✈️ Aircraft Risk Analysis — Data Science Project

1. Business Understanding

📌 Project Overview

As part of its expansion strategy, our company is exploring entry into the aviation sector by acquiring aircraft for commercial and private use. However, the leadership team has limited knowledge of the operational and safety risks associated with different types of aircraft.

This project aims to leverage historical aviation accident data to help identify **which aircraft types pose the lowest risk**, enabling the business to make **data-driven decisions** about its initial investments.

🎯 Business Objective

The goal is to analyze patterns in aviation accidents from 1962 to 2023 to:

- Identify key factors contributing to aircraft risk,
- Determine which aircraft types are historically safest,
- Deliver **three concrete recommendations** for which aircraft the company should prioritize for purchase.

The final output will support the **head of the aviation division** with strategic insights to inform acquisition decisions.

---

2. Audience & Approach

This notebook is intended for a **technical data science audience** and outlines the full analytical process using Python and Markdown. The results will be presented separately in a non-technical format for business stakeholders.

👣 Project Steps:

1. **Data Understanding** — Explore and understand the dataset structure and content
2. **Data Preparation** — Clean, transform, and engineer relevant features
3. **Data Analysis** — Visualize trends, compare aircraft categories, and assess risk
4. **Recommendations** — Deliver insights with business impact

All visualizations and conclusions are tied directly to the core business question:

> *Which aircraft types are the lowest-risk investments for our company?*

---

1. Data Understanding

In [1]:
```
# First, we're going to import the necessary libraries.
import pandas as pd
import matplotlib.pyplot as plt
import numpy as numby
```

1.1. Exploring the Aircraft Accident Dataset

To begin our analysis, we first need to understand the structure and contents of the dataset. The aviation accident data comes from the National Transportation Safety Board (NTSB) and includes over 90,000 records from 1962 to 2023. Each row represents an aviation event, with details ranging from the event date and location to aircraft specifications, injuries, weather, and flight purpose.

Below is the first step: loading the dataset and inspecting its columns, types, and missing values.

In [2]:
```
# import the dataset
path = './data/Aviation_Data.csv'
aviation_data = pd.read_csv(path, dtype='str')

# display basic info
aviation_data.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  object
 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  object
 24  Total.Serious.Injuries  76379 non-null  object
 25  Total.Minor.Injuries    76956 non-null  object
 26  Total.Uninjured         82977 non-null  object
 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: object(31)
memory usage: 21.4+ MB
```

In [3]:

```
# display first few rows
aviation_data.head()
```

Out[3]:

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

5 rows × 31 columns

✳️ 1.2. Selected Features for Risk Assessment

To conduct a meaningful and targeted analysis, the following features were selected from the dataset. These variables are directly tied to **aircraft safety, accident outcomes**, and **operational conditions**, and are thus essential for deriving **actionable insights** for low-risk aircraft recommendations.

Feature	Description
Make & Model	Identify aircraft manufacturers and specific models with safer historical records.
Aircraft.Category	Filter aircraft by type to segment the analysis.
Aircraft.damage	Indicates the extent of physical damage to the aircraft, used as a proxy for incident severity.
Injury.Severity	Qualitative summary of injury outcomes.
Total.Fatal.Injuries	Number of fatalities in an incident.
Total.Serious.Injuries	Number of seriously injured individuals.
Total.Minor.Injuries	Number of minor injuries sustained.
Total.Uninjured	Count of people who were not injured, despite the accident.
Number.of.Engines	Single vs. multi-engine — for comparing their correlation with incident severity.
Engine.Type	Different engine technologies may present different risk profiles.
Purpose.of.flight	Whether the flight was private, commercial, etc. — useful for contextual analysis.

Feature	Description
Weather.Condition	Understand how weather affects accident outcomes.
Broad.phase.of.flight	Identify the riskiest phases.
Amateur.Built	Filter out homebuilt aircraft which typically have higher risk profiles.
Event.Date	Date of the incident

> 🟢 **Rationale**: These features are most relevant to quantifying accident outcomes, understanding flight risk conditions, and analyzing aircraft specifications — all critical to evaluating **which aircraft types present the lowest operational risk**.

In [4]:
```
# Select the relevant columns
selected_columns = [
    "Make",
    "Model",
    "Aircraft.Category",
    "Aircraft.damage",
    "Injury.Severity",
    "Total.Fatal.Injuries",
    "Total.Serious.Injuries",
    "Total.Minor.Injuries",
    "Total.Uninjured",
    "Number.of.Engines",
    "Engine.Type",
    "Purpose.of.flight",
    "Weather.Condition",
    "Broad.phase.of.flight",
    "Amateur.Built",
    "Event.Date"
]
```

2. Data Preparation

Before diving into analysis, it is crucial to prepare the dataset to ensure accuracy, consistency, and usability. This phase involves cleaning and transforming the raw data into a structured form that supports meaningful insights.

Objectives of this Phase:

- Select only relevant columns related to aircraft safety and risk.
- Handle missing or inconsistent values appropriately.
- Convert data types where necessary.
- Standardize and normalize categorical fields to reduce redundancy.
- Remove duplicate or irrelevant entries.

The ultimate goal is to create a clean, reliable dataset that accurately reflects real-world safety patterns and is suitable for further exploration and modeling.

In [5]:
```
# We'll use only the relevant colummns to reduce noise
aviation_data = aviation_data[selected_columns]
```

In [6]:
```
aviation_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 16 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   Make                    88826 non-null  object
 1   Model                   88797 non-null  object
 2   Aircraft.Category       32287 non-null  object
 3   Aircraft.damage         85695 non-null  object
 4   Injury.Severity         87889 non-null  object
 5   Total.Fatal.Injuries    77488 non-null  object
 6   Total.Serious.Injuries  76379 non-null  object
 7   Total.Minor.Injuries    76956 non-null  object
 8   Total.Uninjured         82977 non-null  object
 9   Number.of.Engines       82805 non-null  object
 10  Engine.Type             81793 non-null  object
 11  Purpose.of.flight       82697 non-null  object
 12  Weather.Condition       84397 non-null  object
 13  Broad.phase.of.flight   61724 non-null  object
 14  Amateur.Built           88787 non-null  object
 15  Event.Date              88889 non-null  object
dtypes: object(16)
memory usage: 11.0+ MB
```

In [7]:
```
aviation_data.head()
```

Out[7]:

	Make	Model	Aircraft.Category	Aircraft.damage	Injury.Severity	Total.Fatal.Injuries
0	Stinson	108-3	NaN	Destroyed	Fatal(2)	2.0
1	Piper	PA24-180	NaN	Destroyed	Fatal(4)	4.0
2	Cessna	172M	NaN	Destroyed	Fatal(3)	3.0
3	Rockwell	112	NaN	Destroyed	Fatal(2)	2.0
4	Cessna	501	NaN	Destroyed	Fatal(1)	1.0

2.1. Handling missing or inconsistent values

> The dataFrame has over 90 000 records, as we can see the **'Aircraft.Category'** column contains 32,287 non-null values. It's better to remove this column as it contains too many null values..
>
> We'll assume that the null values in columns containing numerical data are equal to their respective medians..

These columns are :

1. **Total.Fatal.Injuries**
2. **Total.Serious.Injuries**
3. **Total.Minor.Injuries**
4. **Total.Uninjured**
5. **Number.of.Engines**

> *We use the median** to impute missing values in the injury and engine-related columns because these features are often **skewed** due to extreme outliers, and the median is more **robust** to such irregularities than the mean.*

In [8]:
```
# Let's remove the 'Aircraft.Category'.
to_drop = "Aircraft.Category"
aviation_data.drop(to_drop, axis=1, inplace=True)
```

In [9]:
```
aviation_data.columns
```

Out[9]:
```
Index(['Make', 'Model', 'Aircraft.damage', 'Injury.Severity',
       'Total.Fatal.Injuries', 'Total.Serious.Injuries',
       'Total.Minor.Injuries', 'Total.Uninjured', 'Number.of.Engines',
       'Engine.Type', 'Purpose.of.flight', 'Weather.Condition',
       'Broad.phase.of.flight', 'Amateur.Built', 'Event.Date'],
      dtype='object')
```

2.2. Converting data types where necessary

Before replacing the null values, let's convert the columns containing numerical values to their respective types.

In [10]:
```
"""
let's convert the columns containing numerical values to 'float' types and
replace the null values for columns in 'numeric_col'.
"""

numeric_col = [
    'Total.Fatal.Injuries',
    'Total.Serious.Injuries',
    'Total.Minor.Injuries',
    'Total.Uninjured',
    'Number.of.Engines',

]
```

```
for col in numeric_col:
    aviation_data[col] = aviation_data[col].astype(float)
    aviation_data[col] = aviation_data[col].fillna(aviation_data[col].median())
```

2.3. Handle missing values for categorical columns and remove all duplicate rows.

> To preserve the integrity of our dataset and avoid losing valuable records, we chose to **replace missing values** with a placeholder string: `NULL_V`. This approach was applied to selected **categorical columns** that are critical for our risk analysis but had a significant number of missing entries:

In [11]:
```
# handle missing values for categorical columns
# Define a list of categorical columns where we want to handle missing values
categorical_col = [
    'Broad.phase.of.flight',     # General phase of the flight (e.g., in-flight, on
    'Engine.Type',               # Type of engine
    'Purpose.of.flight',         # Purpose of the flight (commercial, private, etc.
    'Weather.Condition',         # Weather conditions (VMC, IMC, etc.)
    'Amateur.Built',             # Whether the aircraft was amateur-built
    'Injury.Severity',           # Severity of injuries (minor, serious, fatal)
    'Aircraft.damage'            # Type/level of aircraft damage
]

# Replace missing values in each of these categorical columns with the placeholder
for col in categorical_col:
    aviation_data[col] = aviation_data[col].fillna('NULL_V')

# Convert all values in the 'Weather.Condition' column to uppercase for consistency
aviation_data[categorical_col[3]] = aviation_data[categorical_col[3]].str.upper()

# Convert values in the 'Make' column (aircraft manufacturer) to uppercase
aviation_data['Make'] = aviation_data['Make'].str.upper()

# Normalize manufacturer names:
# If the 'Make' value contains the word "DOUGLAS", replace it entirely with "MCDONN
aviation_data['Make'] = aviation_data['Make'].map(
    lambda x: "MCDONNELL DOUGLAS" if isinstance(x, str) and 'DOUGLAS' in x else x
)

# Convert values in the 'Model' column (aircraft model) to uppercase
aviation_data['Model'] = aviation_data['Model'].str.upper()

# Convert the 'Event.Date' column to datetime format (important for time-based anal
aviation_data['Event.Date'] = pd.to_datetime(aviation_data['Event.Date'])

# Extract the year from the 'Event.Date' and store it in a new column called 'year'
aviation_data['year'] = aviation_data['Event.Date'].dt.year
```

In [12]:
```
aviation_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 16 columns):
 #   Column                  Non-Null Count  Dtype         
---  ------                  --------------  -----         
 0   Make                    88826 non-null  object        
 1   Model                   88797 non-null  object        
 2   Aircraft.damage         90348 non-null  object        
 3   Injury.Severity         90348 non-null  object        
 4   Total.Fatal.Injuries    90348 non-null  float64       
 5   Total.Serious.Injuries  90348 non-null  float64       
 6   Total.Minor.Injuries    90348 non-null  float64       
 7   Total.Uninjured         90348 non-null  float64       
 8   Number.of.Engines       90348 non-null  float64       
 9   Engine.Type             90348 non-null  object        
 10  Purpose.of.flight       90348 non-null  object        
 11  Weather.Condition       90348 non-null  object        
 12  Broad.phase.of.flight   90348 non-null  object        
 13  Amateur.Built           90348 non-null  object        
 14  Event.Date              88889 non-null  datetime64[ns]
 15  year                    88889 non-null  float64       
dtypes: datetime64[ns](1), float64(6), object(9)
memory usage: 11.0+ MB
```

> For the **Make** and **Model** columns, we can't replace the missing values because these fields uniquely identify the aircraft's manufacturer and specific type. Any imputation, such as using a common value or placeholder, would introduce inaccurate information that could lead to false conclusions about which aircraft are safest. Since our goal is to assess risk by aircraft type, keeping only rows with known Make and Model ensures the reliability of our insights.

In [13]:
```python
# let's drop all rows with missing and duplicates values
aviation_data.drop_duplicates(inplace=True)
aviation_data.dropna(inplace=True)
aviation_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 88664 entries, 0 to 90347
Data columns (total 16 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Make                    88664 non-null  object
 1   Model                   88664 non-null  object
 2   Aircraft.damage         88664 non-null  object
 3   Injury.Severity         88664 non-null  object
 4   Total.Fatal.Injuries    88664 non-null  float64
 5   Total.Serious.Injuries  88664 non-null  float64
 6   Total.Minor.Injuries    88664 non-null  float64
 7   Total.Uninjured         88664 non-null  float64
 8   Number.of.Engines       88664 non-null  float64
 9   Engine.Type             88664 non-null  object
 10  Purpose.of.flight       88664 non-null  object
 11  Weather.Condition       88664 non-null  object
 12  Broad.phase.of.flight   88664 non-null  object
 13  Amateur.Built           88664 non-null  object
 14  Event.Date              88664 non-null  datetime64[ns]
 15  year                    88664 non-null  float64
dtypes: datetime64[ns](1), float64(6), object(9)
memory usage: 11.5+ MB
```

In [14]:
```
# aviation_data_copy = aviation_data.to_csv('clean_aviation_data.csv', index=False)
aviation_data.head()
```

Out[14]:

	Make	Model	Aircraft.damage	Injury.Severity	Total.Fatal.Injuries	Total.Serious.Inju
0	STINSON	108-3	Destroyed	Fatal(2)	2.0	
1	PIPER	PA24-180	Destroyed	Fatal(4)	4.0	
2	CESSNA	172M	Destroyed	Fatal(3)	3.0	
3	ROCKWELL	112	Destroyed	Fatal(2)	2.0	
4	CESSNA	501	Destroyed	Fatal(1)	1.0	

> To facilitate aircraft-specific risk analysis, we combined the **Make** and **Model** columns into a single **Aircraft.Type** column. This allows us to treat each unique aircraft configuration as a distinct entity for clearer comparison and aggregation.

In [15]:
```
# Define the new column name for aircraft type
a_t_str = 'Aircraft.Type'
```

```
aviation_data_copy = aviation_data.copy()
# Create 'Aircraft.Type' column by combining 'Make' and 'Model' with a separator
aviation_data[a_t_str] = aviation_data['Make'].str.strip() + " -- " + aviation_data

# Specify the columns to be removed after merging them into 'Aircraft.Type'
to_drop = ['Make', 'Model']

# Drop the 'Make' and 'Model' columns from the dataframe
aviation_data.drop(to_drop, axis=1, inplace=True)

# Remove the 'Aircraft.Type' column from its current position
a_t = aviation_data.pop(a_t_str)

# Insert the 'Aircraft.Type' column at the beginning of the dataframe for better re
aviation_data.insert(0, a_t_str, a_t)

# Display the first few rows of the updated dataframe
aviation_data.head()
```

Out[15]:

	Aircraft.Type	Aircraft.damage	Injury.Severity	Total.Fatal.Injuries	Total.Serious.Injuries
0	STINSON -- 108-3	Destroyed	Fatal(2)	2.0	0.0
1	PIPER -- PA24-180	Destroyed	Fatal(4)	4.0	0.0
2	CESSNA -- 172M	Destroyed	Fatal(3)	3.0	0.0
3	ROCKWELL -- 112	Destroyed	Fatal(2)	2.0	0.0
4	CESSNA -- 501	Destroyed	Fatal(1)	1.0	2.0

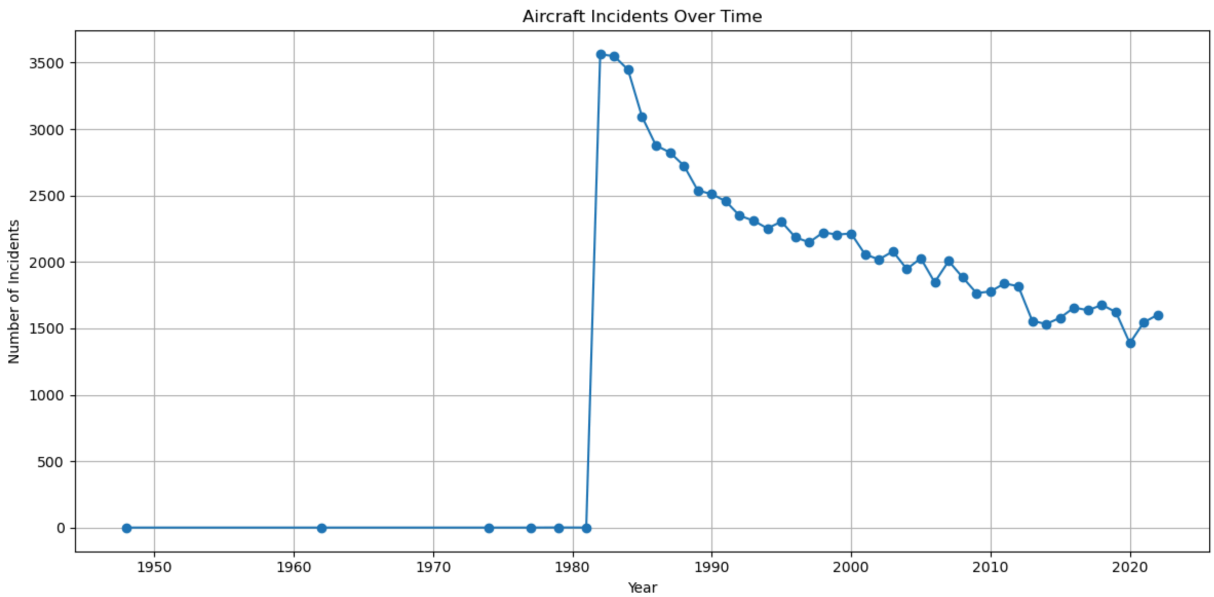
3. Data Analysis

In this phase, we explore the cleaned dataset to uncover patterns, trends, and key insights related to aircraft safety and accident risks, with the goal of identifying low-risk aircraft for business recommendations.

Trend of Aircraft Incidents Over Time

To begin our analysis, we explore how aircraft incidents have evolved over the years. This helps us understand whether the overall risk has increased or decreased with time, and may also reveal patterns influenced by industry regulations, technological advancements, or operational changes.

In [16]:
```
# Count incidents per year
incidents_per_year = aviation_data['year'].value_counts().sort_index()

# Plot
fig, ax = plt.subplots(figsize=(12, 6))
ax.plot(incidents_per_year.index, incidents_per_year.values, marker='o')
ax.set_title('Aircraft Incidents Over Time')
ax.set_xlabel('Year')
ax.set_ylabel('Number of Incidents')
plt.grid(True)
plt.tight_layout()
plt.show()
```



Interpretation:

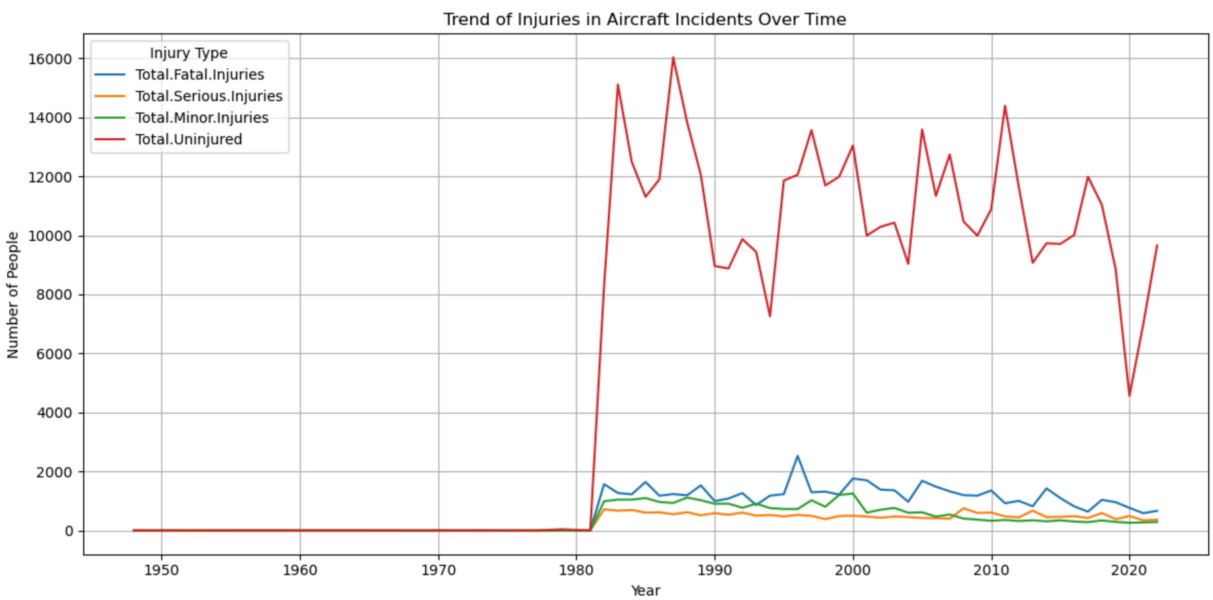
The graph above illustrates the trend of aircraft incidents over time. We can observe a clear decrease in the number of incidents as the years progress. The peak occurred around 1980, after which there has been a steady decline. This trend may suggest improvements in aviation technology, stricter safety regulations, and better training over the decades.

Evolution of accident severity over time

To better understand the evolution of accident severity over time, I will now analyze the yearly trends for different types of injuries, including fatal, serious, minor, and uninjured cases.

In [17]:
```
# Define the list of columns that represent different types of injuries
injury_cols = ['Total.Fatal.Injuries', 'Total.Serious.Injuries', 'Total.Minor.Injur

# Group the dataset by 'year' and calculate the total sum for each injury type per
group_by_year = aviation_data.groupby('year')[injury_cols].sum()

# Plot the trend of injuries over the years as a line chart
group_by_year.plot(figsize=(12, 6), kind='line')  # Line plot with custom figure si
```

```
# Set the title of the plot
plt.title('Trend of Injuries in Aircraft Incidents Over Time')

# Label the x-axis as "Year"
plt.xlabel('Year')

# Label the y-axis as "Number of People"
plt.ylabel('Number of People')

# Add a legend with the title "Injury Type"
plt.legend(title='Injury Type')

# Add a grid for better readability
plt.grid(True)

# Adjust layout to prevent clipping of labels
plt.tight_layout()

# Display the plot
plt.show()
```



Interpretation

Aviation Injury Trends Over Time

Key Observations:

- **Fatal Injuries:**
  - Peaked 1990-2000
  - General downward trend post-peak
  - Non-linear but consistent improvement
- **Serious vs. Minor Injuries:**

    - Serious injuries consistently lower than minor
    - Both show gradual decline after peaks
    - Similar fluctuation patterns
- **Uninjured Cases:**
    - Peak occurrence 1980-1990
    - Subsequent decrease with high variability

Interpretation:

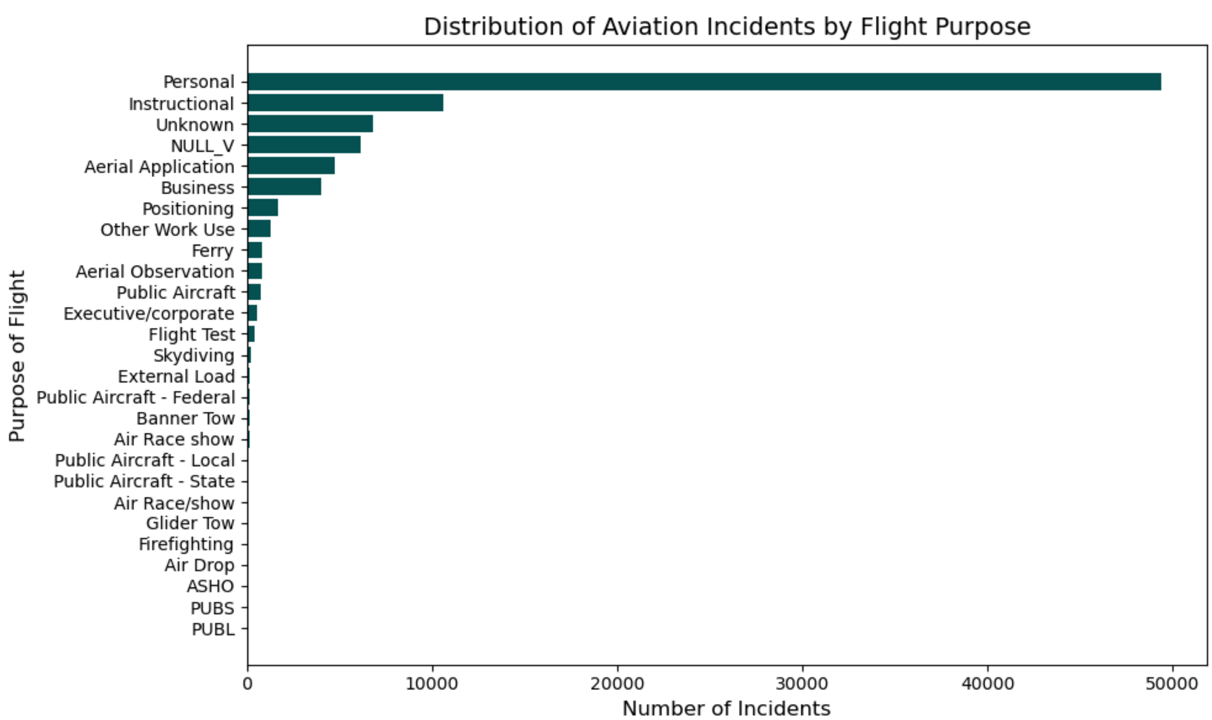
1. **Safety Improvements:**
    - Reduction in all injury categories suggests:
        - Enhanced safety technologies
        - Improved operational procedures
        - Better training standards
2. **Notable Patterns:**
    - Fatal injury decline most significant
    - Serious/minor injury parallel trends may indicate:
        - Similar causal factors
        - Consistent reporting practices
3. **Uninjured Case Analysis:**
    - Decreasing trend could reflect:
        - Fewer total incidents
        - Changes in reporting thresholds
        - Evolving classification standards
4. **Overall Implications:**
    - Positive safety trajectory evident
    - Continued monitoring needed for:
        - Emerging risk factors
        - Changing operational environments

Analyze by purpose of flight

To better understand the operational context of the incidents, the following chart displays the distribution of accidents by the **purpose of flight**. This helps identify which types of operations—such as personal, instructional, or commercial—are more frequently involved in accidents, offering valuable insight into risk levels associated with flight intent.

In [18]:
```
# Count the number of occurrences for each flight purpose
purpose_of_flight = aviation_data['Purpose.of.flight'].value_counts()
```

```
# Sort the values in ascending order for better readability
purpose_of_flight = purpose_of_flight.sort_values()

# Set up the figure and axis with a custom size
fig, ax = plt.subplots(figsize=(10, 6))

# Extract x (categories) and y (counts) for plotting
x = purpose_of_flight.index
y = purpose_of_flight.values

# Create a horizontal bar chart
ax.barh(x, y, color='#075252')

# Add axis labels and a title
ax.set_xlabel('Number of Incidents', fontsize=12)
ax.set_ylabel('Purpose of Flight', fontsize=12)
ax.set_title('Distribution of Aviation Incidents by Flight Purpose', fontsize=14)

# Optional: Improve layout and spacing
plt.tight_layout()

# Display the plot
plt.show()
```



Flight Purpose Distribution in Aviation Incidents

Findings:

- **Personal Flights:** Highest incident count
- **Instructional:** Second highest
- **Aerial Application:** Significant incidents

- **Business Flights:** Lower incident count
- **Unknown/NULL_V:** Substantial portion of data

Interpretation:

1. **Risk Distribution:**

    - Non-commercial operations (**Personal/Instructional**) dominate incident statistics
    - **Aerial Application** (e.g., crop dusting) shows elevated risk profile
    - **Business flights** demonstrate relatively lower incident frequency

2. **Operational Factors:**

    - Higher incident rates in personal/training flights may reflect:
        - Less experienced pilots
        - Variable operating conditions
        - Potentially less stringent maintenance standards
    - Commercial operations show better safety performance

3. **Data Limitations:**

    - Significant **Unknown/NULL_V** values limit complete analysis
    - Findings represent only reported/known flight purposes
    - General trends should be interpreted with appropriate caution

4. **Consistency with Industry Knowledge:**

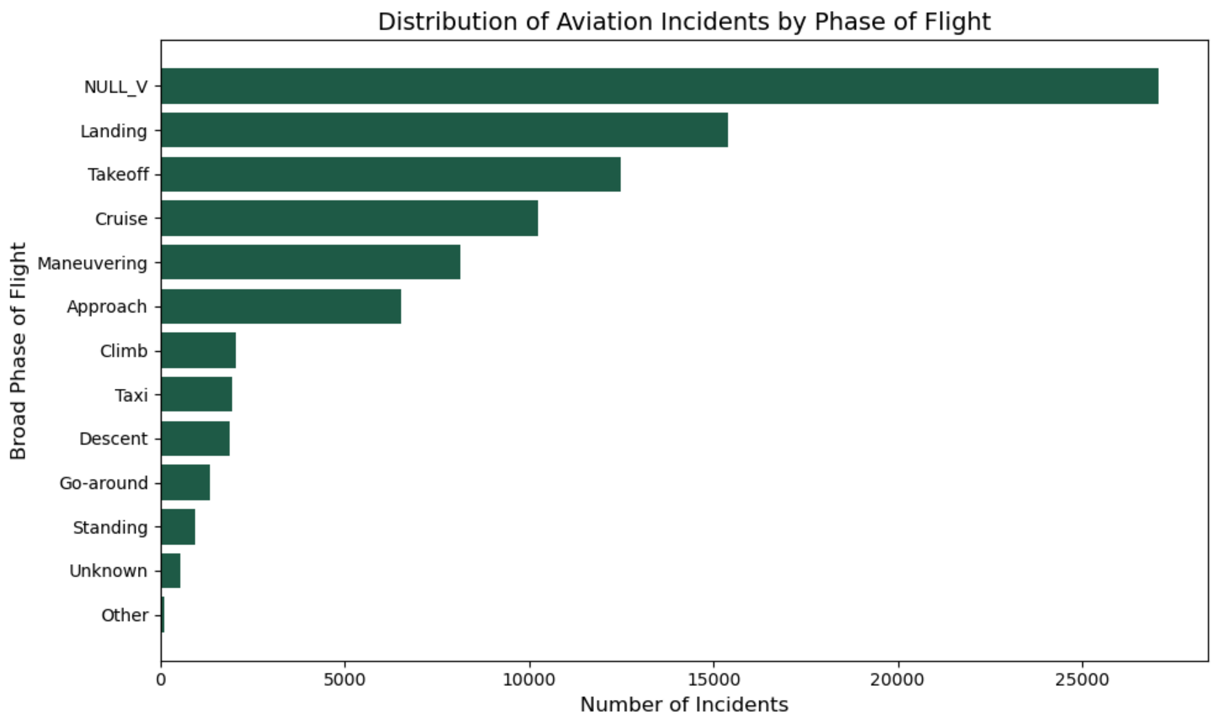
    - Pattern aligns with known aviation risk profiles
    - Confirms higher vulnerability in general aviation sector

Analyze by broad phase of flight

Next, we analyze the distribution of incidents by the **broad phase of flight** to evaluate which stages (such as takeoff, cruise, and landing) are most prone to accidents. Although some values are missing and labeled as 'Unknown' or 'NULL_V', this graph will still provide valuable insights into the operational contexts that may influence risk.

In [19]:
```
# Count the number of occurrences for each phase
phase_of_flight = aviation_data['Broad.phase.of.flight'].value_counts()

# Sort the values in ascending order for better readability
phase_of_flight = phase_of_flight.sort_values()

# Set up the figure and axis
fig, ax = plt.subplots(figsize=(10, 6))

# Extract x (categories) and y (counts) for plotting
x = phase_of_flight.index
y = phase_of_flight.values

# Create a horizontal bar chart
```

```
ax.barh(x, y, color='#205B4A')

# Add axis labels and a title
ax.set_xlabel('Number of Incidents', fontsize=12)
ax.set_ylabel('Broad Phase of Flight', fontsize=12)
ax.set_title('Distribution of Aviation Incidents by Phase of Flight', fontsize=14)

# Optional: Improve layout and spacing
plt.tight_layout()

# Display the plot
plt.show()
```



Flight Phase Distribution in Aviation Incidents

Findings:

- **NULL_V (Missing Data):** Majority of records
- Among known phases:
  - **Landing:** Highest incident count
  - **Takeoff:** Second highest
  - **Cruise:** Moderate incident count
  - **Maneuvering:** Notable incidents
  - **Approach & Climb:** Fewer incidents

Interpretation:

1. **Data Limitations:**

   - Significant portion of records contain missing flight phase data (`NULL_V`)

- Analysis limited to available phase information

2. **High-Risk Phases:**

   - **Landing** shows highest incident frequency, likely due to:
     - Precise speed/altitude requirements
     - Time pressure and pilot workload
   - **Takeoff** as second-highest risk phase involves:
     - Critical power management
     - Configuration changes

3. **Operational Patterns:**

   - Transitional phases (landing/takeoff) dominate incident statistics
   - Cruise flight shows moderate risk despite longer duration
   - Approach/climb incidents may relate to:
     - Airspace congestion
     - ATC communication

4. **Research Alignment:**

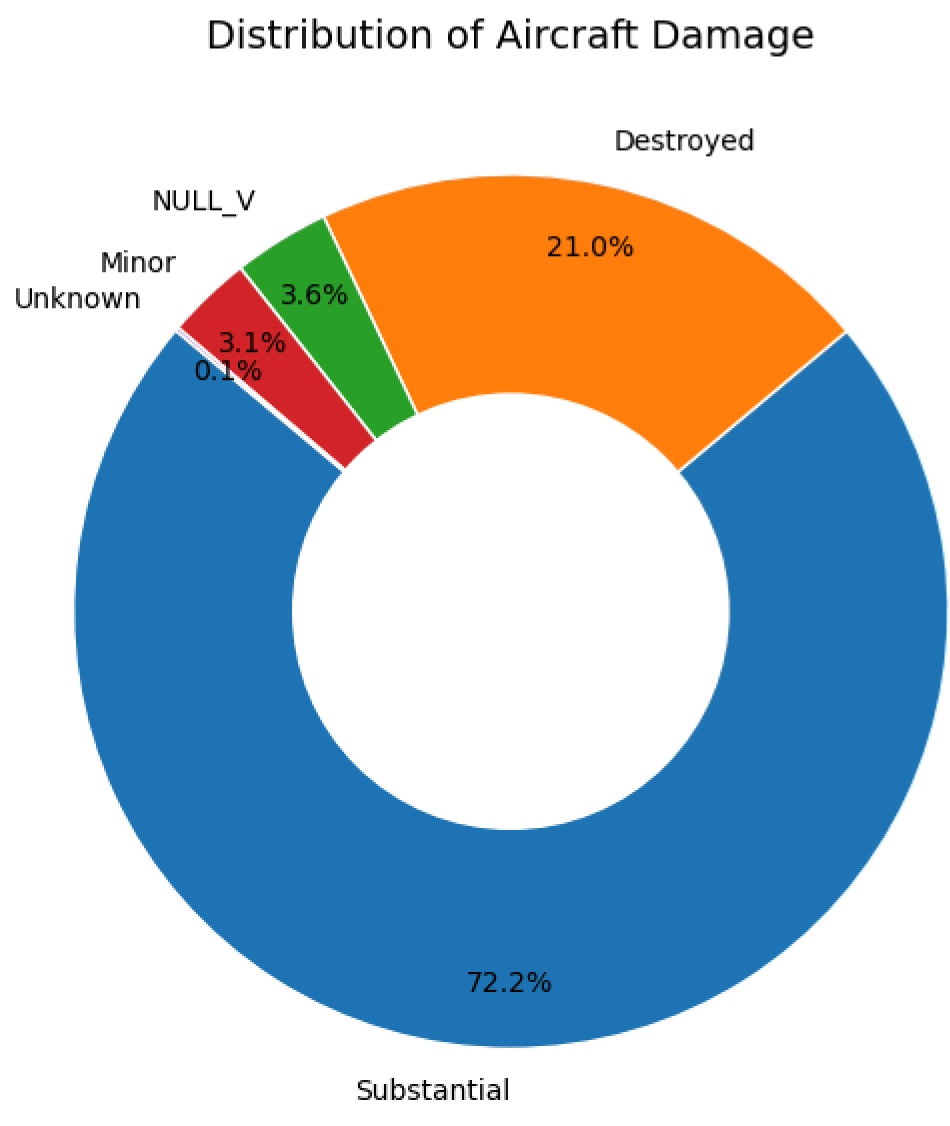
   - Results consistent with established aviation safety literature
   - Confirms known risk distribution across flight phases

Aircraft.damage distribution

To better understand the impact of aviation incidents, I visualize the **Aircraft.damage** distribution using a pie chart. This helps identify how often accidents result in **minor**, **substantial**, or **destroyed** aircraft, while also accounting for **unknown** and missing (**NULL_V**) values.

In [20]:
```
# Count the number of occurrences for each aircraft damage category
aircraft_damage = aviation_data['Aircraft.damage'].value_counts()

# Create a figure and axis object for the pie chart
fig, ax = plt.subplots(figsize=(8, 6))

# Extract values and labels
x = aircraft_damage.values  # The counts for each category
y = aircraft_damage.index   # The category labels

# Plot the pie chart
ax.pie(
    x,
    labels=y,
    autopct='%1.1f%%',      # Display percentages with 1 decimal
    startangle=140,         # Rotate start for better layout
    pctdistance=0.85,       # Distance of percentage text from center
    labeldistance=1.1,      # Distance of labels from center
    wedgeprops={'edgecolor': 'white'}  # Add white borders between slices
)
```

```
# Draw a circle at the center to make it a donut chart
centre_circle = plt.Circle((0, 0), 0.50, fc='white')
fig.gca().add_artist(centre_circle)

# Add title
plt.title('Distribution of Aircraft Damage', fontsize=14)

# Show the plot
plt.tight_layout()
plt.show()
```



Aircraft Damage Severity Distribution

Findings:

- **Substantial Damage:** 72.2% of incidents
- **Destroyed:** 21% of incidents

- **Minor Damage:** 3.1% of incidents
- **NULL_V (Missing Data):** 3.6%
- **Unknown:** 0.1%

Interpretation:

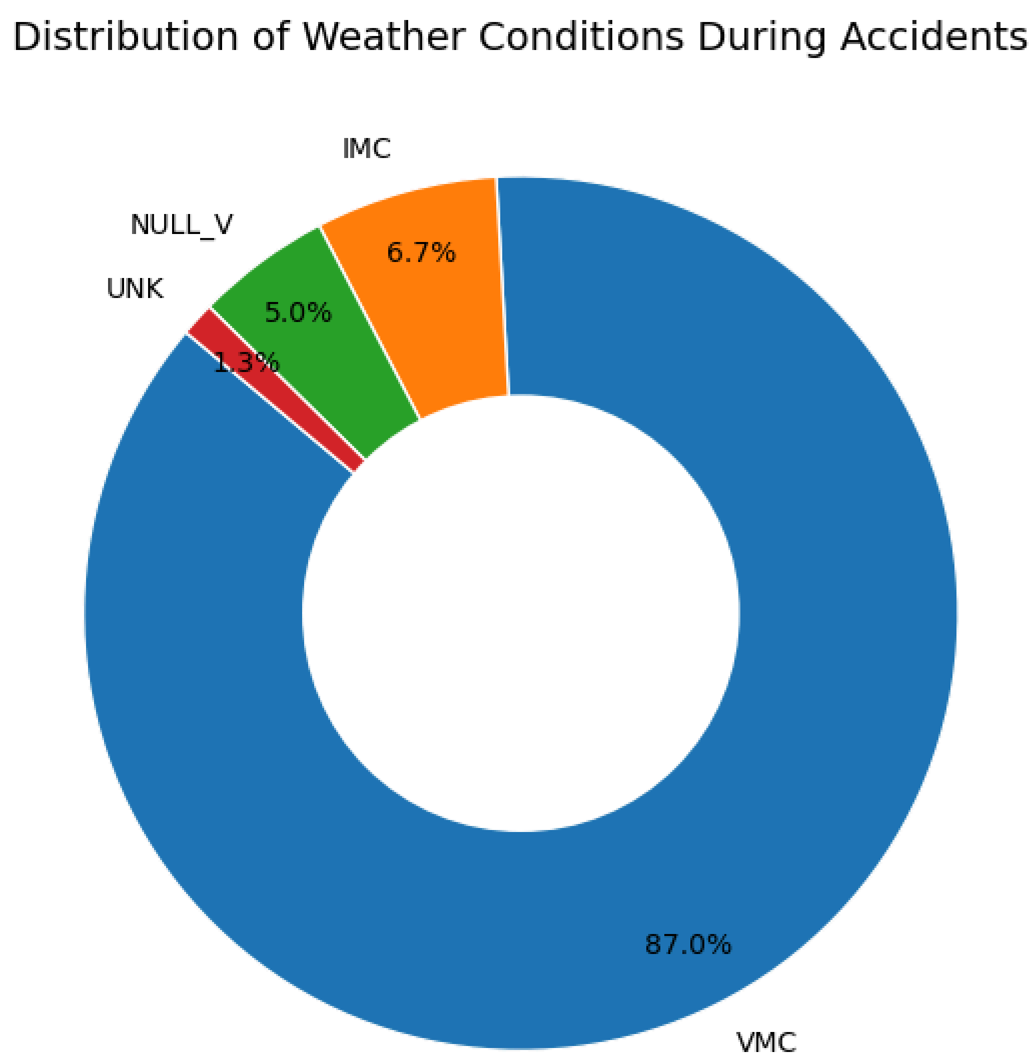
1. The overwhelming majority (72.2%) of incidents result in **substantial damage**, indicating:
   - Most accidents cause significant but not complete airframe loss
   - Potential for costly repairs and operational downtime
2. **Destroyed aircraft (21%)** represent:
   - The most severe accident outcomes
   - Complete hull losses with major financial implications
3. **Minor damage cases (3.1%)** are notably rare, suggesting:
   - Either low-severity accidents are uncommon
   - Or there may be underreporting of minor incidents
4. Data quality considerations:
   - Minimal missing/unknown values (3.7% combined)
   - Overall dataset appears reliable for analysis

Distribution of weather conditions during incidents

To better understand the role of environmental factors in aviation accidents, the following pie chart illustrates the distribution of weather conditions during incidents. This visualization is essential for identifying whether poor weather significantly contributes to accident risk and helps inform decisions about operational safety and risk mitigation.

In [21]:
```
# Count the number of occurrences for each weather condition category
weather_condition = aviation_data['Weather.Condition'].value_counts()

# Create a figure and axis object for the pie chart
fig, ax = plt.subplots(figsize=(8, 6))

# Extract values and labels
x = weather_condition.values  # The counts for each condition
y = weather_condition.index   # The category labels

# Plot the pie chart
ax.pie(
    x,
    labels=y,
    autopct='%1.1f%%',        # Show percentages with 1 decimal place
    startangle=140,           # Rotate to start from a better angle
    pctdistance=0.85,         # Set distance of percentage labels from center
```

```
    labeldistance=1.1,        # Set distance of labels from center
    wedgeprops={'edgecolor': 'white'}  # White edges for separation
)

# Optional: add a white circle to create a donut chart
centre_circle = plt.Circle((0, 0), 0.50, fc='white')
fig.gca().add_artist(centre_circle)

# Add title
plt.title('Distribution of Weather Conditions During Accidents', fontsize=14)

# Display the plot
plt.tight_layout()
plt.show()
```



Weather Condition Distribution in Aviation Accidents

Findings:

- **VMC (Clear Weather):** 87% of accidents
- **IMC (Poor Weather):** 6.7% of accidents
- **UNK (Unknown):** 5%
- **NULL_V (Missing Data):** 1.3%

Interpretation:

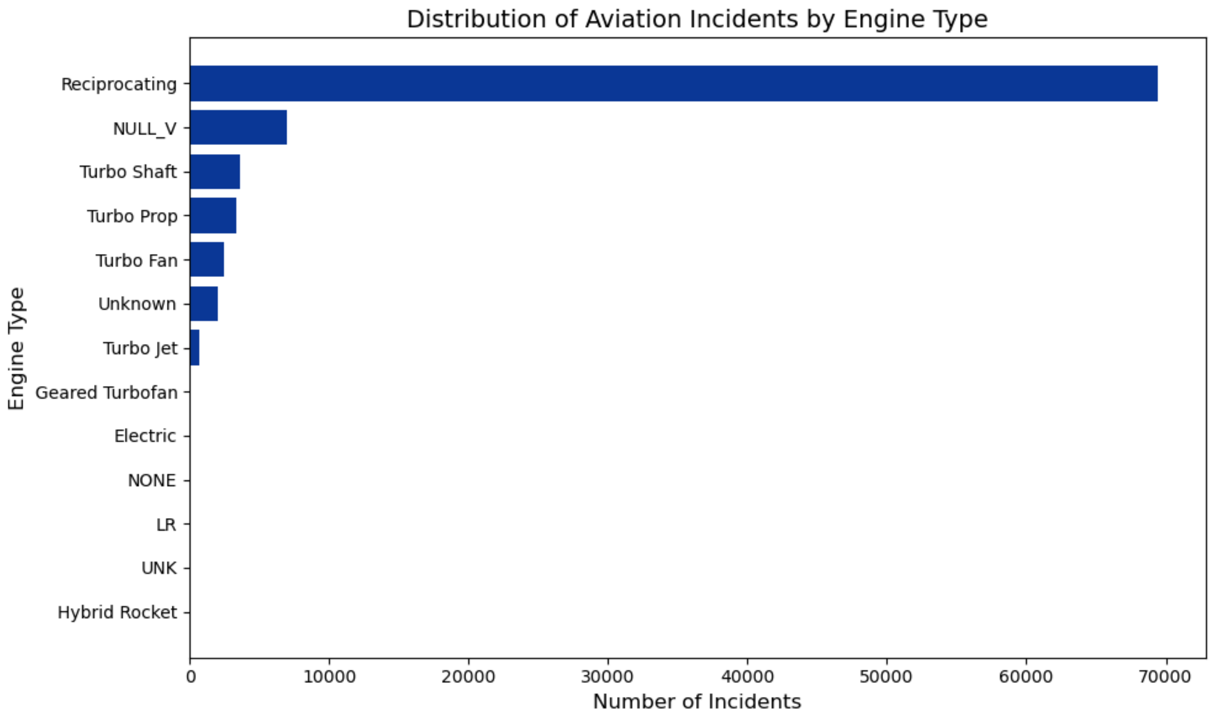
1. The vast majority (87%) of accidents occur in **visual flight conditions (VMC)**, suggesting:
   - Human factors (pilot decision-making, situational awareness) may dominate accident causes
   - Potential complacency in good weather conditions
2. While **IMC accidents are rare (6.7%)**, they are:
   - Typically more severe (higher likelihood of fatal outcomes)
   - Often involve spatial disorientation or system failures
3. Data quality appears reliable with:
   - Only 5% unknown weather status
   - Minimal (1.3%) missing values

Incident Distribution by Engine Type

This chart reveals which engine types are involved in the most aviation incidents. The results help identify higher-risk propulsion systems that may require additional safety measures or operational restrictions.

In [22]:
```
# Count the number of occurrences for each engine type
engine_type = aviation_data['Engine.Type'].value_counts()

# Sort the values in ascending order for better readability
engine_type = engine_type.sort_values()

# Set up the figure and axis
fig, ax = plt.subplots(figsize=(10, 6))

# Extract x (categories) and y (counts) for plotting
x = engine_type.index
y = engine_type.values

# Create a horizontal bar chart
ax.barh(x, y, color='#0C3B97')  # Using the same green color as before

# Add axis labels and a title
ax.set_xlabel('Number of Incidents', fontsize=12)
ax.set_ylabel('Engine Type', fontsize=12)
```

```
ax.set_title('Distribution of Aviation Incidents by Engine Type', fontsize=14)

# Optional: Improve layout and spacing
plt.tight_layout()

# Display the plot
plt.show()
```



Engine Type Incident Analysis

Key Findings:

1. **Reciprocating (Piston) Engines**
   - Highest incident rate
   - Common in general aviation (smaller aircraft)
   - Higher maintenance requirements
2. **Turboshaft/Turboprop Engines**
   - Moderate incident frequency
   - Used in helicopters/regional aircraft
3. **Turbofan Engines**
   - Lower incident occurrence
   - Typical in commercial airliners

Data Notes:

- Significant `NULL_V` values present (affects completeness)

- Results align with known industry risk profiles

Implications:
Piston-engine aircraft may require:
✓ Enhanced maintenance protocols
✓ Additional pilot training
✓ More frequent inspections

Aviation Safety Analysis by Injury Severity

Objective:
Identify the safest aircraft models by analyzing four injury severity categories:

1. **Fatal Injuries** - Highest-risk models to avoid
2. **Serious Injuries** - Frequent severe accident models
3. **Minor Injuries** - Common low-severity incident models
4. **Uninjured Cases** - Best-performing safety models

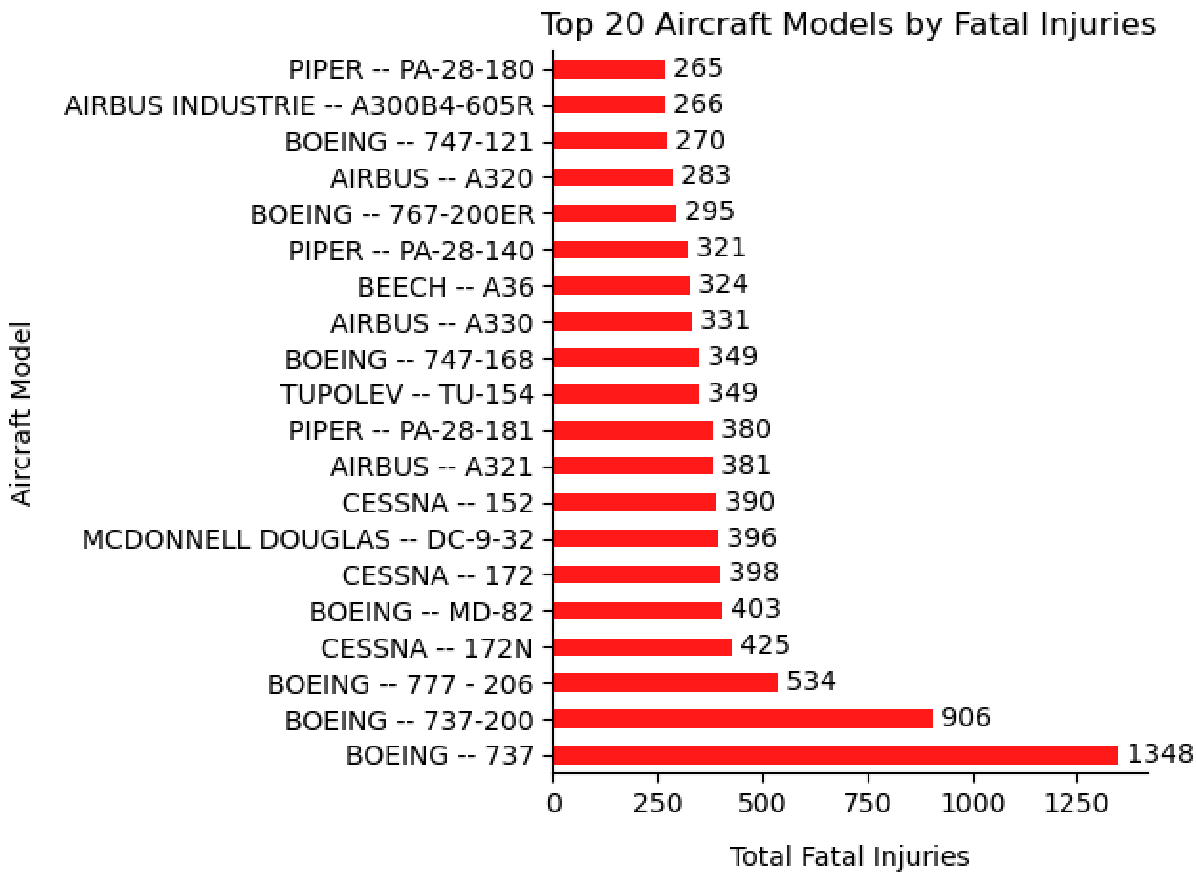
Methodology:

- Data: Combined `Make + Model` as `Aircraft.Type`
- Metrics: Use **median** injury counts per aircraft type to reduce the influence of outliers.
- Sorting: Highest to lowest risk for each category

Visualization Guide: Each subsequent graph shows model performance for one injury category, enabling comparative safety assessment.

In [23]:
```python
fatal_by_model = (
    aviation_data.groupby('Aircraft.Type')[['Total.Fatal.Injuries']]
    .sum()
    .sort_values('Total.Fatal.Injuries', ascending=False)
    .head(20)  # Top 20 most fatal models
)

# Plot with custom colors
fatal_by_model.plot(
    kind='barh',
    color='red',
    alpha=0.9,
    legend=False
)

# Add titles and labels
plt.title('Top 20 Aircraft Models by Fatal Injuries')
plt.xlabel('Total Fatal Injuries', labelpad=10)
plt.ylabel('Aircraft Model', labelpad=10)

# Add value labels at the end of each bar
```

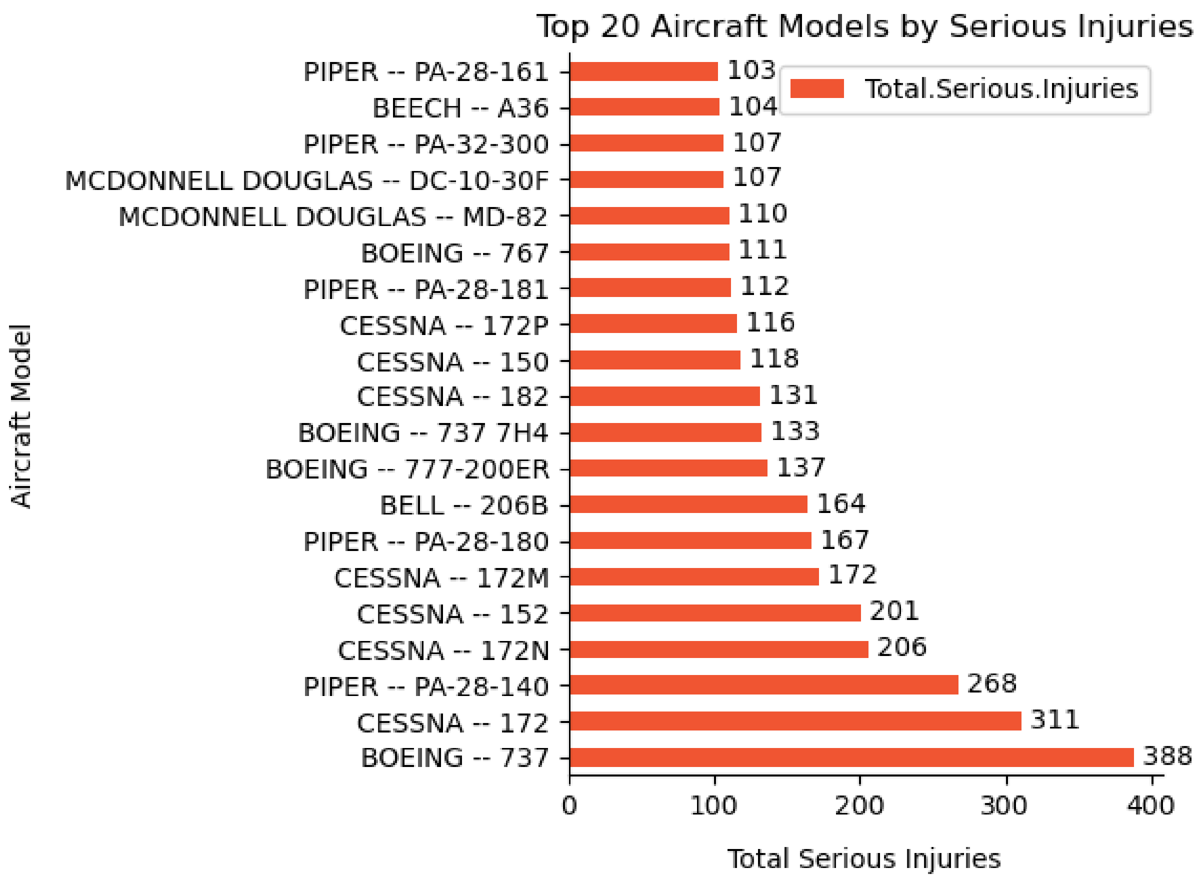
```
for index, value in enumerate(fatal_by_model['Total.Fatal.Injuries']):
    plt.text(value, index, f' {int(value)}', va='center')

# Remove top and right borders
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)

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



In [24]:

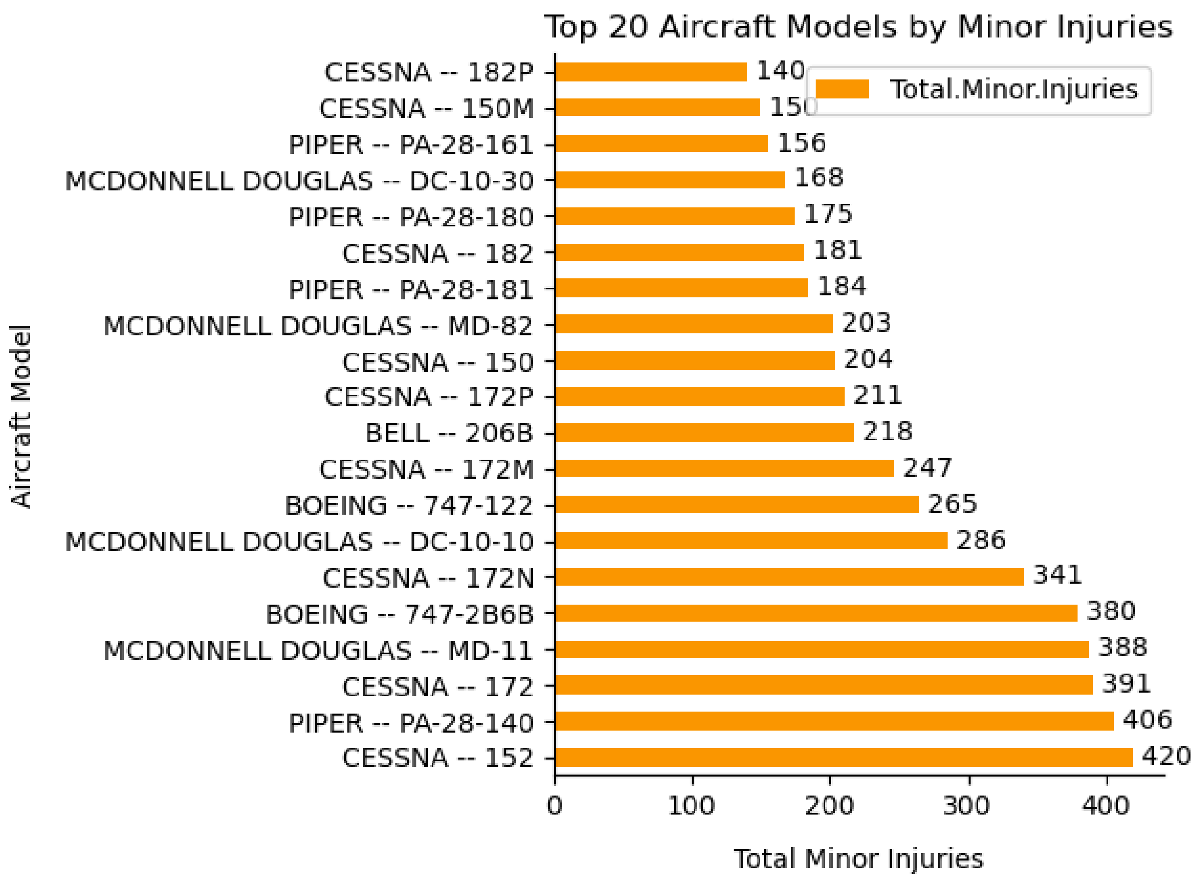
```
serious_by_model = (
    aviation_data.groupby('Aircraft.Type')[['Total.Serious.Injuries']]
    .sum()
    .sort_values('Total.Serious.Injuries', ascending=False)
    .head(20)  # Top 20 models with most serious injuries
)
serious_by_model.plot(kind='barh', color='#F05532')
# Add titles and labels
plt.title('Top 20 Aircraft Models by Serious Injuries')
plt.xlabel('Total Serious Injuries', labelpad=10)
plt.ylabel('Aircraft Model', labelpad=10)

# Add value labels at the end of each bar
for index, value in enumerate(serious_by_model['Total.Serious.Injuries']):
    plt.text(value, index, f' {int(value)}', va='center')

# Remove top and right borders
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
```

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



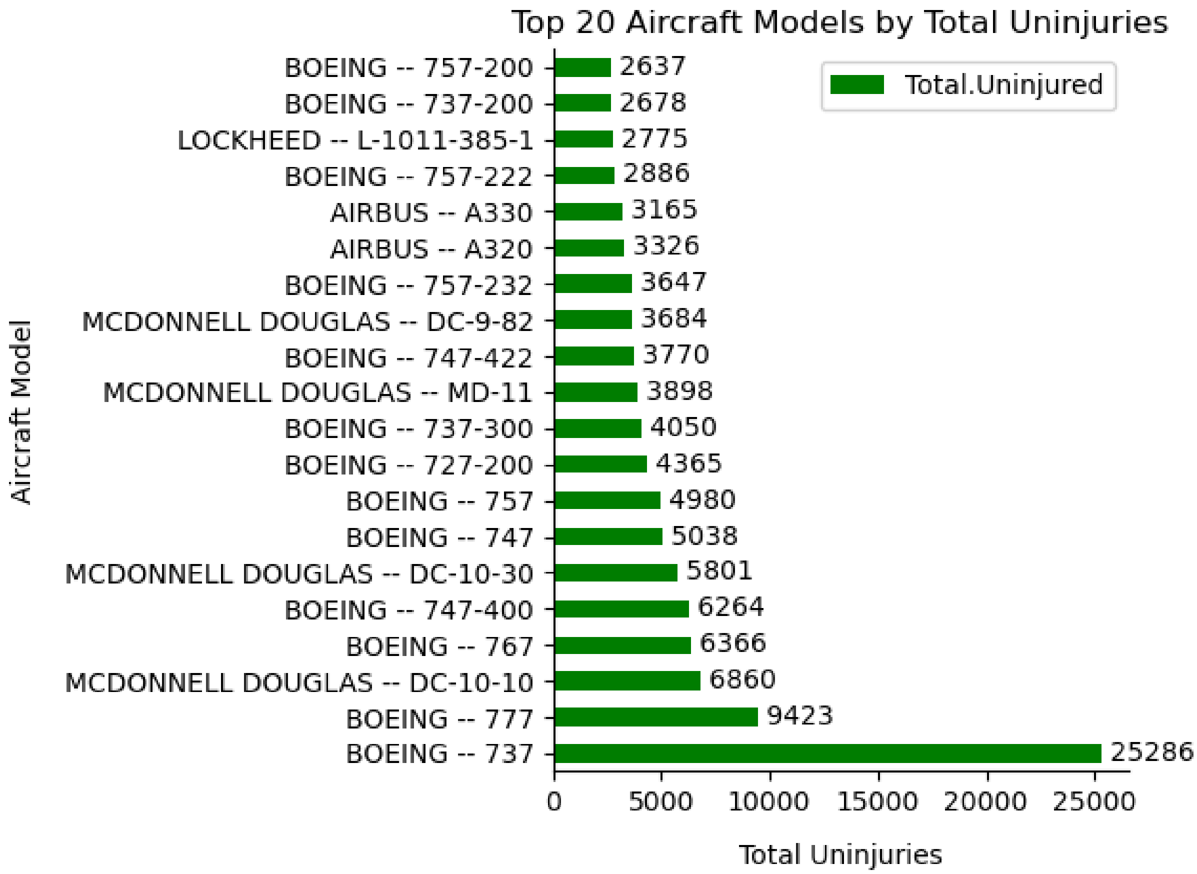
In [25]:

```
minor_by_model = (
    aviation_data.groupby('Aircraft.Type')[['Total.Minor.Injuries']]
    .sum()
    .sort_values('Total.Minor.Injuries', ascending=False)
    .head(20)  # Top 20 models with most minor injuries
)
minor_by_model.plot(kind='barh', color='#FE9900')
# Add titles and labels
plt.title('Top 20 Aircraft Models by Minor Injuries')
plt.xlabel('Total Minor Injuries', labelpad=10)
plt.ylabel('Aircraft Model', labelpad=10)

# Add value labels at the end of each bar
for index, value in enumerate(minor_by_model['Total.Minor.Injuries']):
    plt.text(value, index, f' {int(value)}', va='center')

# Remove top and right borders
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)

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

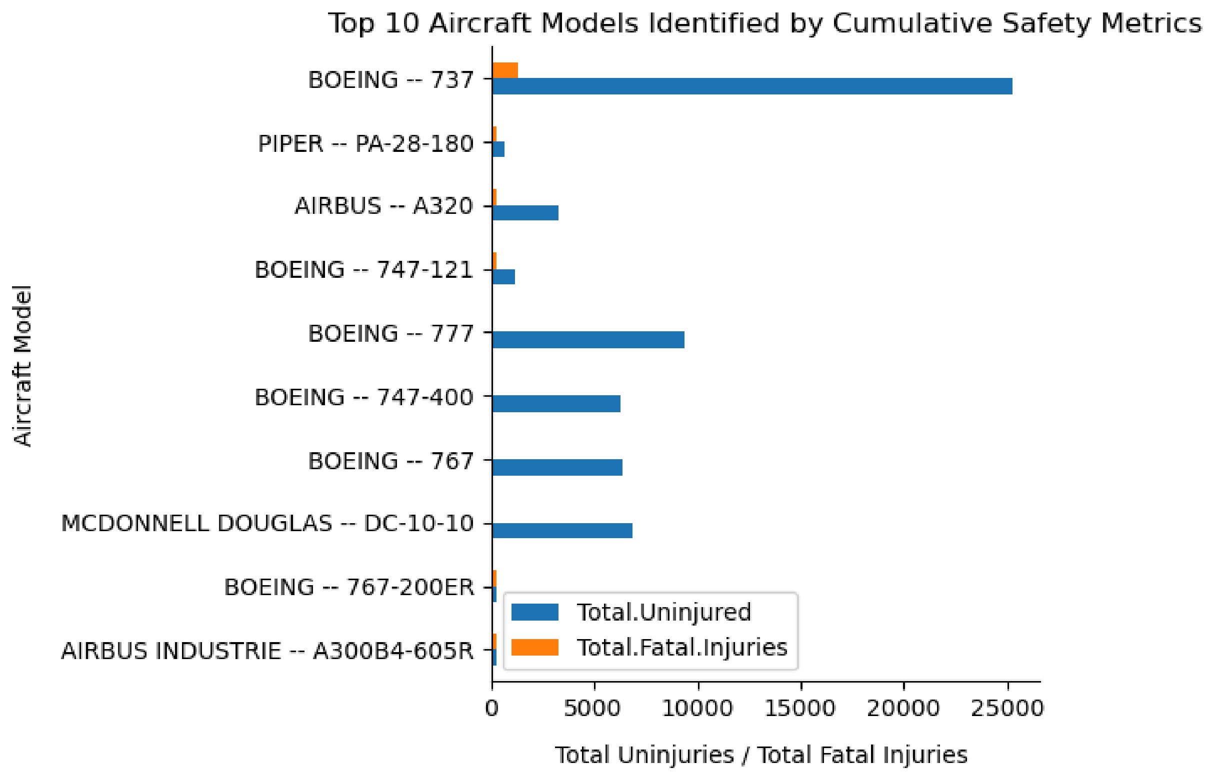


In [26]:

```
safe_by_model = (
    aviation_data.groupby('Aircraft.Type')[['Total.Uninjured']]
    .sum()
    .sort_values('Total.Uninjured', ascending=False)
    .head(20)  # Top 20 safest models
)
safe_by_model.plot(kind='barh', color='green')
# Add titles and labels
plt.title('Top 20 Aircraft Models by Total Uninjuries')
plt.xlabel('Total Uninjuries', labelpad=10)
plt.ylabel('Aircraft Model', labelpad=10)

# Add value labels at the end of each bar
for index, value in enumerate(safe_by_model['Total.Uninjured']):
    plt.text(value, index, f' {int(value)}', va='center')

# Remove top and right borders
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)

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



In [27]:
```
# Step 1: Get top 10 safest models (high uninjured, low injuries)
top_safe = safe_by_model.index[:5].tolist()  # Top 5 uninjured models

# Step 2: Get least fatal models (bottom of fatal list = safer)
least_fatal = fatal_by_model.index[-5:].tolist()[::-1]  # Reverse to ascending

# Step 3: Combine and deduplicate
recommended_models = list(set(top_safe + least_fatal))

top_10_recommended_models = (
    aviation_data.groupby('Aircraft.Type')[['Total.Uninjured', 'Total.Fatal.Injurie
    .sum()
    .sort_values('Total.Fatal.Injuries', ascending=False)
)
top_10_recommended_models.loc[recommended_models].plot(kind='barh')
# Add titles and labels
plt.title('Top 10 Aircraft Models Identified by Cumulative Safety Metrics')
plt.xlabel('Total Uninjuries / Total Fatal Injuries ', labelpad=10)
plt.ylabel('Aircraft Model', labelpad=10)


# Remove top and right borders
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)

plt.tight_layout()
```



4. Final Recommendations

Top 10 Aircraft Models Identified by Cumulative Safety Metrics

Based on injury data and incident analysis from over 90,000 aviation records, we identified the following aircraft models as having the **lowest overall risk**, based on high rates of uninjured outcomes and low fatality scores:

- **BOEING -- 767-200ER**
- **MCDONNELL DOUGLAS -- DC-10-30**
- **BOEING -- 767**
- **AIRBUS -- A320**
- **MCDONNELL DOUGLAS -- DC-10-10**
- **PIPER -- PA-28-180**
- **BOEING -- 747-121**
- **AIRBUS INDUSTRIE -- A300B4-605R**
- **BOEING -- 777**
- **BOEING -- 747-400**

Focus on Modern and Commercially Viable Models

Among the list above, some models are dated or better suited for non-commercial purposes (e.g. the **PIPER PA-28-180** is mainly for private or training use). For business expansion into

commercial or private aviation, we recommend focusing on **modern, proven aircraft still widely supported and operated**.

Final Recommended Aircraft for Acquisition:

✅ **AIRBUS -- A320**
✅ **BOEING -- 777**
✅ **BOEING -- 767**

These models are:

- **Widely used** in both domestic and international commercial routes.
- **Supported with robust maintenance infrastructure** and spare parts availability.
- **Backed by strong safety records**, as shown in the analysis.
- **Flexible**: suitable for short, medium, and long-haul operations.

Business Recommendations

1. **Invest in Modern, Proven Aircraft Models**
   Prioritize aircraft such as the **A320**, **Boeing 767**, and **Boeing 777**, which offer a solid balance of capacity, performance, and safety.

2. **Avoid Obsolete or High-Risk Models**
   Models like the **DC-10** series or **747-121** are aging, with decreasing industry support. Their operational and safety risks are comparatively higher due to limited parts and aging airframes.

3. **Align Fleet Selection with Mission Profile**
   Choose aircraft not only for safety, but also for the type of operation:

   - **A320**: ideal for regional and short-to-medium haul commercial use.
   - **Boeing 777**: excellent for long-haul and international routes.
   - **Boeing 767**: versatile mid-size wide-body for both cargo and passenger services.

By basing the acquisition strategy on data-backed safety insights and modern aircraft trends, the company can minimize operational risks while ensuring long-term value and fleet reliability.

In [ ]:

```

```