In [1]:

```
import pandas as pd

# Load the CSV with encoding fixed
df = pd.read_csv("Downloads/archive/AviationData.csv", encoding='latin1')

# Show the first few rows
df.head()
```

```
C:\Users\AngelaC\AppData\Local\Temp\ipykernel_31652\4268235836.py:4: DtypeWarning: Column
s (6,7,28) have mixed types. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv("Downloads/archive/AviationData.csv", encoding='latin1')
```

Out[1]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.C
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	NaN	N
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	NaN	N
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.922223	-81.878056	N
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	NaN	N
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	NaN	N

5 rows × 31 columns

In [2]:

```
# Load US State Codes
states = pd.read_csv("Downloads/archive/USState_Codes.csv", encoding='latin1')

# Preview the state codes data
states.head()
```

Out[2]:

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

In [3]:

```
# Check shape (rows, columns)
print("Shape:", df.shape)

# Check all columns
print("\nColumn Names:")
print(df.columns)

# Check for null values
print("\nMissing Values per Column:")
print(df.isna().sum())
```

```python
# Check datatypes
print("\nData Types:")
print(df.dtypes)
```

```
Shape: (88889, 31)

Column Names:
Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Date',
       'Location', 'Country', 'Latitude', 'Longitude', 'Airport.Code',
       'Airport.Name', 'Injury.Severity', 'Aircraft.damage',
       'Aircraft.Category', 'Registration.Number', 'Make', 'Model',
       'Amateur.Built', 'Number.of.Engines', 'Engine.Type', 'FAR.Description',
       'Schedule', 'Purpose.of.flight', 'Air.carrier', 'Total.Fatal.Injuries',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured',
       'Weather.Condition', 'Broad.phase.of.flight', 'Report.Status',
       'Publication.Date'],
      dtype='object')

Missing Values per Column:
Event.Id                      0
Investigation.Type            0
Accident.Number               0
Event.Date                    0
Location                     52
Country                     226
Latitude                  54507
Longitude                 54516
Airport.Code              38757
Airport.Name              36185
Injury.Severity            1000
Aircraft.damage            3194
Aircraft.Category         56602
Registration.Number        1382
Make                         63
Model                        92
Amateur.Built               102
Number.of.Engines          6084
Engine.Type                7096
FAR.Description           56866
Schedule                  76307
Purpose.of.flight          6192
Air.carrier               72241
Total.Fatal.Injuries      11401
Total.Serious.Injuries    12510
Total.Minor.Injuries      11933
Total.Uninjured            5912
Weather.Condition          4492
Broad.phase.of.flight     27165
Report.Status              6384
Publication.Date          13771
dtype: int64

Data Types:
Event.Id                  object
Investigation.Type        object
Accident.Number           object
Event.Date                object
Location                  object
Country                   object
Latitude                  object
Longitude                 object
Airport.Code              object
Airport.Name              object
Injury.Severity           object
Aircraft.damage           object
Aircraft.Category         object
Registration.Number       object
Make                      object
Model                     object
Amateur.Built             object
Number.of.Engines        float64
Engine.Type               object
```

```
FAR.Description            object
Schedule                   object
Purpose.of.flight          object
Air.carrier                object
Total.Fatal.Injuries      float64
Total.Serious.Injuries    float64
Total.Minor.Injuries      float64
Total.Uninjured           float64
Weather.Condition          object
Broad.phase.of.flight      object
Report.Status              object
Publication.Date           object
dtype: object
```

In [4]:

```
# Show percentage of missing values
missing_percent = df.isna().sum() / len(df) * 100
missing_percent.sort_values(ascending=False)
```

Out[4]:

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

In [5]:

```
# Drop columns with too much missing data
df_cleaned = df.drop(columns=[
    'Schedule', 'Air.carrier', 'FAR.Description', 'Aircraft.Category',
    'Latitude', 'Longitude', 'Airport.Code', 'Airport.Name'
])

# Preview cleaned data
df_cleaned.head()
```

Out[5]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Injury.Severity	Aircraft.damage
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	Fatal(2)	Destroyed

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Injury.Severity	Aircraft.damage
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	Fatal(4)	Destroyed
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	Fatal(3)	Destroyed
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	Fatal(2)	Destroyed
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	Fatal(1)	Destroyed

5 rows × 23 columns

In [6]:

```
# Convert Event.Date to datetime format
df_cleaned['Event.Date'] = pd.to_datetime(df_cleaned['Event.Date'], errors='coerce')

# Create a new column for the year
df_cleaned['Event_Year'] = df_cleaned['Event.Date'].dt.year

# Check the first few rows
df_cleaned[['Event.Date', 'Event_Year']].head()
```

Out[6]:

	Event.Date	Event_Year
0	1948-10-24	1948
1	1962-07-19	1962
2	1974-08-30	1974
3	1977-06-19	1977
4	1979-08-02	1979

In [7]:

```
# Group accidents by year
accidents_per_year = df_cleaned['Event_Year'].value_counts().sort_index()

# Preview the counts
accidents_per_year.head()
```

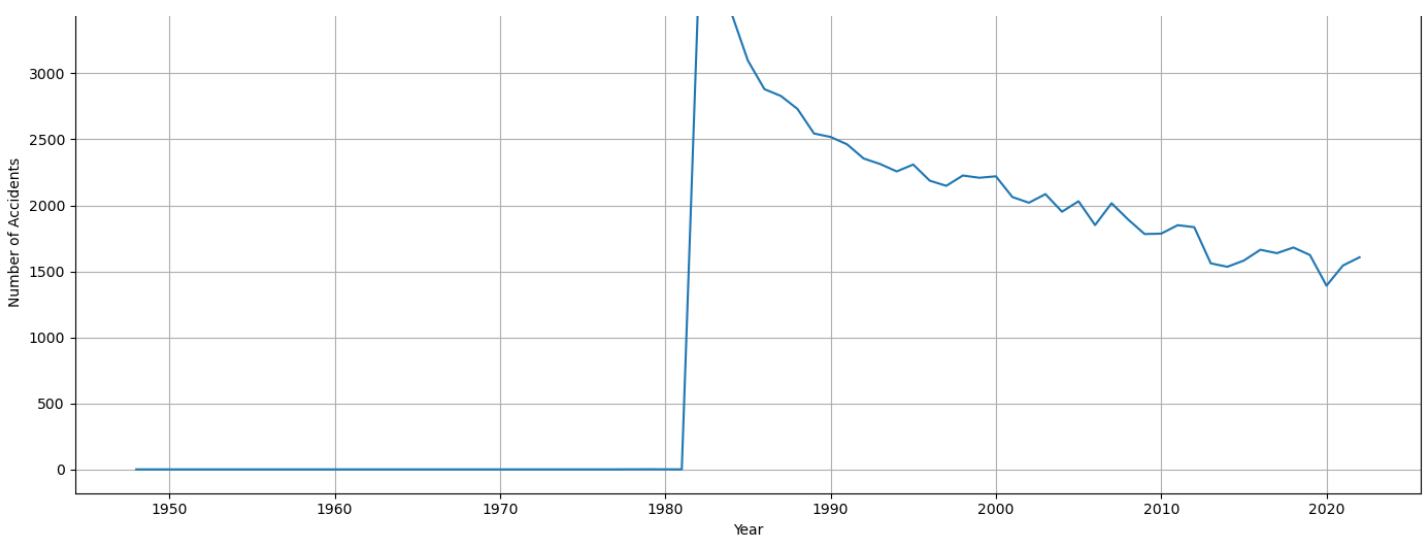
Out[7]:

```
Event_Year
1948    1
1962    1
1974    1
1977    1
1979    2
Name: count, dtype: int64
```

In [8]:

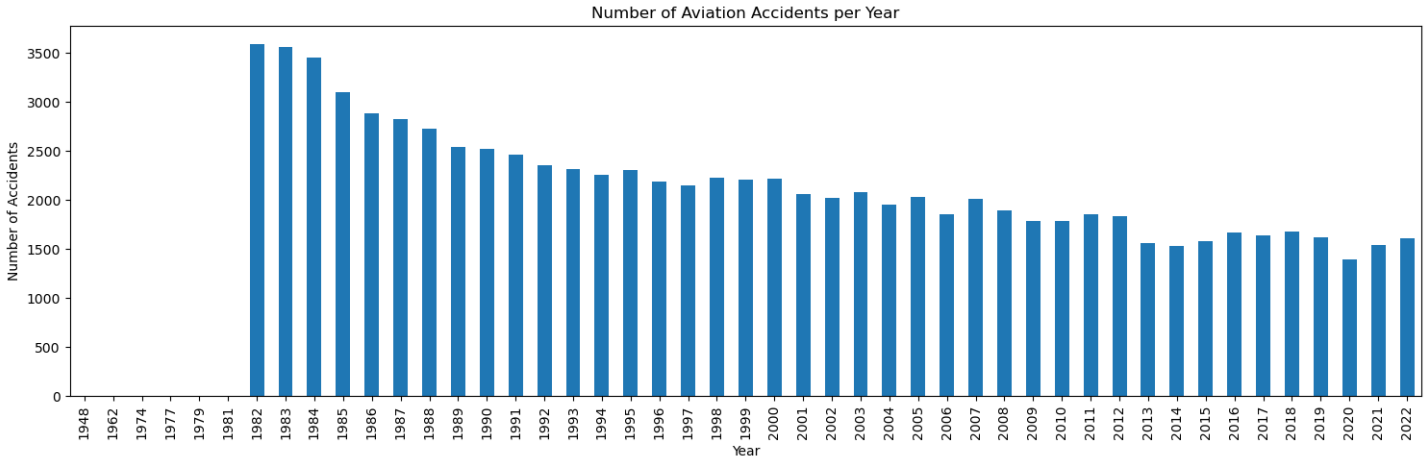
```
# Import the required plotting library
import matplotlib.pyplot as plt

# Plot accidents per year
accidents_per_year.plot(kind='line', figsize=(14, 6))
plt.title('Number of Aviation Accidents Per Year')
plt.xlabel('Year')
plt.ylabel('Number of Accidents')
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [9]:

```
accidents_per_year.plot(kind='bar', figsize=(15,5))
plt.title('Number of Aviation Accidents per Year')
plt.xlabel('Year')
plt.ylabel('Number of Accidents')
plt.tight_layout()
plt.show()
```



Line chart showing the trend of accidents over the years

Bar chart comparing number of accidents per year

In [12]:

```
df_cleaned.columns
```

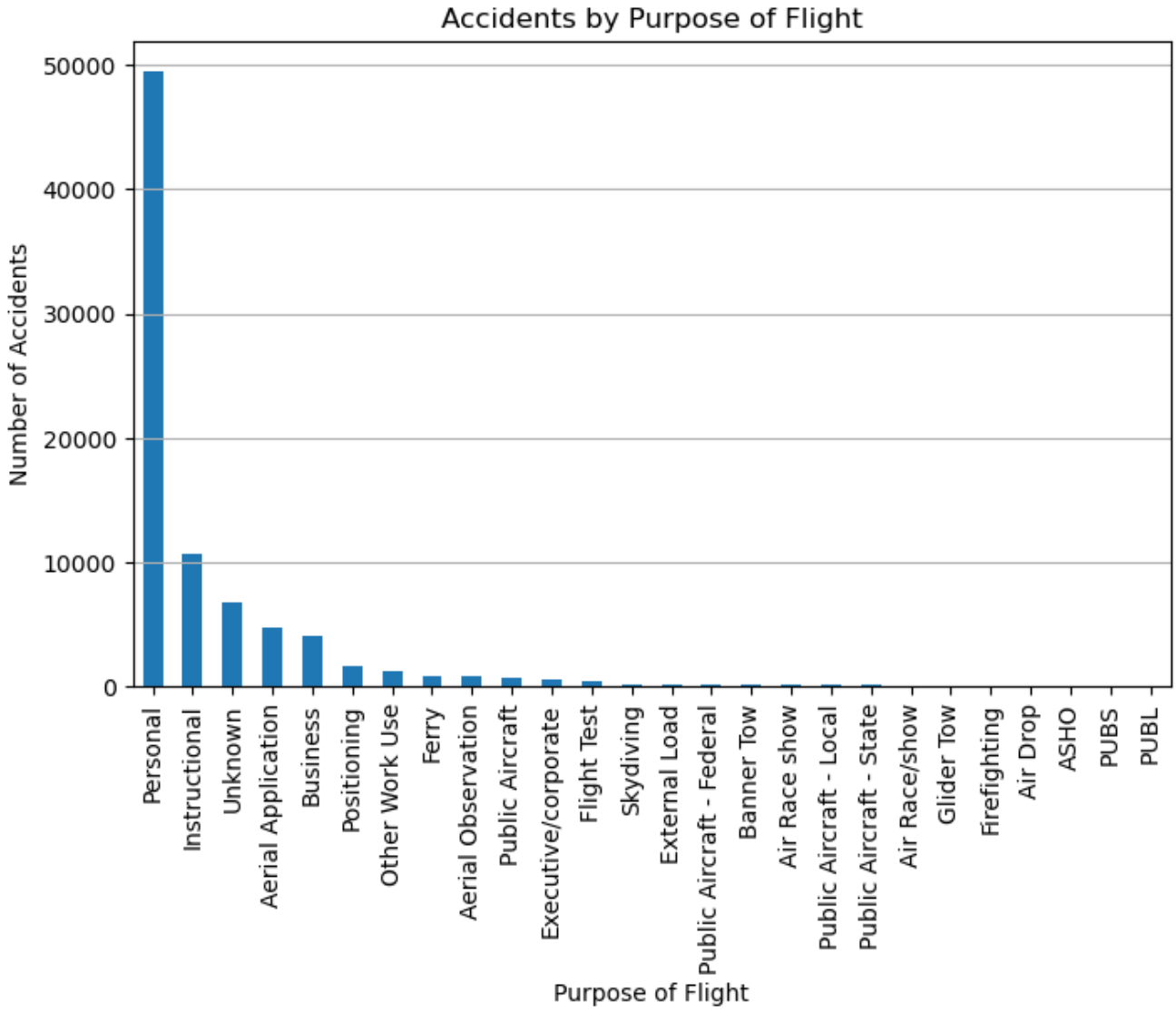
Out[12]:

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

In [13]:

```
# Count of accidents by purpose of flight
purpose_counts = df_cleaned['Purpose.of.flight'].value_counts()
```

```
# Bar chart for purpose of flight
purpose_counts.plot(kind='bar', figsize=(8,5), title='Accidents by Purpose of Flight')
plt.xlabel('Purpose of Flight')
plt.ylabel('Number of Accidents')
plt.grid(axis='y')
plt.show()
```



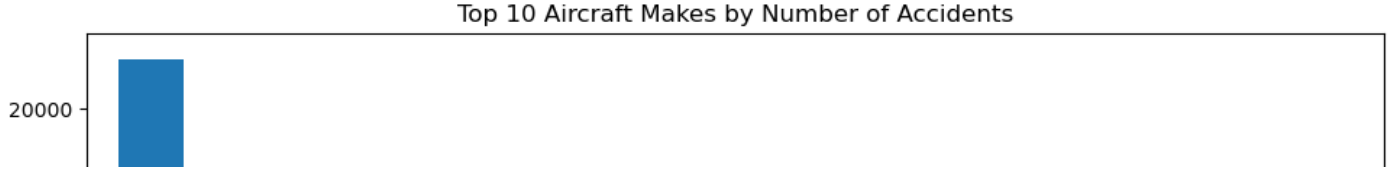
Accidents by Purpose of Flight

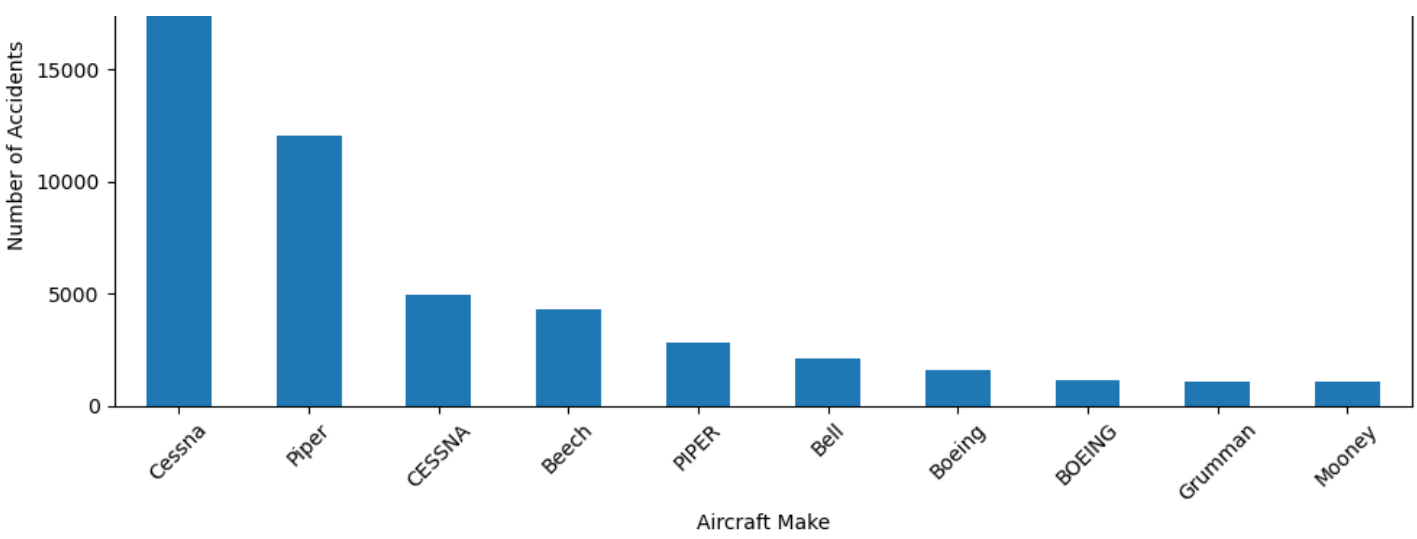
This chart shows the number of accidents for each flight purpose.
Personal flights had the most, followed by instructional and business.
This helps identify high-risk flight categories for the company to consider.

In [15]:

```
# Top 10 aircraft makes by number of accidents
top_makes = df_cleaned['Make'].value_counts().head(10)

# Plotting
top_makes.plot(kind='bar', figsize=(10,5))
plt.title('Top 10 Aircraft Makes by Number of Accidents')
plt.xlabel('Aircraft Make')
plt.ylabel('Number of Accidents')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```





Accidents by Aircraft Make

This chart shows the top 10 aircraft manufacturers involved in accidents.

Understanding which makes appear most frequently in the data helps the company identify models with higher incident rates, which may require extra scrutiny before making purchase decisions.

Recommendation 1: Accident Trends Over Time

Accidents have decreased steadily over the years, suggesting that modern aircraft and improved regulations have enhanced safety. The company should focus on *newer aircraft models* (post-2000) for lower risk.

Recommendation 2: Flight Purpose

Personal flights account for the highest number of accidents. The company should *avoid or minimize private charter/personal flying*, and instead focus on commercial or instructional flights which have lower risk.

Recommendation 3: Aircraft Make

Cessna and Piper appear most frequently in accident data. The company should *prioritize thorough inspection and history checks* before purchasing Cessna or Piper models, or consider *alternative manufacturers* with lower incident counts.

Summary

The analysis revealed that personal flights and certain aircraft makes (like Cessna and Piper) are most involved in accidents. By focusing on safer flight types and thoroughly assessing commonly used aircraft, the company can reduce risk as it enters the aviation industry.

In [ ]: