```
11               Firefighting       0.315789       0.486842             40.0
0                        ASHO       0.062500       0.875000              6.0
```

In [64]:

```python
# Analyze by weather condition
weather_safety = df.groupby('Weather.Condition').apply(calculate_safety_score).reset_in
weather_safety = weather_safety.sort_values('Survival_Rate', ascending=False)
print("\nSafety by Weather Condition:")
print(weather_safety[['Weather.Condition', 'Survival_Rate', 'Fatality_Rate', 'Total_Inc
```

```
Safety by Weather Condition:
  Weather.Condition  Survival_Rate  Fatality_Rate  Total_Incidents
2               Unk       0.928524       0.042991            262.0
3               VMC       0.821402       0.069183          77303.0
1               UNK       0.763603       0.178428            856.0
0               IMC       0.703767       0.209690           5976.0
```

In [65]:

```python
# Temporal analysis: fatality rate by year
yearly_safety = df.groupby('Year').apply(calculate_safety_score).reset_index()

yearly_safety
```

Out[65]:

	Year	Total_Incidents	Total_Fatal_Injuries	Total_Serious_Injuries	Total_Minor_Injuries	Total_Uninjure
0	1948.0	1.0	2.0	0.0	0.0	0.
1	1962.0	1.0	4.0	0.0	0.0	0.
2	1974.0	1.0	3.0	0.0	0.0	0.
3	1977.0	1.0	2.0	0.0	0.0	0.
4	1979.0	2.0	1.0	2.0	1.0	44.
5	1981.0	1.0	4.0	0.0	0.0	0.
6	1982.0	3593.0	1585.0	727.0	998.0	8314.
7	1983.0	3556.0	1273.0	673.0	1048.0	15106.
8	1984.0	3457.0	1229.0	697.0	1047.0	12495.
9	1985.0	3096.0	1648.0	612.0	1108.0	11292.
10	1986.0	2880.0	1180.0	619.0	970.0	11890.
11	1987.0	2828.0	1237.0	554.0	936.0	16021.
12	1988.0	2730.0	1195.0	620.0	1117.0	14188.
13	1989.0	2544.0	1532.0	518.0	1029.0	12221.
14	1990.0	2518.0	999.0	589.0	908.0	8959.
15	1991.0	2462.0	1087.0	535.0	913.0	8857.
16	1992.0	2355.0	1273.0	609.0	775.0	9869.
17	1993.0	2313.0	865.0	505.0	910.0	9431.
18	1994.0	2257.0	1183.0	529.0	763.0	7252.
19	1995.0	2309.0	1236.0	480.0	731.0	11854.
20	1996.0	2187.0	2533.0	532.0	729.0	12043.
21	1997.0	2148.0	1296.0	497.0	1026.0	13538.

	Year	Total_Incidents	Total_Fatal_Injuries	Total_Serious_Injuries	Total_Minor_Injuries	Total_Uninjure
22	1998.0	2226.0	1325.0	388.0	807.0	11660.
23	1999.0	2209.0	1221.0	491.0	1206.0	11958.
24	2000.0	2220.0	1765.0	501.0	1256.0	12991.
25	2001.0	2063.0	1709.0	478.0	612.0	9189.
26	2002.0	2020.0	1386.0	432.0	706.0	9488.
27	2003.0	2085.0	1374.0	480.0	772.0	9702.
28	2004.0	1952.0	978.0	457.0	603.0	8248.
29	2005.0	2031.0	1689.0	426.0	620.0	12946.
30	2006.0	1851.0	1489.0	420.0	473.0	10607.
31	2007.0	2016.0	1335.0	402.0	543.0	12040.
32	2008.0	1893.0	1201.0	763.0	407.0	10478.
33	2009.0	1783.0	1184.0	597.0	371.0	10095.
34	2010.0	1786.0	1370.0	615.0	333.0	11083.
35	2011.0	1850.0	931.0	479.0	361.0	14395.
36	2012.0	1835.0	1035.0	451.0	331.0	11804.
37	2013.0	1561.0	822.0	675.0	348.0	9161.
38	2014.0	1535.0	1428.0	455.0	313.0	9733.
39	2015.0	1582.0	1101.0	464.0	346.0	9711.
40	2016.0	1664.0	820.0	488.0	307.0	10110.
41	2017.0	1638.0	640.0	426.0	285.0	11987.
42	2018.0	1681.0	1044.0	594.0	343.0	11039.
43	2019.0	1624.0	960.0	386.0	294.0	8859.
44	2020.0	1392.0	770.0	493.0	264.0	4570.
45	2021.0	1545.0	589.0	346.0	277.0	6997.
46	2022.0	1607.0	668.0	372.0	291.0	9664.

In [66]:

```
# Filter data from year 2000 onwards
df_recent = df[df['Year'] >= 2000]
```

In [67]:

```
# Redo aircraft safety analysis for recent data (2000 onwards)
aircraft_safety_recent = df_recent.groupby(['Make', 'Model']).apply(calculate_safety_sc

# Filter models with at least 10 incidents in the recent period
reliable_recent_models = aircraft_safety_recent[aircraft_safety_recent['Total_Incidents
reliable_recent_models = reliable_recent_models.sort_values('Survival_Rate', ascending=
```

```
print("Top 10 Safest Aircraft Models (2000 onwards):")
print(reliable_recent_models[['Make', 'Model', 'Survival_Rate', 'Fatality_Rate', 'Total_
```

```
Top 10 Safest Aircraft Models (2000 onwards):
                        Make         Model  Survival_Rate  Fatality_Rate  \
4069                  Cessna          180J       1.000000            0.0
2800                  Boeing           747       1.000000            0.0
4806  DIAMOND AIRCRAFT IND INC    DA 20 C1       1.000000            0.0
1828                  BOEING       737-800       0.998681            0.0
3914                Canadair   CL-600-2B19       0.996965            0.0
1930                  BOEING           787       0.996735            0.0
2759                  Boeing           737       0.996525            0.0
1914                  BOEING           777       0.995280            0.0
1868                  BOEING           757       0.995236            0.0
1825                  BOEING       737-7H4       0.992801            0.0

      Total_Incidents
4069             10.0
2800             11.0
4806             11.0
1828             20.0
3914             14.0
1930             25.0
2759             43.0
1914             83.0
1868             31.0
1825             13.0
```

In [68]:
```
# Analyze by number of engines
engine_count_safety = df_recent.groupby('Number.of.Engines').apply(calculate_safety_sco
engine_count_safety = engine_count_safety.sort_values('Survival_Rate', ascending=False)
print("\nSafety by Number of Engines (2000 onwards):")
print(engine_count_safety[['Number.of.Engines', 'Survival_Rate', 'Fatality_Rate', 'Tota
```

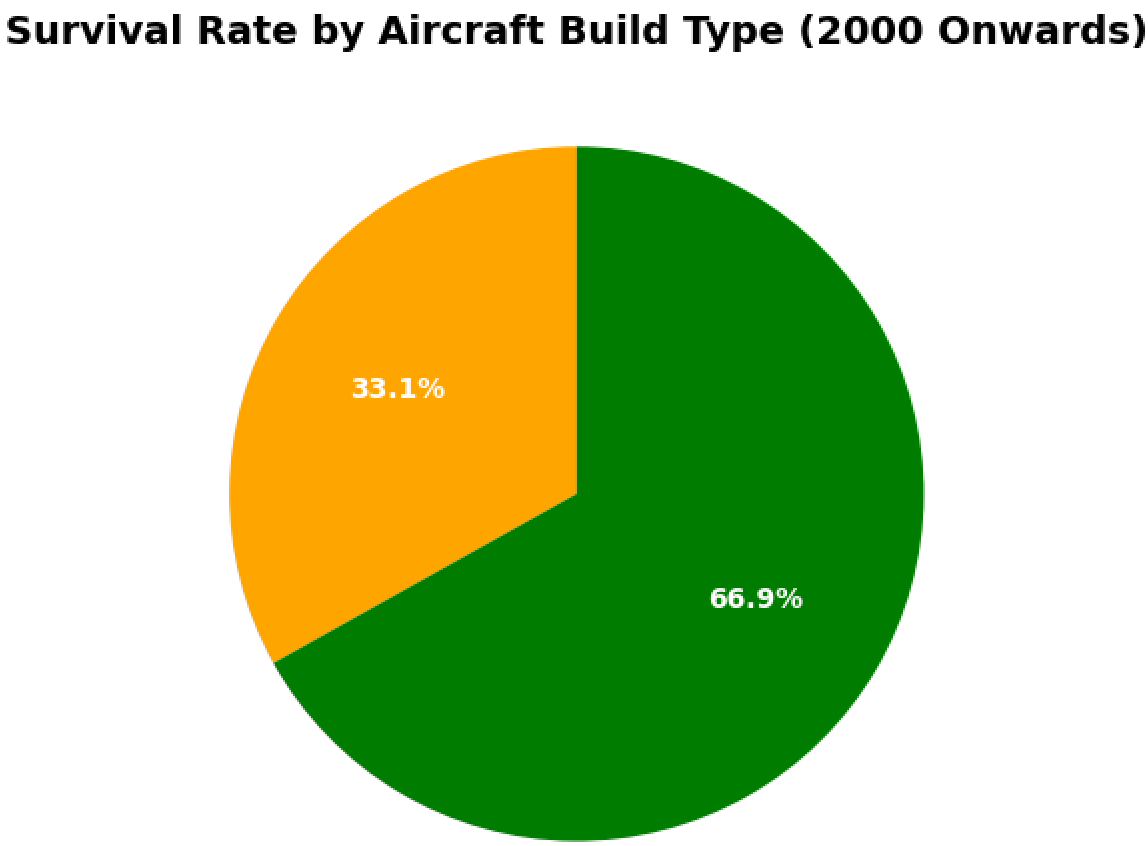
```
Safety by Number of Engines (2000 onwards):
   Number.of.Engines  Survival_Rate  Fatality_Rate  Total_Incidents
4                4.0       0.979299       0.004551            144.0
2                2.0       0.932169       0.040680           4929.0
3                3.0       0.930799       0.053606             91.0
0                0.0       0.613100       0.061691            548.0
1                1.0       0.577269       0.175564          30551.0
6                8.0       0.314286       0.000000              3.0
5                6.0       0.000000       0.000000              1.0
```

In [69]:
```
# Analyze amateur-built aircraft
amateur_safety = df_recent.groupby('Amateur.Built').apply(calculate_safety_score).reset_
amateur_safety = amateur_safety.sort_values('Survival_Rate', ascending=False)
print("\nSafety by Amateur-Built (2000 onwards):")
print(amateur_safety[['Amateur.Built', 'Survival_Rate', 'Fatality_Rate', 'Total_Inciden
```

```
Safety by Amateur-Built (2000 onwards):
  Amateur.Built  Survival_Rate  Fatality_Rate  Total_Incidents
0            No       0.841814       0.088549          36442.0
1           Yes       0.416536       0.226434           4672.0
```

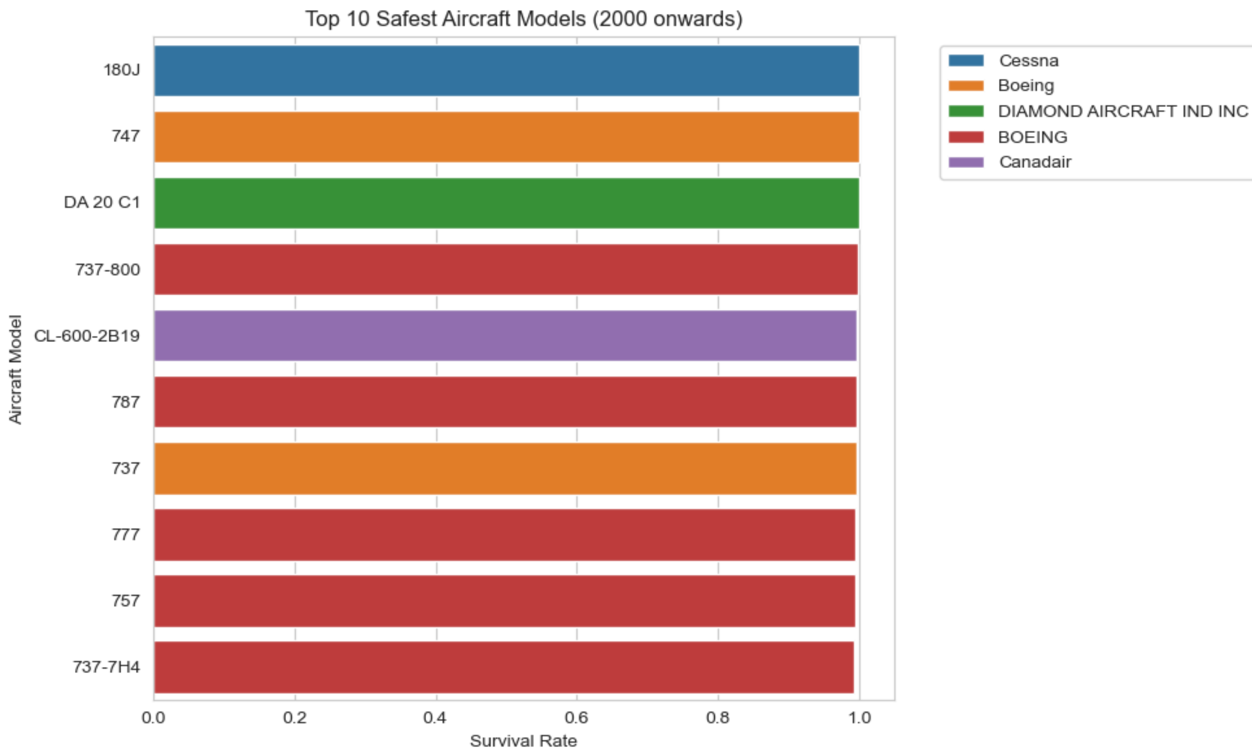
In [70]:
```
import matplotlib.pyplot as plt

# Data
labels = ['Amateur Built', 'Not Amateur Built']
sizes = [0.416536, 0.841814]  # survival rates
colors = ['orange', 'green']

# Pie chart
plt.figure(figsize=(6, 6))
```

```
plt.pie(
    sizes,
    labels=labels,
    autopct='%1.1f%%',
    startangle=90,
    colors=colors,
    textprops={'color': 'white', 'weight': 'bold'}
)

plt.title('Survival Rate by Aircraft Build Type (2000 Onwards)', fontsize=14, weight='b
plt.tight_layout()
plt.show()
```



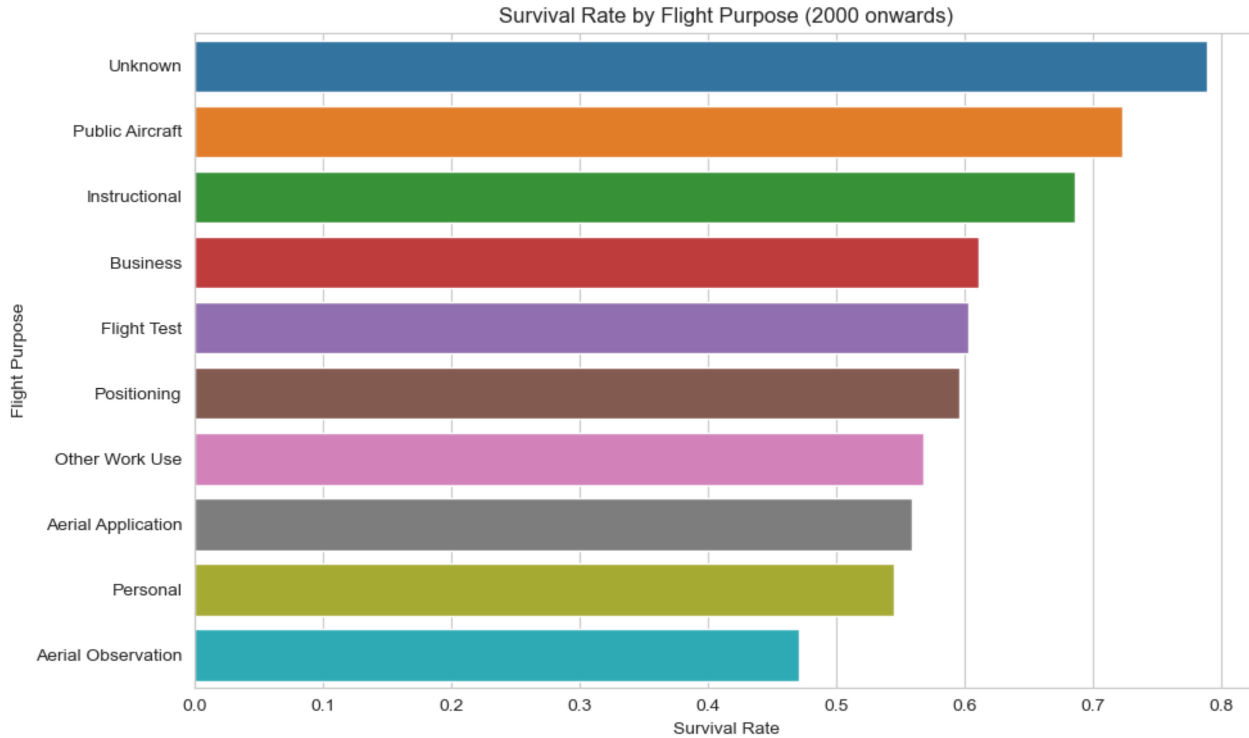
In [71]:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Set style for better looking plots
sns.set_style("whitegrid")

# Plot 1: Top 10 safest aircraft models (2000 onwards)
top_10_aircraft = reliable_recent_models.head(10)

plt.figure(figsize=(10, 6))
sns.barplot(data=top_10_aircraft, x='Survival_Rate', y='Model', hue='Make', dodge=False
plt.title('Top 10 Safest Aircraft Models (2000 onwards)')
plt.xlabel('Survival Rate')
plt.ylabel('Aircraft Model')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

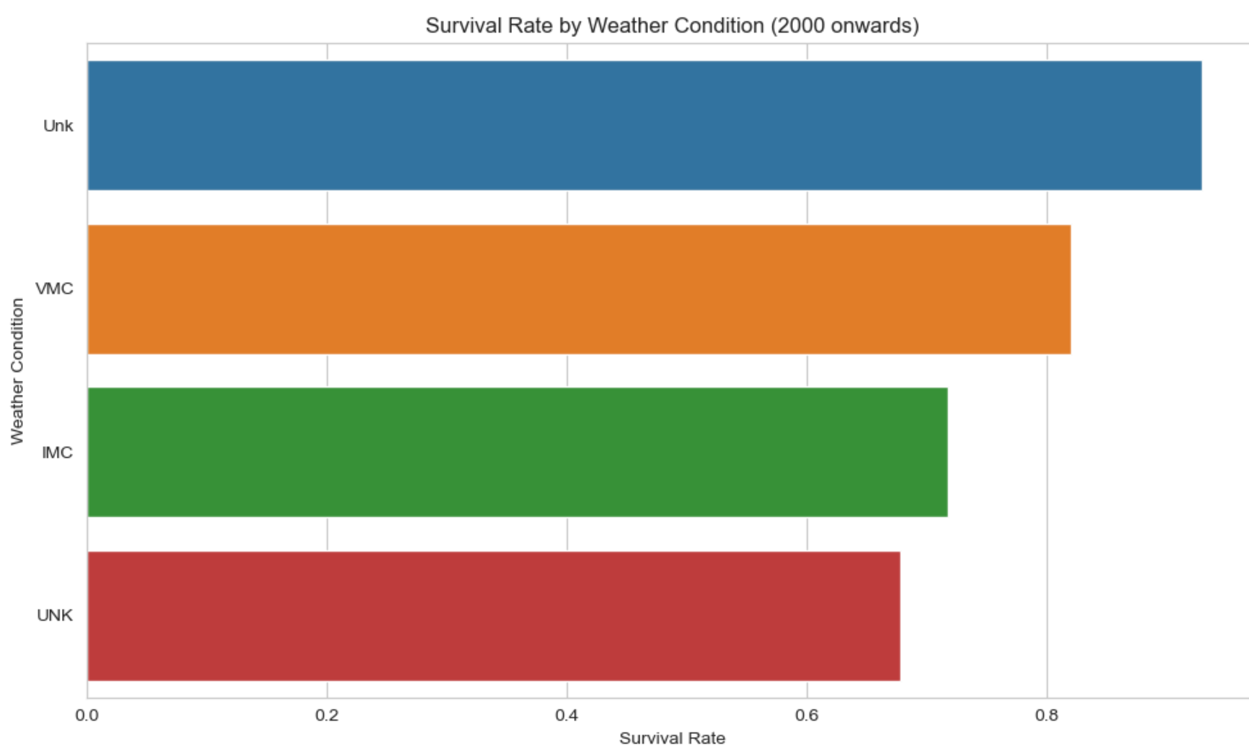


In [72]:

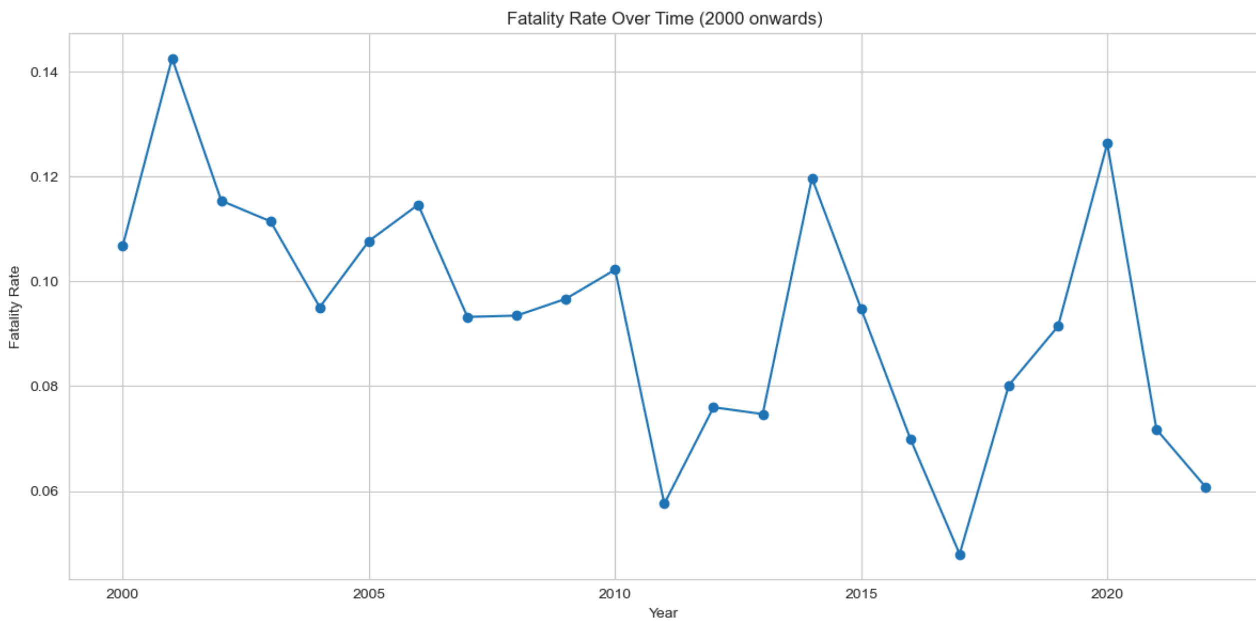
```
# Plot 2: Survival Rate by Flight Purpose (for top 10 purposes by incident count)
top_purposes = df_recent['Purpose.of.flight'].value_counts().head(10).index
purpose_safety_recent = df_recent[df_recent['Purpose.of.flight'].isin(top_purposes)].gr
purpose_safety_recent = purpose_safety_recent.sort_values('Survival_Rate', ascending=Fa

plt.figure(figsize=(10, 6))
sns.barplot(data=purpose_safety_recent, x='Survival_Rate', y='Purpose.of.flight')
plt.title('Survival Rate by Flight Purpose (2000 onwards)')
plt.xlabel('Survival Rate')
plt.ylabel('Flight Purpose')
plt.tight_layout()
plt.show()
```



In [73]:
```
# Plot 3: Survival Rate by Weather Condition
weather_safety_recent = df_recent.groupby('Weather.Condition').apply(calculate_safety_s
weather_safety_recent = weather_safety_recent.sort_values('Survival_Rate', ascending=Fa

plt.figure(figsize=(10, 6))
sns.barplot(data=weather_safety_recent, x='Survival_Rate', y='Weather.Condition')
plt.title('Survival Rate by Weather Condition (2000 onwards)')
plt.xlabel('Survival Rate')
plt.ylabel('Weather Condition')
plt.tight_layout()
plt.show()
```



In [74]:
```
# Plot 4: Fatality Rate Over Time (2000 onwards)
yearly_safety_recent = df_recent.groupby('Year').apply(calculate_safety_score).reset_in

plt.figure(figsize=(12, 6))
plt.plot(yearly_safety_recent['Year'], yearly_safety_recent['Fatality_Rate'], marker='o
plt.title('Fatality Rate Over Time (2000 onwards)')
plt.xlabel('Year')
plt.ylabel('Fatality Rate')
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [75]:
```
# Export the recent data for Tableau
df_recent.to_csv('aviation_safety_recent.csv', index=False)
```

In [76]:
```
# Amateur-built analysis for recent data
amateur_safety_recent = df_recent.groupby('Amateur.Built').apply(calculate_safety_score
print(amateur_safety_recent[['Amateur.Built', 'Survival_Rate', 'Fatality_Rate', 'Total_
```

```
  Amateur.Built  Survival_Rate  Fatality_Rate  Total_Incidents
0            No       0.841814       0.088549          36442.0
1           Yes       0.416536       0.226434           4672.0
```

Explore Operational Factors

In [77]:
```
# Analyze safety by flight purpose
purpose_safety = df.groupby('Purpose.of.flight').agg({
    'Total.Fatal.Injuries': 'sum',
    'Total.Uninjured': 'sum',
    'Event.Id': 'count'
}).reset_index()

purpose_safety['Safety_Score'] = purpose_safety['Total.Uninjured'] / (
    purpose_safety['Total.Fatal.Injuries'] + purpose_safety['Total.Uninjured'] + 0.1
)

print("Safety by Flight Purpose:")
print(purpose_safety.sort_values('Safety_Score', ascending=False))
```

```
Safety by Flight Purpose:
           Purpose.of.flight  Total.Fatal.Injuries  Total.Uninjured  \
17                      PUBS                   0.0              5.0   
16                      PUBL                   0.0              2.0   
25                   Unknown                9789.0         166487.0   
22    Public Aircraft - Local                 13.0             96.0   
14             Instructional                1913.0          12580.0   
21  Public Aircraft - Federal                 41.0            267.0   
1          Aerial Application                549.0           2944.0   
20            Public Aircraft                406.0           1671.0   
15             Other Work Use                511.0           1878.0   
12                Flight Test                130.0            461.0   
19                Positioning                635.0           2122.0   
23    Public Aircraft - State                 23.0             65.0   
7                    Business               2313.0           6471.0   
18                   Personal              18762.0          52052.0   
6                  Banner Tow                 19.0             52.0   
8          Executive/corporate               598.0           1611.0   
24                 Skydiving                 234.0            555.0   
2          Aerial Observation                414.0            912.0   
13                 Glider Tow                 16.0             32.0   
9               External Load                 39.0             69.0   
10                     Ferry                 386.0            634.0   
4               Air Race show                 42.0             65.0   
5               Air Race/show                 34.0             38.0   
3                    Air Drop                 10.0             10.0   
11              Firefighting                 37.0             24.0   
0                       ASHO                 14.0              1.0   

    Event.Id  Safety_Score  
17         4      0.980392  
16         1      0.952381  
25      6802      0.944467  
22        74      0.879927  
14     10601      0.867999  
21       105      0.866602  
1       4712      0.842804  
20       720      0.804487  
15      1264      0.786070  
12       405      0.779902  
19      1646      0.769649  
23        64      0.737798  
7       4018      0.736672  
18     49448      0.735051  
6        101      0.731364  
8        553      0.729256  
24       182      0.703333  
2        794      0.687731  
13        53      0.665281  
9        123      0.638298  
10       812      0.621508  
4         99      0.606909  
5         59      0.527046  
3         11      0.497512  
11        40      0.392799  
0          6      0.066225  
```

In [78]:

```python
# Analyze safety by weather conditions
weather_safety = df.groupby('Weather.Condition').agg({
    'Total.Fatal.Injuries': 'sum',
    'Total.Uninjured': 'sum',
    'Event.Id': 'count'
}).reset_index()
```

```
weather_safety['Safety_Score'] = weather_safety['Total.Uninjured'] / (
    weather_safety['Total.Fatal.Injuries'] + weather_safety['Total.Uninjured'] + 0.1
)

print("Safety by Weather Condition:")
print(weather_safety.sort_values('Safety_Score', ascending=False))
```

```
Safety by Weather Condition:
  Weather.Condition  Total.Fatal.Injuries  Total.Uninjured  Event.Id  \
2               Unk                 326.0           7041.0       262
3               VMC               25558.0         303449.0     77303
1               UNK                2407.0          10301.0       856
0               IMC               11824.0          39684.0      5976

   Safety_Score
2      0.955736
3      0.922317
1      0.810585
0      0.770442
```

In [79]:

```
# Analyze safety by engine type
engine_safety = df.groupby('Engine.Type').agg({
    'Total.Fatal.Injuries': 'sum',
    'Total.Uninjured': 'sum',
    'Event.Id': 'count'
}).reset_index()

engine_safety['Safety_Score'] = engine_safety['Total.Uninjured'] / (
    engine_safety['Total.Fatal.Injuries'] + engine_safety['Total.Uninjured'] + 0.1
)

print("Safety by Engine Type:")
print(engine_safety.sort_values('Safety_Score', ascending=False))
```

```
Safety by Engine Type:
        Engine.Type  Total.Fatal.Injuries  Total.Uninjured  Event.Id  \
1   Geared Turbofan                   0.0            121.0        12
3                LR                   0.0             11.0         2
6         Turbo Fan                4560.0         211048.0      2481
7         Turbo Jet                 862.0          34072.0       703
4              NONE                   0.0              2.0         2
8        Turbo Prop                2568.0          16835.0      3391
11          Unknown                3770.0          12794.0      2051
0          Electric                   2.0              7.0        10
5     Reciprocating               23642.0          75246.0     69530
9       Turbo Shaft                1695.0           4858.0      3609
2     Hybrid Rocket                   1.0              0.0         1
10              UNK                   0.0              0.0         1

    Safety_Score
1       0.999174
3       0.990991
6       0.978850
7       0.975322
4       0.952381
8       0.867645
11      0.772393
0       0.769231
5       0.760921
9       0.741329
2       0.000000
10      0.000000
```

In [80]:
```
# Parameters (tune if needed)
vmc_label = 'VMC'       # label for clear weather in your dataset
min_events = 20         # minimum VMC events to consider a Make+Model (change to 30 for .
top_n = 20              # how many riskiest to show

# Work on a copy so df1 remains unchanged
df = df1.copy()

# Make sure Weather.Condition standardized and uppercase
df['Weather.Condition'] = df['Weather.Condition'].astype(str).str.upper().str.strip()

# Filter to clear-weather events (VMC) only
df_vmc = df[df['Weather.Condition'] == vmc_label].copy()

# Ensure totals exist
df_vmc['total_casualties'] = (
    df_vmc['Total.Fatal.Injuries'].fillna(0)
    + df_vmc['Total.Serious.Injuries'].fillna(0)
    + df_vmc['Total.Minor.Injuries'].fillna(0)
)
df_vmc['people_involved'] = (df_vmc['total_casualties'] + df_vmc['Total.Uninjured'].fil

# safe mode helper
def first_mode(s):
    m = s.mode()
    return m.iat[0] if len(m) > 0 else np.nan

# Group by Make + Model and compute stats in VMC
vmc_stats = (
    df_vmc
    .groupby(['Make','Model'], dropna=False)
    .agg(
        events = ('Event.Id','size'),
        total_fatal = ('Total.Fatal.Injuries','sum'),
        total_casualties = ('total_casualties','sum'),
        total_uninjured = ('Total.Uninjured','sum'),
        most_common_injury = ('Injury.Severity', lambda s: first_mode(s))
    )
    .reset_index()
)

# compute denom and rates
vmc_stats['denom'] = (vmc_stats['total_casualties'] + vmc_stats['total_uninjured']).rep
vmc_stats['fatality_rate'] = vmc_stats['total_fatal'] / vmc_stats['denom']           #
vmc_stats['survival_rate'] = 1 - vmc_stats['fatality_rate']

# filter by minimum events to get reliable samples
vmc_reliable = vmc_stats[vmc_stats['events'] >= min_events].copy()

# Sort to get riskiest (highest fatality_rate) and safest (highest survival_rate)
riskiest_vmc = vmc_reliable.sort_values(by=['fatality_rate','events'], ascending=[False
safest_vmc = vmc_reliable.sort_values(by=['survival_rate','events'], ascending=[False,

# Display top results
print(f"Riskiest Make+Model in VMC (top {top_n}, min events = {min_events}):")
display(riskiest_vmc[['Make','Model','events','total_fatal','fatality_rate','survival_r

print(f"\nSafest Make+Model in VMC (top {top_n}, min events = {min_events}):")
display(safest_vmc[['Make','Model','events','total_fatal','fatality_rate','survival_rat
```

```
# Save CSV outputs for reporting
vmc_reliable.to_csv('vmc_make_model_stats.csv', index=False)
riskiest_vmc.to_csv('vmc_riskiest_make_model.csv', index=False)
safest_vmc.to_csv('vmc_safest_make_model.csv', index=False)
print("\nSaved CSVs: vmc_make_model_stats.csv, vmc_riskiest_make_model.csv, vmc_safest_

# Quick bar chart of top 10 riskiest (fatality_rate %)
plot_n = min(10, len(riskiest_vmc))
if plot_n > 0:
    plot_df = riskiest_vmc.head(plot_n).copy()
    plot_df['label'] = plot_df['Make'].astype(str) + " — " + plot_df['Model'].astype(st
    plot_df['fatality_pct'] = (plot_df['fatality_rate'] * 100).round(3)

    plt.figure(figsize=(11,6))
    plt.barh(plot_df['label'][::-1], plot_df['fatality_pct'][::-1], color='#C04000')
    plt.xlabel('Fatality rate in VMC (%)')
    plt.title(f'Top {plot_n} Riskiest Make+Model in Clear Weather (VMC)')
    for i, (pct, ev) in enumerate(zip(plot_df['fatality_pct'][::-1], plot_df['events'][
        plt.text(pct + 0.01, i, f"{pct:.3f}%", va='center', fontsize=10)
        plt.text(max(plot_df['fatality_pct'].max()*1.1, 1.0) + 0.3, i, f"{int(ev)} even
    plt.tight_layout()
    plt.savefig('vmc_riskiest_bar.png', dpi=300, bbox_inches='tight')
    plt.show()
else:
    print("No Make+Model meets the min_events threshold in VMC to plot.")
```

```
Riskiest Make+Model in VMC (top 20, min events = 20):
```

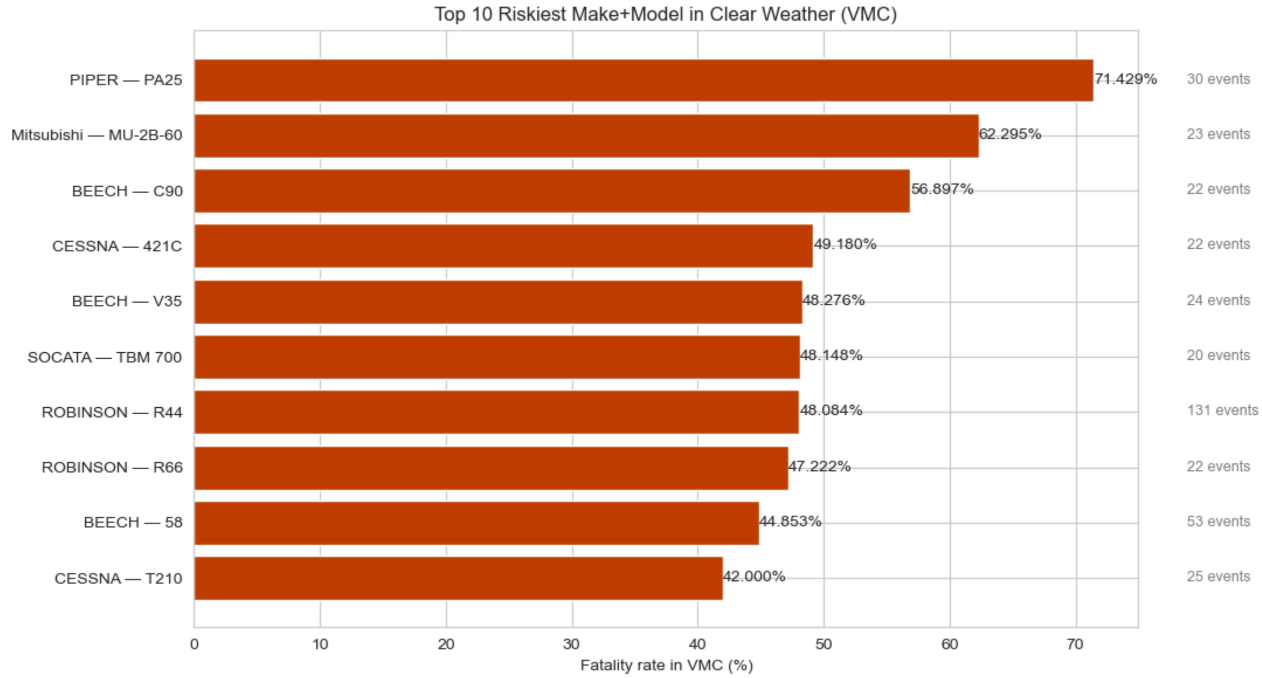
	Make	Model	events	total_fatal	fatality_rate	survival_rate	most_common_injury
13844	PIPER	PA25	30	20.0	0.714286	0.285714	Fatal
12792	Mitsubishi	MU-2B-60	23	38.0	0.622951	0.377049	Non-Fatal
1942	BEECH	C90	22	33.0	0.568966	0.431034	Fatal
4826	CESSNA	421C	22	30.0	0.491803	0.508197	Fatal
1998	BEECH	V35	24	28.0	0.482759	0.517241	Fatal
16446	SOCATA	TBM 700	20	26.0	0.481481	0.518519	Non-Fatal
15256	ROBINSON	R44	131	138.0	0.480836	0.519164	Fatal
15261	ROBINSON	R66	22	17.0	0.472222	0.527778	Fatal
1858	BEECH	58	53	61.0	0.448529	0.551471	Non-Fatal
4914	CESSNA	T210	25	21.0	0.420000	0.580000	Non-Fatal
15247	ROBINSON	R22	58	37.0	0.415730	0.584270	Non-Fatal
5847	Cessna	A150K	21	14.0	0.411765	0.588235	Non-Fatal
3232	Beech	V35	43	35.0	0.406977	0.593023	Non-Fatal
4953	CESSNA	U206F	21	29.0	0.402778	0.597222	Non-Fatal
2929	Beech	A36TC	44	49.0	0.401639	0.598361	Non-Fatal
3178	Beech	F35	22	14.0	0.400000	0.600000	Non-Fatal

	Make	Model	events	total_fatal	fatality_rate	survival_rate	most_common_injury
13876	PIPER	PA34	30	25.0	0.396825	0.603175	Non-Fatal
9388	Grumman American	AA-5	26	22.0	0.392857	0.607143	Non-Fatal
12098	MOONEY	M20E	25	16.0	0.363636	0.636364	Non-Fatal
6113	Cessna	T303	20	17.0	0.361702	0.638298	Non-Fatal

```
Safest Make+Model in VMC (top 20, min events = 20):
```

	Make	Model	events	total_fatal	fatality_rate	survival_rate	most_common_injury
2344	BOEING	777	81	0.0	0.0	1.0	Non-Fatal
16954	Schweizer	SGS 2-33A	53	0.0	0.0	1.0	Non-Fatal
9416	Grumman-schweizer	G-164A	48	0.0	0.0	1.0	Non-Fatal
2323	BOEING	767	46	0.0	0.0	1.0	Non-Fatal
3802	Boeing	737	45	0.0	0.0	1.0	Non-Fatal
3754	Boeing	727-200	35	0.0	0.0	1.0	Non-Fatal
3082	Beech	C-23	33	0.0	0.0	1.0	Non-Fatal
4078	Boeing	E75	29	0.0	0.0	1.0	Non-Fatal
2305	BOEING	757	27	0.0	0.0	1.0	Non-Fatal
12297	Maule	M-4-220C	26	0.0	0.0	1.0	Non-Fatal
13739	PIPER	PA-22-160	25	0.0	0.0	1.0	Non-Fatal
2360	BOEING	787	24	0.0	0.0	1.0	Non-Fatal
4747	CESSNA	195	24	0.0	0.0	1.0	Non-Fatal
8862	GRUMMAN ACFT ENG COR-SCHWEIZER	G-164B	24	0.0	0.0	1.0	Non-Fatal
4710	CESSNA	180H	23	0.0	0.0	1.0	Non-Fatal
13670	PIPER	PA 28	23	0.0	0.0	1.0	Non-Fatal
4711	CESSNA	180J	22	0.0	0.0	1.0	Non-Fatal
580	AVIAT AIRCRAFT INC	A-1B	21	0.0	0.0	1.0	Non-Fatal
9361	Grumman	G164B	21	0.0	0.0	1.0	Non-Fatal
11523	Let	BLANIK L-13	21	0.0	0.0	1.0	Non-Fatal

```
Saved CSVs: vmc_make_model_stats.csv, vmc_riskiest_make_model.csv, vmc_safest_make_mode
l.csv
```



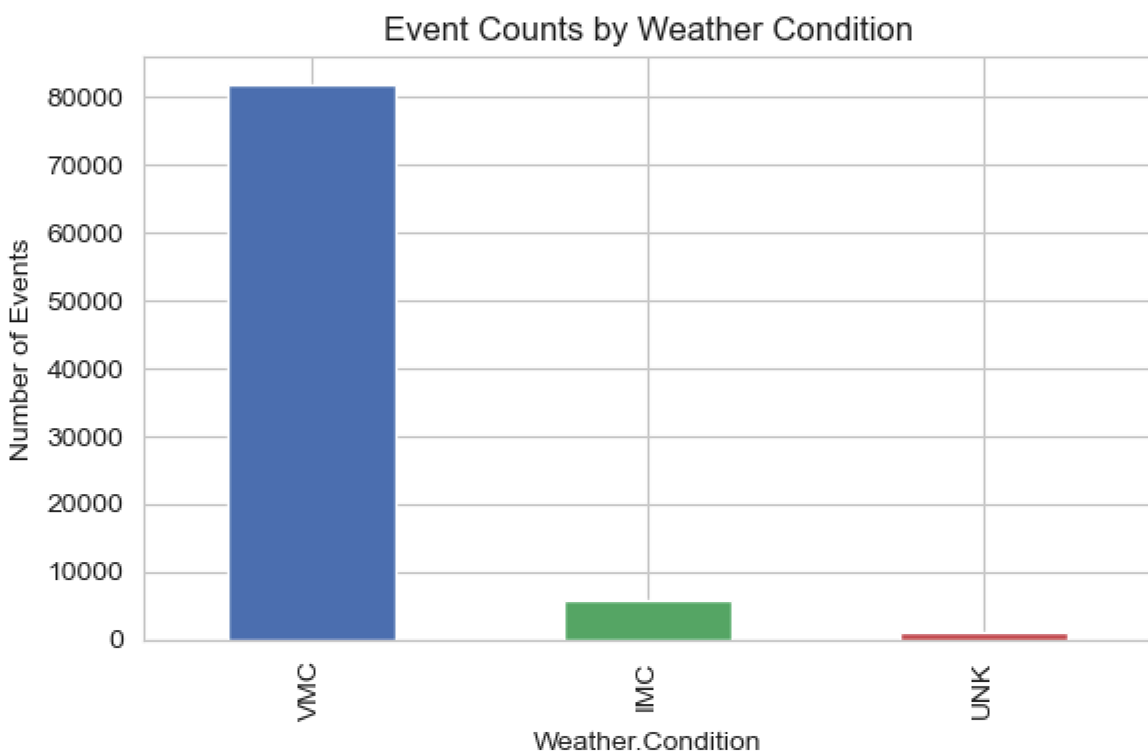
In [81]:
```
df = df1.copy()

# standardize weather labels
df['Weather.Condition'] = df['Weather.Condition'].astype(str).str.upper().str.strip()
df['Weather.Condition'] = df['Weather.Condition'].replace({'UNK':'UNK', 'UNk':'UNK', 'U

# computed fields
df['total_casualties'] = df['Total.Fatal.Injuries'].fillna(0) + df['Total.Serious.Injur
df['people_involved'] = (df['total_casualties'] + df['Total.Uninjured'].fillna(0)).repl

# aggregate by weather
weather = (
    df.groupby('Weather.Condition', dropna=False)
      .agg(
          Total_Fatal_Injuries = ('Total.Fatal.Injuries','sum'),
          Total_Uninjured = ('Total.Uninjured','sum'),
          Events = ('Event.Id','size'),
          People_Involved = ('people_involved','sum')
      )
      .reset_index()
)

# compute fatality & survival rates and a safety_score (survival fraction)
weather['Fatality_Rate'] = weather['Total_Fatal_Injuries'] / weather['People_Involved']
weather['Survival_Rate'] = 1 - weather['Fatality_Rate']
weather['Safety_Score'] = weather['Survival_Rate']  # or any custom formula you prefer

# sort and display
weather = weather.sort_values(by='Events', ascending=False)
print(weather[['Weather.Condition','Events','Total_Fatal_Injuries','Total_Uninjured','F
```

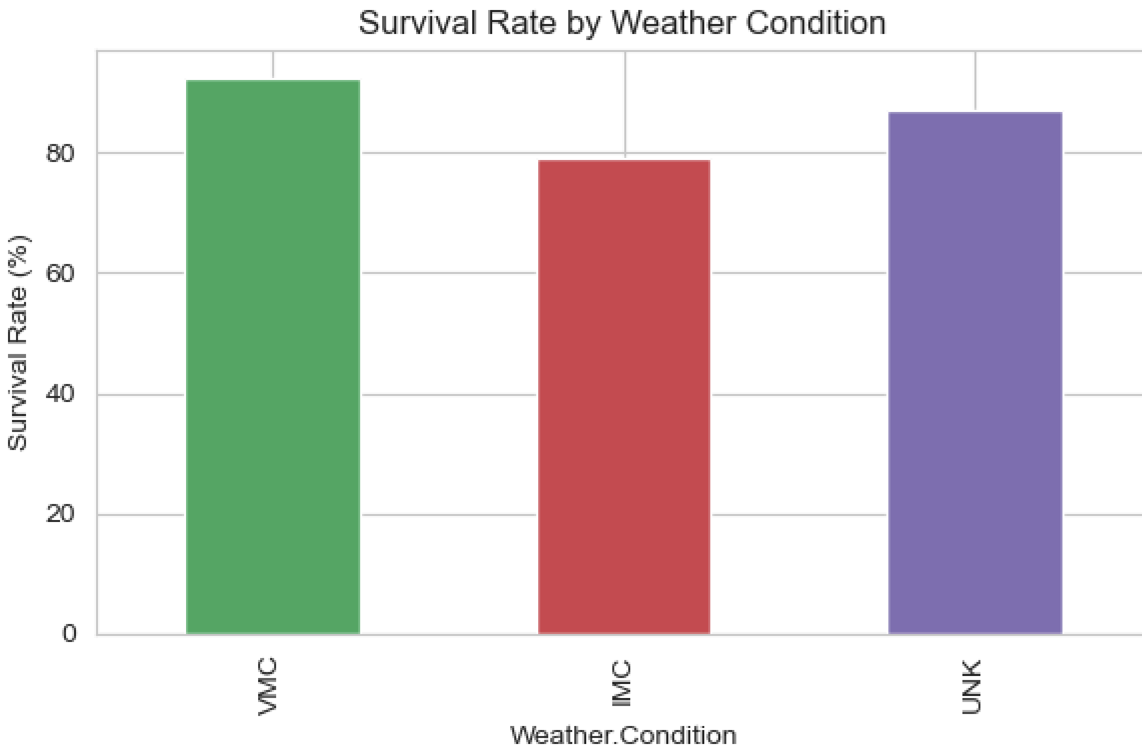
```
  Weather.Condition  Events  Total_Fatal_Injuries  Total_Uninjured  \
2               VMC   81795               35644.0         384863.0
0               IMC    5976               11824.0          39684.0
1               UNK    1118                2733.0          17342.0

   Fatality_Rate  Survival_Rate  Safety_Score
2       0.076904       0.923096      0.923096
```

```
0       0.209690       0.790310       0.790310
1       0.129692       0.870308       0.870308
```

In [82]:

```
# 1) Event share
plt.figure(figsize=(6,4))
weather.set_index('Weather.Condition')['Events'].plot(kind='bar', color=['#4C72B0','#55
plt.ylabel('Number of Events')
plt.title('Event Counts by Weather Condition')
plt.tight_layout()
plt.savefig('weather_event_counts.png', dpi=300)
plt.show()

# 2) Survival (or Fatality) Rate
plt.figure(figsize=(6,4))
(weather.set_index('Weather.Condition')['Survival_Rate']*100).plot(kind='bar', color=['
plt.ylabel('Survival Rate (%)')
plt.title('Survival Rate by Weather Condition')
plt.tight_layout()
plt.savefig('weather_survival_rate.png', dpi=300)
plt.show()
```

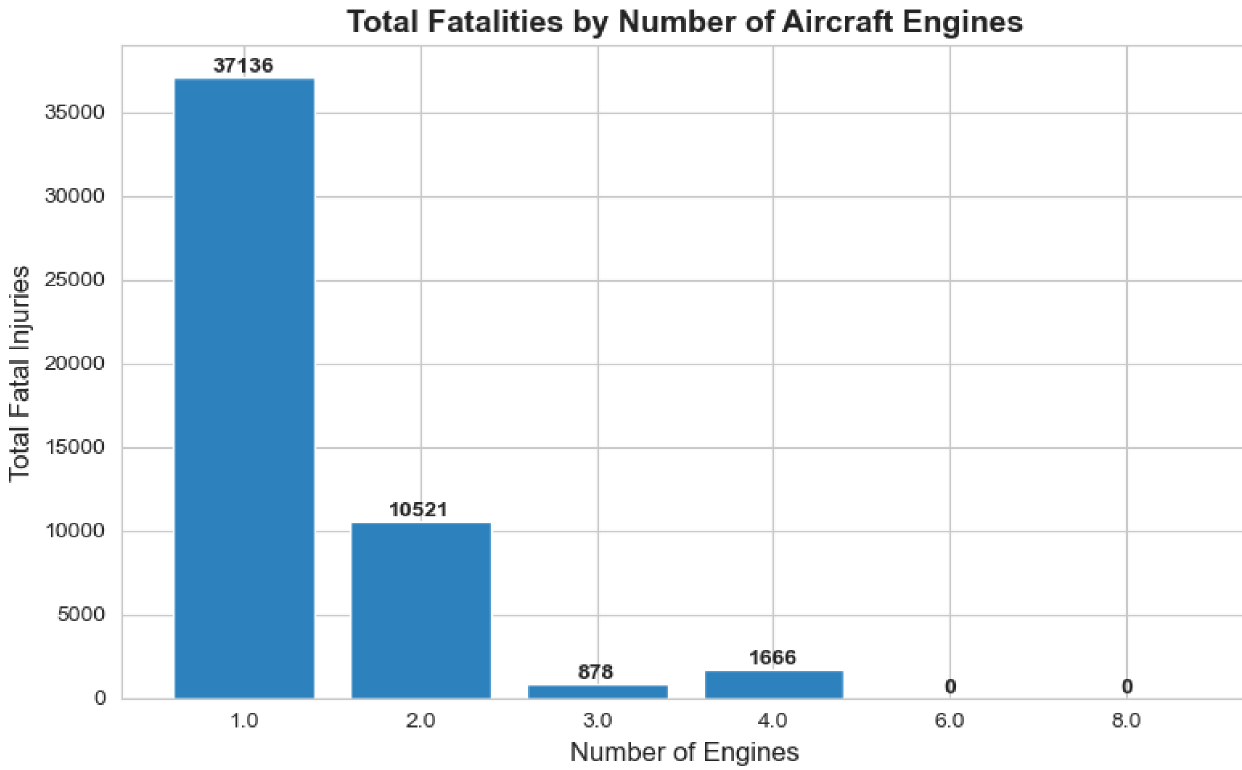




In [83]:

```
import matplotlib.pyplot as plt

# Group data by Number of Engines
engine_fatality = df1.groupby('Number.of.Engines')['Total.Fatal.Injuries'].sum().reset_

# Sort by number of engines for cleaner visuals
engine_fatality = engine_fatality.sort_values('Number.of.Engines')

# Plot
plt.figure(figsize=(8, 5))
bars = plt.bar(
    engine_fatality['Number.of.Engines'].astype(str),
    engine_fatality['Total.Fatal.Injuries'],
    color='#2E86C1'
)

# Labels and title
plt.title('Total Fatalities by Number of Aircraft Engines', fontsize=14, weight='bold')
plt.xlabel('Number of Engines', fontsize=12)
plt.ylabel('Total Fatal Injuries', fontsize=12)

# Add data labels
for bar in bars:
    height = bar.get_height()
    plt.text(
        bar.get_x() + bar.get_width() / 2,
        height,
        f'{int(height)}',
        ha='center',
        va='bottom',
        fontsize=10,
        fontweight='bold'
    )
```

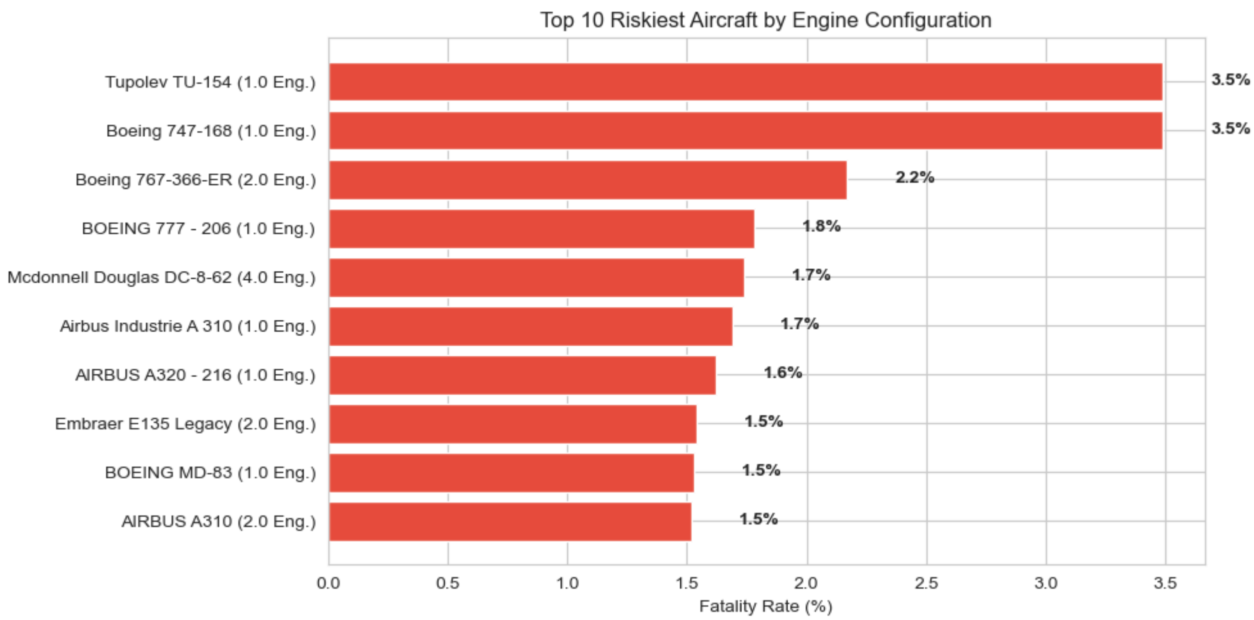
```
plt.tight_layout()
plt.show()
```



In [84]:

```
import matplotlib.pyplot as plt

# Group by Make, Model, and Number of Engines
engine_risk = (
    df1.groupby(['Make', 'Model', 'Number.of.Engines'])
    .agg({'Total.Fatal.Injuries': 'sum', 'Event.Id': 'count'})
    .reset_index()
)

# Calculate fatality rate per incident
engine_risk['Fatality_Rate'] = engine_risk['Total.Fatal.Injuries'] / engine_risk['Event

# Top 10 riskiest aircraft configurations
top10_engine_risk = engine_risk.sort_values('Fatality_Rate', ascending=False).head(10)

# Combine Make + Model for display
top10_engine_risk['Aircraft'] = (
    top10_engine_risk['Make'] + ' ' +
    top10_engine_risk['Model'] +
    ' (' + top10_engine_risk['Number.of.Engines'].astype(str) + ' Eng.)'
)

# Plot
plt.figure(figsize=(10, 5))
bars = plt.barh(
    top10_engine_risk['Aircraft'],
    top10_engine_risk['Fatality_Rate'] * 0.01,
    color='#E74C3C'
)
plt.xlabel('Fatality Rate (%)')
plt.title('Top 10 Riskiest Aircraft by Engine Configuration')
plt.gca().invert_yaxis()
```

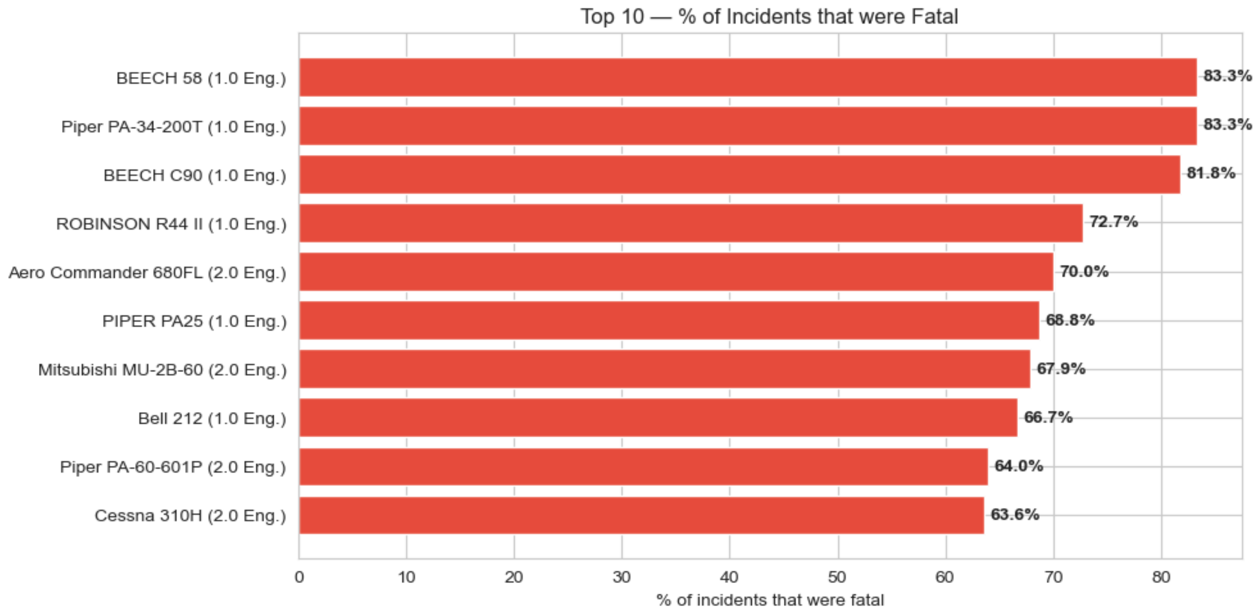
```
# Add labels
for bar in bars:
    width = bar.get_width()
    plt.text(width + 0.2, bar.get_y() + bar.get_height()/2,
             f'{width:.1f}%', va='center', fontsize=10, fontweight='bold')

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



In [85]:

```
# Option A: % of incidents that were fatal (recommended)
# Assume df1 is incident-level and Event.Id identifies incidents

# compute per-incident flag
df1['fatal_incident_flag'] = (df1['Total.Fatal.Injuries'] > 0).astype(int)

# group and aggregate
engine_risk = (
    df1.groupby(['Make', 'Model', 'Number.of.Engines'])
    .agg(total_fatalities=('Total.Fatal.Injuries', 'sum'),
         total_incidents=('Event.Id', 'count'),
         fatal_incidents=('fatal_incident_flag', 'sum'))
    .reset_index()
)

# percent of incidents that were fatal
engine_risk['pct_fatal_incidents'] = engine_risk['fatal_incidents'] / engine_risk['tota

# filter small samples
engine_risk = engine_risk[engine_risk['total_incidents'] >= 10]

# top 10 riskiest by this metric
top10 = engine_risk.sort_values('pct_fatal_incidents', ascending=False).head(10)

# display / plot
top10['Aircraft'] = top10['Make'] + ' ' + top10['Model'] + ' (' + top10['Number.of.Engi

plt.figure(figsize=(10,5))
bars = plt.barh(top10['Aircraft'], top10['pct_fatal_incidents'], color='#E74C3C')
plt.xlabel('% of incidents that were fatal')
```

```
plt.title('Top 10 — % of Incidents that were Fatal')
plt.gca().invert_yaxis()
for bar in bars:
    plt.text(bar.get_width() + 0.5, bar.get_y() + bar.get_height()/2,
             f'{bar.get_width():.1f}%', va='center', fontsize=10, fontweight='bold')
plt.tight_layout()
plt.show()
```



CONCLUSION

Prioritize Certified, Professionally Manufactured Aircraft Amateur-built aircraft have less than half the survival rate. This is non-negotiable for a corporate fleet. Procure from the Vetted "Top 10 Safest Models" List Base purchasing decisions on our data-driven list of models with proven safety records since the year 2000. Apply Strict Safety Thresholds Only consider aircraft meeting these minimums: Survival Rate ≥ 0.85 Fatality Rate ≤ 0.07 ≥ 10 Recorded Incidents (for statistical significance)