Phase 1 Project: Aviation Safety Analysis *(Additional Notes)*

Business Understanding

Objective

The purpose of this project is to identify low-risk aircraft models and operational strategies to support the company's entry into the aviation sector.

Key Deliverables

1. Recommendations for low-risk aircraft.
2. Insights into operational risks (e.g., flight phases, weather conditions).
3. Strategic guidance for improving safety in operations.

Data Understanding

Dataset Overview

- **Source**: National Transportation Safety Board (1962–2023)
- **Scope**: Aviation accidents and incidents across various models, flight phases, and weather conditions.

Initial Observations

- The dataset contained missing values, mixed data types, and columns with varying relevance to the analysis.
- Preprocessing was needed to clean and prepare the data for meaningful analysis.

In [41]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


# Try using an alternative encoding
Aviation_df = pd.read_csv('AviationData.csv', encoding='latin1')

# Preview the first few rows to ensure the file loaded correctly
Aviation_df
```

```
c:\Users\maktr\anaconda3\envs\learn-env\lib\site-packages\IPython\core\interactiveshell.py:3145: DtypeWarning: Columns (6,
7,28) have mixed types.Specify dtype option on import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

Out[41]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	NaN	NaN
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	NaN	NaN
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.9222	-81.8781	NaN
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	NaN	NaN
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...
88884	20221227106491	Accident	ERA23LA093	2022-12-26	Annapolis, MD	United States	NaN	NaN	NaN
88885	20221227106494	Accident	ERA23LA095	2022-12-26	Hampton, NH	United States	NaN	NaN	NaN
88886	20221227106497	Accident	WPR23LA075	2022-12-26	Payson, AZ	United States	341525N	1112021W	PAN
88887	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	NaN	NaN	NaN
88888	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	NaN	NaN	NaN

88889 rows × 31 columns

Calculating Missing Data

- Goal is to calculate and see how much of the missing values each category in the dataset have.
- That way, we can determine which columns we should probably keep, remove, and such.

In [42]:

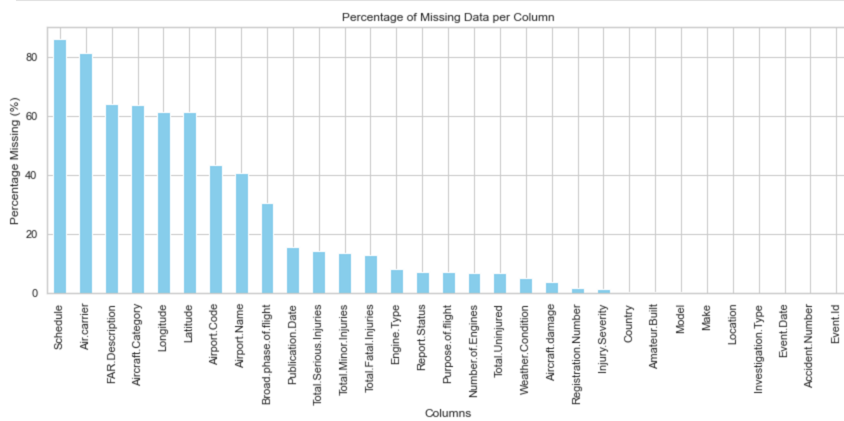
```
# Calculate missing values per column
missing_data = Aviation_df.isnull().sum()

# Calculate the percentage of missing data for each column
missing_percentage = (missing_data / len(Aviation_df)) * 100

# Combine into a single DataFrame for better readability
missing_summary = pd.DataFrame({
    "Missing Values": missing_data,
    "Percentage Missing (%)": missing_percentage
}).sort_values(by="Percentage Missing (%)", ascending=False)

# Display the summary
print("Summary of Missing Data:")
print(missing_summary)
```

```
Summary of Missing Data:
                        Missing Values  Percentage Missing (%)
```

```
Schedule                      76307            85.845268
Air.carrier                   72241            81.271023
FAR.Description               56866            63.974170
Aircraft.Category             56602            63.677170
Longitude                     54516            61.330423
Latitude                      54507            61.320298
Airport.Code                  38640            43.469946
Airport.Name                  36099            40.611324
Broad.phase.of.flight         27165            30.560587
Publication.Date              13771            15.492356
Total.Serious.Injuries        12510            14.073732
Total.Minor.Injuries          11933            13.424608
Total.Fatal.Injuries          11401            12.826109
Engine.Type                    7077             7.961615
Report.Status                  6381             7.178616
Purpose.of.flight              6192             6.965991
Number.of.Engines              6084             6.844491
Total.Uninjured                5912             6.650992
Weather.Condition              4492             5.053494
Aircraft.damage                3194             3.593246
Registration.Number            1317             1.481623
Injury.Severity                1000             1.124999
Country                         226             0.254250
Amateur.Built                   102             0.114750
Model                            92             0.103500
Make                             63             0.070875
Location                         52             0.058500
Investigation.Type                0             0.000000
Event.Date                        0             0.000000
Accident.Number                   0             0.000000
Event.Id                          0             0.000000
```

In [43]:

```python
# Optional: Visualize missing data
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 6))
missing_summary["Percentage Missing (%)"].plot(kind='bar', color='skyblue')
plt.title("Percentage of Missing Data per Column")
plt.ylabel("Percentage Missing (%)")
plt.xlabel("Columns")
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



Creation of new Column 'Total.Injured'

In [44]:

```python
Aviation_df['Total.injured'] = Aviation_df['Total.Serious.Injuries'] +  Aviation_df['Total.Fatal.Injuries']
```

Data Analysis

Analysis of Every Key Dataset and correlations to Injuries

- The goal was too analyze and see, based on each Data category, how much did each correlate to each number of injuries and non-injuries.
- In addition, most of the tables are sorted out by the number of times or moments this or that category was mentioned in the data set.

Model

Analysis from the Data Sets:

- **Frequent Use, Low Injury Models:** Models like the 737 show that frequent use does not necessarily mean higher injury rates, which may reflect their overall robustness and safety.
- **Infrequent Use, High Injury Models:** The PA-28-181 and PA-28-180 show that even with fewer incidents, a higher injury rate signals a more dangerous model that might need better safety improvements or modifications.
- **Moderate Risk Models:** Aircraft like the 172 and PA-28-161 are moderately used and moderately risky, suggesting a balanced risk profile.

Conclusion: Ultimately, the number of incidents and injury percentages together provide a clearer picture of both the frequency and severity of incidents involving different aircraft models. Some models may benefit from additional safety measures, especially those with higher injury percentages, even if their usage is lower.

In [45]:

```python
# Simplified Model_summary calculation
Model_summary = Aviation_df.groupby('Model').agg(
    Total_Injured=('Total.injured', 'sum'),
    Total_Uninjured=('Total.Uninjured', 'sum'),
    Total_Model=('Model', 'size')
)

# Calculate Injured and Non-injured Percentages
Model_summary['Injured Percentage (%)'] = Model_summary['Total_Injured'] / (Model_summary[['Total_Injured', 'Total_Uninju
Model_summary['Non-injured Percentage (%)'] = Model_summary['Total_Uninjured'] / (Model_summary[['Total_Injured', 'Total_U
```

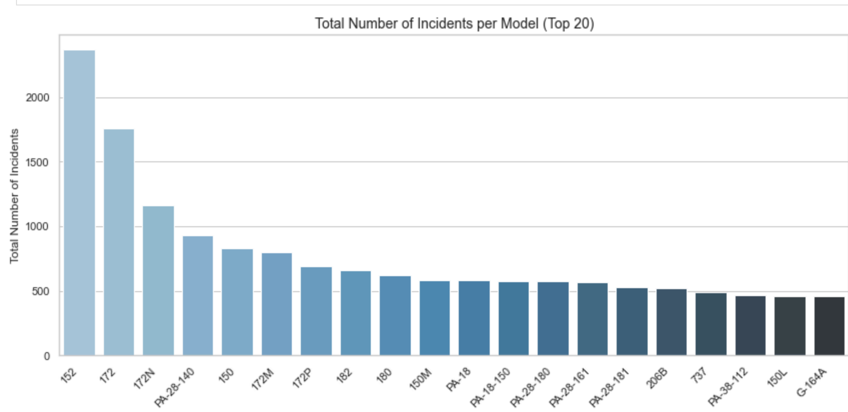
```python
# Sort by 'Total_Model' and get top 20 models
top_20_models = Model_summary.sort_values('Total_Model', ascending=False).head(20)
top_20_models
```

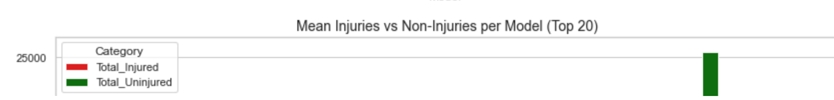
Out[45]:

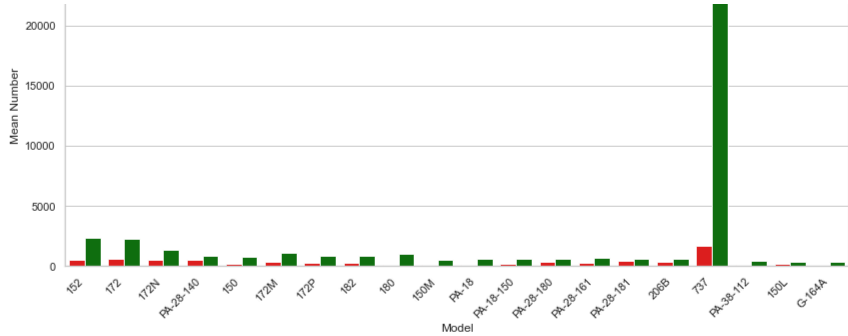
Model	Total_Injured	Total_Uninjured	Total_Model	Injured Percentage (%)	Non-injured Percentage (%)
152	540.0	2364.0	2367	18.595041	81.404959
172	657.0	2253.0	1756	22.577320	77.422680
172N	542.0	1350.0	1164	28.646934	71.353066
PA-28-140	515.0	844.0	932	37.895511	62.104489
150	225.0	763.0	829	22.773279	77.226721
172M	378.0	1095.0	798	25.661914	74.338086
172P	302.0	857.0	689	26.056946	73.943054
182	313.0	844.0	659	27.052723	72.947277
180	151.0	997.0	622	13.153310	86.846690
150M	148.0	565.0	585	20.757363	79.242637
PA-18	146.0	626.0	581	18.911917	81.088083
PA-18-150	170.0	589.0	578	22.397892	77.602108
PA-28-180	370.0	598.0	572	38.223140	61.776860
PA-28-161	295.0	686.0	569	30.071356	69.928644
PA-28-181	440.0	644.0	532	40.590406	59.409594
206B	350.0	584.0	524	37.473233	62.526767
737	1735.0	25441.0	489	6.384310	93.615690
PA-38-112	145.0	493.0	469	22.727273	77.272727
150L	195.0	360.0	461	35.135135	64.864865
G-164A	58.0	341.0	460	14.536341	85.463659

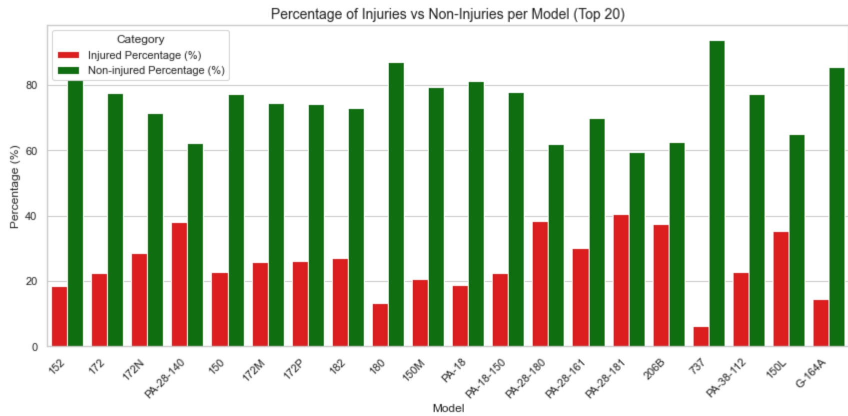
In [46]:

```python
import seaborn as sns

# Bar Graph: Total Numbers of Each Model using Seaborn
plt.figure(figsize=(12, 6))
sns.barplot(x=top_20_models.index, y='Total_Model', data=top_20_models.reset_index(), palette='Blues_d')
plt.title('Total Number of Incidents per Model (Top 20)', fontsize=14)
plt.ylabel('Total Number of Incidents', fontsize=12)
plt.xlabel('Model', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()

# Bar Graph: Mean Injuries vs Non-Injuries per Top 20 Models using Seaborn
plt.figure(figsize=(12, 6))
injuries_uninjuries = top_20_models[['Total_Injured', 'Total_Uninjured']].reset_index().melt(
id_vars='Model', var_name='Category', value_name='Mean'
)
sns.barplot(x='Model', y='Mean', hue='Category', data=injuries_uninjuries, palette=['red', 'green'])
plt.title('Mean Injuries vs Non-Injuries per Model (Top 20)', fontsize=14)
plt.ylabel('Mean Number', fontsize=12)
plt.xlabel('Model', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.legend(title='Category')
plt.tight_layout()
plt.show()

# Bar Graph: Percent of Injuries vs Non-Injuries per Top 20 Models using Seaborn
plt.figure(figsize=(12, 6))
percentages = top_20_models[['Injured Percentage (%)', 'Non-injured Percentage (%)']].reset_index().melt(
    id_vars='Model', var_name='Category', value_name='Percentage'
)
sns.barplot(x='Model', y='Percentage', hue='Category', data=percentages, palette=['red', 'green'])
plt.title('Percentage of Injuries vs Non-Injuries per Model (Top 20)', fontsize=14)
plt.ylabel('Percentage (%)', fontsize=12)
plt.xlabel('Model', fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.legend(title='Category')
plt.tight_layout()
plt.show()
```









Broad.Phase.of.Flight

Analysis made on the Table

Insights and Key Observations

- Maneuvering and go-around are riskiest with high injury rates, while taxi and standing are safest. Landing has frequent incidents, but injury risk is low.

Overall Interpretation:

- Focus on improving safety in high-risk phases (maneuvering, go-around, cruise) while maintaining effective protocols for landing. Taxi and standing remain low-risk, requiring minimal intervention.

In [47]:

```
# Group by 'Broad.phase.of.flight' and calculate required statistics
Phase_summary = Aviation_df.groupby('Broad.phase.of.flight').agg(
    Total_Injured=('Total.injured', 'sum'),
    Total_Uninjured=('Total.Uninjured', 'sum'),
    Total_Times_Mentioned=('Broad.phase.of.flight', 'count')
)

# Calculate Injured and Non-injured Percentages
Phase_summary['Injured Percentage (%)'] = Phase_summary['Total_Injured'] / Phase_summary[['Total_Injured', 'Total_Uninjur
Phase_summary['Non-injured Percentage (%)'] = Phase_summary['Total_Uninjured'] / Phase_summary[['Total_Injured', 'Total_U

# Sort by 'Total_Times' and display top 10 results
sorted_Phase_summary = Phase_summary.sort_values('Total_Times_Mentioned', ascending=False).head(10)

sorted_Phase_summary
```

Out[47]:

	Total_Injured	Total_Uninjured	Total_Times_Mentioned	Injured Percentage (%)	Non-injured Percentage (%)
Broad.phase.of.flight					
Landing	1437.0	48533.0	15428	2.875725	97.124275
Takeoff	6010.0	45083.0	12493	11.762864	88.237136
Cruise	6836.0	45757.0	10269	12.997927	87.002073
Maneuvering	5836.0	5447.0	8144	51.723832	48.276168
Approach	4865.0	21538.0	6546	18.425936	81.574064
Climb	2025.0	19508.0	2034	9.404170	90.595830
Taxi	182.0	38277.0	1958	0.473231	99.526769
Descent	1168.0	18958.0	1887	5.803438	94.196562
Go-around	802.0	2045.0	1353	28.170004	71.829996
Standing	329.0	18612.0	945	1.736973	98.263027

Anaylisis made on the Graphs

Insights and Key Observations:

- **Landing Phase:** Aircraft models like "152" and "172" exhibit a high number of incidents during landing, contributing significantly to the overall total.

- **Takeoff Phase:** The takeoff phase has a consistent share of incidents across most aircraft, with the "152" model standing out as having the highest proportion of takeoff-related accidents.

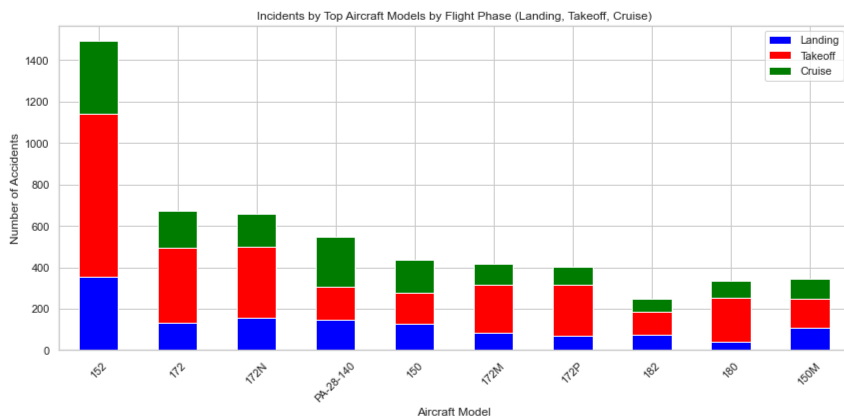
- **Cruise Phase:** The cruise phase appears to account for a large portion of incidents in models such as "172N," "PA-28-140," and "180." This suggests that cruise-related challenges are prominent for these models.

Overall Interpretation:

- **Landing Focus:** Aircraft models such as "152" require enhanced landing safety protocols, given the substantial incident numbers during this phase.
- **Cruise Safety:** Models like "172N" and "PA-28-140" should prioritize cruise safety measures to mitigate risks associated with long-distance flight.
- **Takeoff Attention:** While less frequent than landing and cruise incidents, takeoff incidents still demand attention, particularly for the "152" model.

In [48]:

```
# Filter dataset for critical phases (Landing, Takeoff)
most_phases = ['Landing', 'Takeoff', 'Cruise']
phase_filtered = Aviation_df[Aviation_df['Broad.phase.of.flight'].isin(most_phases)]

# Count accidents by model and flight phase
phase_model_counts = phase_filtered.groupby(['Model', 'Broad.phase.of.flight']).size().unstack().fillna(0)

# Select top models for analysis
top_10_models = top_20_models.head(10).index
phase_model_counts = phase_model_counts.loc[top_10_models]

# Plot accidents by model and phase
phase_model_counts.plot(kind='bar', stacked=True, figsize=(12, 6), color=['Blue', 'Red', 'Green'])
plt.title("Incidents by Top Aircraft Models by Flight Phase (Landing, Takeoff, Cruise)")
plt.xlabel("Aircraft Model")
plt.ylabel("Number of Accidents")
plt.xticks(rotation=45)
plt.legend(["Landing", "Takeoff", 'Cruise'], loc="upper right")
plt.tight_layout()
plt.show()
```



Weather.Condition

Analyisis Made on the Table & Graph below

- **Data Breakdown:** VMC conditions show a low injury rate of 10.75%, indicating safer traffic incidents in clear weather, while IMC conditions exhibit a higher injury rate of 22.37%, reflecting the increased risk associated with poor visibility and weather.
- **Comparing VMC & IMC:** The injury rate is notably lower in VMC (10.75%) compared to IMC (22.37%), highlighting that clearer weather leads to fewer injuries. Despite both conditions having high non-injured percentages, IMC is more hazardous with increased injury likelihood.
- **Made Conclusion:** Clearer weather (VMC) results in fewer injuries, while poor visibility and adverse weather (IMC) increase the likelihood of injury, emphasizing the importance of weather conditions in traffic safety and the need for caution in less favorable weather.

In [49]:

```
# Group by 'Weather.Condition' and calculate required statistics
Weather_summary = Aviation_df.groupby('Weather.Condition').agg(
    Total_Injured=('Total.injured', 'sum'),
    Total_Uninjured=('Total.Uninjured', 'sum'),
    Total_Times=('Weather.Condition', 'size')
)

# Calculate Injured and Non-injured Percentages
Weather_summary[['Injured Percentage (%)', 'Non-injured Percentage (%)']] = (
    Weather_summary[['Total_Injured', 'Total_Uninjured']]
    .div(Weather_summary[['Total_Injured', 'Total_Uninjured']].sum(axis=1), axis=0) * 100
)

# Sort by 'Total_Times' and display top 10 results
Weather_summary.sort_values('Total_Times', ascending=False).head(10)
```

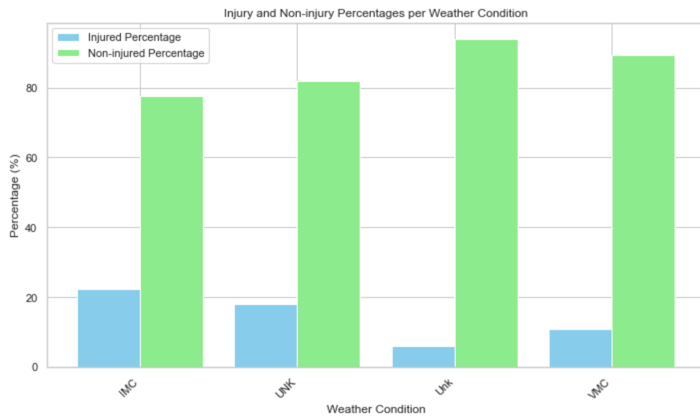
Out[49]:

Weather.Condition	Total_Injured	Total_Uninjured	Total_Times	Injured Percentage (%)	Non-injured Percentage (%)
VMC	36539.0	303449.0	77303	10.747144	89.252856
IMC	11437.0	39684.0	5976	22.372411	77.627589
UNK	2279.0	10301.0	856	18.116057	81.883943
Unk	457.0	7041.0	262	6.094959	93.905041

In [50]:

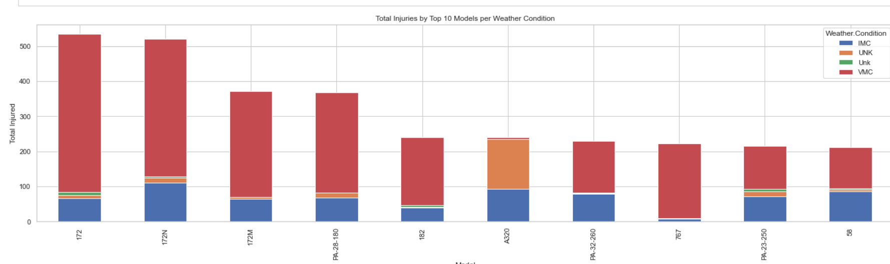
```
import numpy as np

# Plotting the bar chart for Injury and Non-injury Percentages per Weather Condition
```

```python
x = np.arange(len(Weather_summary.index))  # Create an array for the x-axis positions
width = 0.4  # Width of the bars

plt.figure(figsize=(10, 6))

# Bar for Injured Percentage
plt.bar(x - width/2, Weather_summary['Injured Percentage (%)'], width, color='skyblue', label='Injured Percentage')

# Bar for Non-injured Percentage
plt.bar(x + width/2, Weather_summary['Non-injured Percentage (%)'], width, color='lightgreen', label='Non-injured Percenta

# Adding labels and title
plt.xlabel('Weather Condition')
plt.ylabel('Percentage (%)')
plt.title('Injury and Non-injury Percentages per Weather Condition')
plt.xticks(x, Weather_summary.index, rotation=45, ha='right')  # Add weather conditions as x-axis labels
plt.legend()

# Adjust layout to avoid clipping
plt.tight_layout()

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



In [54]:

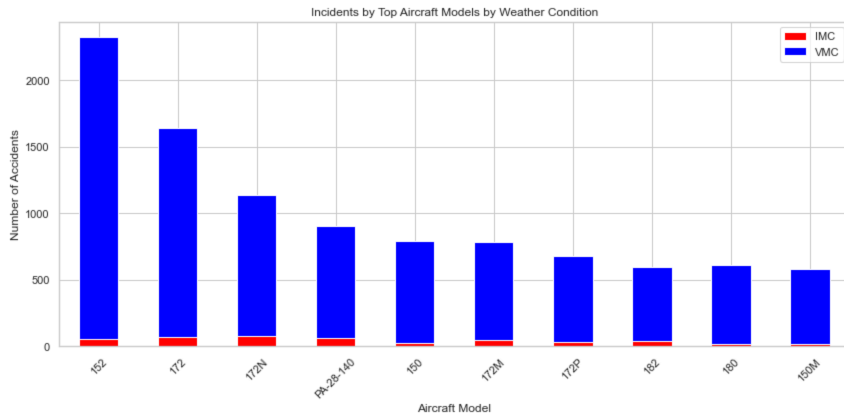
```python
import matplotlib.pyplot as plt

# Create a pivot table for Total.Injured by Model per Weather.Condition
pivot_table2 = Aviation_df.pivot_table(
    values='Total.injured',
    index='Model',
    columns='Weather.Condition',
    aggfunc='sum'
).dropna()

# Calculate the total number of accidents (Total Injured) for each model
pivot_table2['Total.Injured'] = pivot_table2.sum(axis=1)

# Sort the models by the total number of injuries (for each weather condition) and get the top 10
top_10_models = pivot_table2['Total.Injured'].sort_values(ascending=False).head(10).index
pivot_table2 = pivot_table2.loc[top_10_models]

# Plot the bar graph
pivot_table2.drop(columns='Total.Injured').plot(kind='bar', stacked=True, figsize=(20, 6))

# Add title and labels
plt.title('Total Injuries by Top 10 Models per Weather Condition')
plt.xlabel('Model')
plt.ylabel('Total Injured')

# Rotate x-axis labels for better readability
plt.xticks(rotation=90)

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



In [57]:

```python
# Filter dataset for critical weather condtion (IMV, VMC)
most_phases = ['IMC', 'VMC']
phase_filtered = Aviation_df[Aviation_df['Weather.Condition'].isin(most_phases)]

# Count accidents by model and weather condition
phase_model_counts = phase_filtered.groupby(['Model', 'Weather.Condition']).size().unstack().fillna(0)

# Select top models for analysis
top_10_models = top_20_models.head(10).index
phase_model_counts = phase_model_counts.loc[top_10_models]

# Plot accidents by model and phase
phase_model_counts.plot(kind='bar', stacked=True, figsize=(12, 6), color=['Red', 'Blue'])
plt.title("Incidents by Top Aircraft Models by Weather Condition")
plt.xlabel("Aircraft Model")
plt.ylabel("Number of Accidents")
plt.xticks(rotation=45)
plt.legend(["IMC", "VMC", 'Cruise'], loc="upper right")
```

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

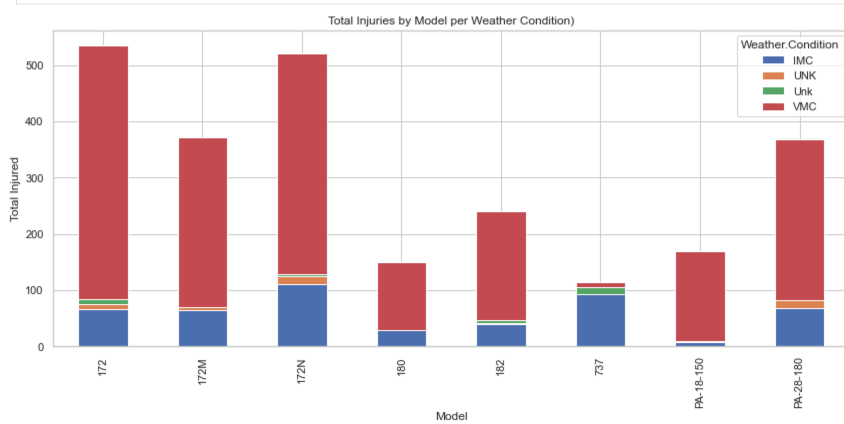


Injuries Graph Analysis

- **Weather Conditions:** VMC accounts for most injuries across models, emphasizing risks from operational or mechanical factors over weather. IMC injuries, present only in the 737, 182, and PA-28-180, remain minimal.
- **Aircraft Models:** General aviation models show injuries almost entirely under VMC, pointing to non-weather-related causes. The 737 reports significant injuries under both VMC and IMC, reflecting challenges in commercial aviation.

In [32]:

```python
import matplotlib.pyplot as plt

# Get the top 20 models based on the count of occurrences in Model_summary
top_20_models = Model_summary.sort_values('Total_Model', ascending=False).head(20).index

# Filter Aviation_df to include only rows where 'Model' is in the top 20 models
Aviation_df['top_20_models'] = Aviation_df['Model'].where(Aviation_df['Model'].isin(top_20_models))

# Drop rows where the 'top_20_models' column is NaN (i.e., models not in the top 20)
Aviation_df_filtered = Aviation_df.dropna(subset=['top_20_models'])

# Create a pivot table for Total.Injured by Model per Weather.Condition
pivot_table2 = Aviation_df_filtered.pivot_table(
    values='Total.injured',
    index='top_20_models',
    columns='Weather.Condition',
    aggfunc='sum'
).dropna()

# Plot the bar graph
pivot_table2.plot(kind='bar', stacked=True, figsize=(12, 6))

# Add title and labels
plt.title('Total Injuries by Model per Weather Condition)')
plt.xlabel('Model')
plt.ylabel('Total Injured')

# Rotate x-axis labels for better readability
plt.xticks(rotation=90)

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



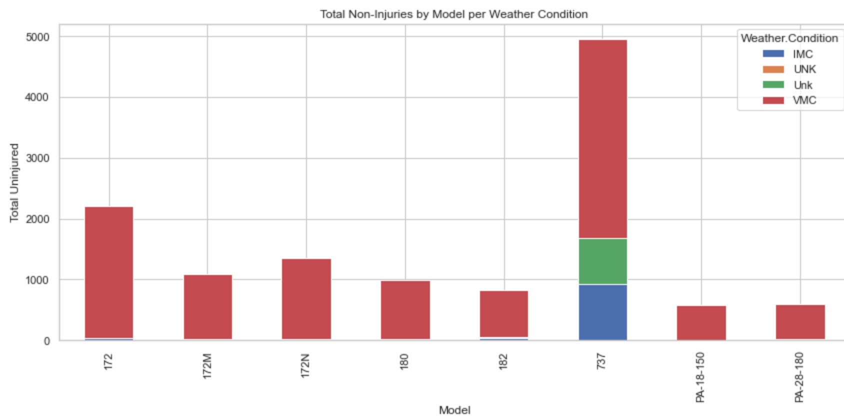
Non-Injuries Graph Analysis

- **Weather Conditions:** VMC incidents dominate across all models, indicating favorable weather does not prevent non-injury occurrences. IMC incidents are minimal, found only in the 737, suggesting effective weather handling in most cases.
- **Aircraft Models:** General aviation models (e.g., 172 series, PA-18-150) show far fewer non-injuries than the 737, with all incidents occurring under VMC. The 737's higher count reflects its operational scope.

In [39]:

```python
import matplotlib.pyplot as plt

# Get the top 20 models based on the count of occurrences in Model_summary
top_20_models = Model_summary.sort_values('Total_Model', ascending=False).head(20).index

# Filter Aviation_df to include only rows where 'Model' is in the top 20 models
Aviation_df['top_20_models'] = Aviation_df['Model'].where(Aviation_df['Model'].isin(top_20_models))
```

```
# Drop rows where the 'top_20_models' column is NaN (i.e., models not in the top 20)
Aviation_df_filtered = Aviation_df.dropna(subset=['top_20_models'])

# Create a pivot table for Total.Injured by Model per Weather.Condition
pivot_table3 = Aviation_df_filtered.pivot_table(
    values='Total.Uninjured',
    index='top_20_models',
    columns='Weather.Condition',
    aggfunc='sum'
).dropna()

# Plot the bar graph
pivot_table3.plot(kind='bar', stacked=True, figsize=(12, 6))

# Add title and labels
plt.title('Total Non-Injuries by Model per Weather Condition')
plt.xlabel('Model')
plt.ylabel('Total Uninjured')

# Rotate x-axis labels for better readability
plt.xticks(rotation=90)

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



Other Datasets

Make

Analysis made based on the Table & Graphs below

- **Way More Incidencies, Way Lower Injury Rate:** Aircraft like Boeing and Grumman have relatively low injury rates despite a high number of incidents, indicating they may be safer in terms of injuries in comparison to other makes.
- **Highest Risk:** Aircraft like Bell, Mooney, and Piper exhibit higher injury rates, particularly in relation to their total incidents, which may suggest that these makes might have a higher risk associated with injuries.
- **Further Invesigations Needed:** The dataset highlights significant variation in injury rates across different makes, with some aircraft types showing much higher injury rates than others, which may warrant further investigation into the underlying causes (e.g., design, usage frequency, types of incidents, or operational environments).

In [34]:
```
Aviation_df['Make'] = Aviation_df['Make'].str.strip().str.lower()

# Group by 'Make' and calculate all required statistics in one step
Make_summary = Aviation_df.groupby('Make').agg(
    Total_Injured=('Total.injured', 'sum'),
    Total_Uninjured=('Total.Uninjured', 'sum'),
    Total_Uses=('Make', 'size')  # Count occurrences of each model
)

# Add percentage columns for injuries and non-injuries
Make_summary['Injured Percentage (%)'] = (
    Make_summary['Total_Injured'] /
    (Make_summary['Total_Injured'] + Make_summary['Total_Uninjured']) * 100
)
Make_summary['Non-injured Percentage (%)'] = (
    Make_summary['Total_Uninjured'] /
    (Make_summary['Total_Injured'] + Make_summary['Total_Uninjured']) * 100
)

# Sort by 'Total_Uses' for the most frequently used models
sorted_Make_summary = Make_summary.sort_values(by='Total_Uses', ascending=False)

# Display the summary
print("Portion of Injured vs Non-Injured by Make Category:")
sorted_Make_summary.head(10)
```

```
Portion of Injured vs Non-Injured by Make Category:
```

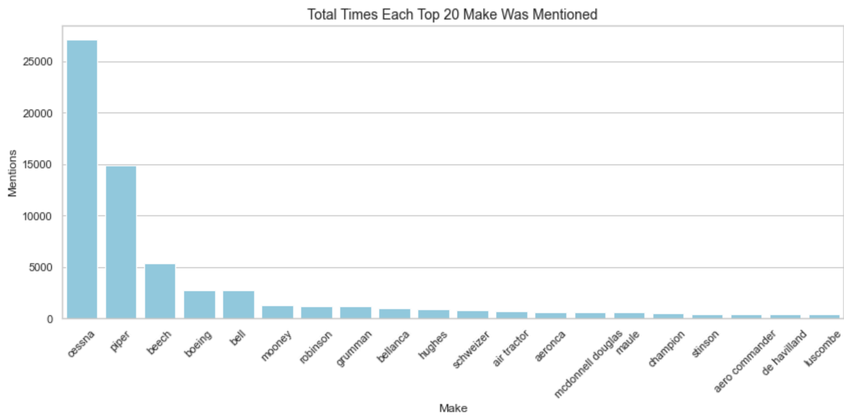
Out[34]:

Make	Total_Injured	Total_Uninjured	Total_Uses	Injured Percentage (%)	Non-injured Percentage (%)
cessna	12425.0	34423.0	27149	26.521943	73.478057
piper	8547.0	17832.0	14870	32.400773	67.599227
beech	4105.0	7891.0	5372	34.219740	65.780260
boeing	8302.0	208375.0	2745	3.831510	96.168490
bell	1925.0	3072.0	2722	38.523114	61.476886
mooney	816.0	1303.0	1334	38.508731	61.491269
robinson	662.0	1132.0	1230	36.900780	63.099220

grumman	340.0	1229.0	1172	21.669853	78.330147
bellanca	489.0	930.0	1045	34.460888	65.539112
hughes	378.0	1118.0	932	25.267380	74.732620

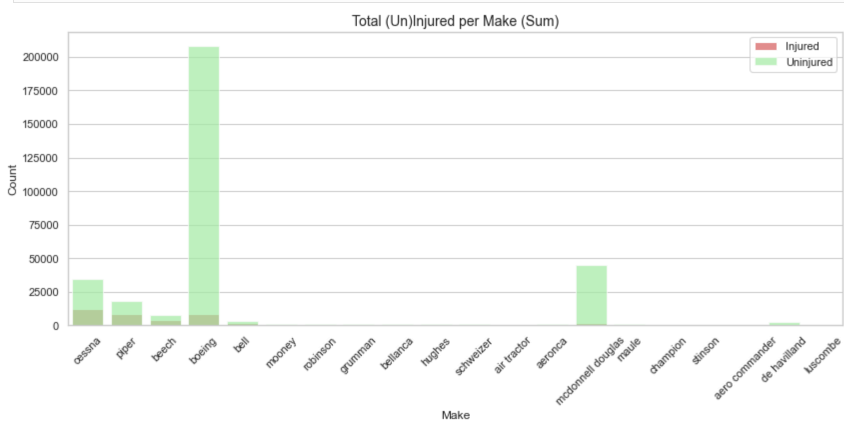
In [ ]:

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

# Set Seaborn style
sns.set_theme(style="whitegrid")

# Graph 1: Total Times Each Make Was Mentioned
plt.figure(figsize=(12, 6))
sns.barplot(data=sorted_Make_summary.head(20), x=sorted_Make_summary.head(20).index, y='Total_Uses', color='skyblue')
plt.title('Total Times Each Top 20 Make Was Mentioned', fontsize=14)
plt.xlabel('Make', fontsize=12)
plt.ylabel('Mentions', fontsize=12)
plt.xticks(rotation=45)
plt.tight_layout()
```



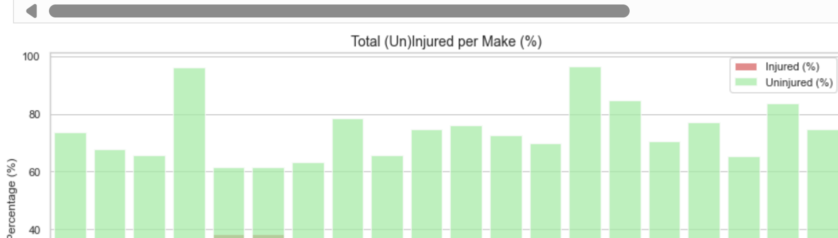
In [59]:

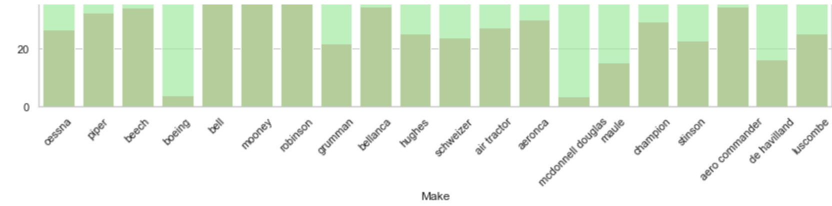
```
# Graph 2: Total Injured vs Uninjured (Sum)
plt.figure(figsize=(12, 6))
sns.barplot(data=sorted_Make_summary.head(20), x=sorted_Make_summary.head(20).index, y='Total_Injured', color='lightcoral
sns.barplot(data=sorted_Make_summary.head(20), x=sorted_Make_summary.head(20).index, y='Total_Uninjured', color='palegreen
plt.title('Total (Un)Injured per Make (Sum)', fontsize=14)
plt.xlabel('Make', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xticks(rotation=45)
plt.legend()
plt.tight_layout()

plt.show()
```



In [60]:

```
# Graph 3: Injured vs Uninjured Percentage
plt.figure(figsize=(12, 6))
sns.barplot(data=sorted_Make_summary.head(20), x=sorted_Make_summary.head(20).index, y='Injured Percentage (%)', color='l
sns.barplot(data=sorted_Make_summary.head(20), x=sorted_Make_summary.head(20).index, y='Non-injured Percentage (%)', colo
plt.title('Total (Un)Injured per Make (%)', fontsize=14)
plt.xlabel('Make', fontsize=12)
plt.ylabel('Percentage (%)', fontsize=12)
plt.xticks(rotation=45)
plt.legend()
plt.tight_layout()

plt.show()
```





Purpose.of.Flight

Analysis on the Data

This dataset provides valuable insights into the relationship between the purpose of flight and the injury risk associated with different aviation activities.

- ***Aerial Observation*** flights have the highest injury rate, potentially indicating the risks associated with surveillance or monitoring activities.
- ***Personal flights*** have a high number of incidents and injuries, suggesting that these are the most common but also the most dangerous type of flight in terms of injury rate.
- ***Instructional flights*** have the lowest injury rate, which could be due to the controlled and supervised nature of the flights
- ***Unknown flights*** have a very low injury rate, possibly due to a large number of incidents with minor or no injuries.
- ***Business, Positioning, and Other Work*** Use flights show moderate injury rates, reflecting the risks of more operational or commercial flights.

In [36]:

```
# Group by 'Make' and calculate all required statistics in one step
Purpose_summary = Aviation_df.groupby('Purpose.of.flight').agg(
    Total_Injured=('Total.injured', 'sum'),
    Total_Uninjured=('Total.Uninjured', 'sum'),
    Total_Times=('Purpose.of.flight', 'size')  # Count occurrences of each model
)

# Add percentage columns for injuries and non-injuries
Purpose_summary['Injured Percentage (%)'] = (
    Purpose_summary['Total_Injured'] /
    (Purpose_summary['Total_Injured'] + Purpose_summary['Total_Uninjured']) * 100
)
Purpose_summary['Non-injured Percentage (%)'] = (
    Purpose_summary['Total_Uninjured'] /
    (Purpose_summary['Total_Injured'] + Purpose_summary['Total_Uninjured']) * 100
)

# Sort by 'Total_Times' for the most frequently used models
sorted_Purpose_summary = Purpose_summary.sort_values(by='Total_Times', ascending=False)

# Display the summary
print("Portion of Injured vs Non-Injured by Weather.Condition:")
sorted_Purpose_summary.head(10)
```

```
Portion of Injured vs Non-Injured by Weather.Condition:
```

Out[36]:

Purpose.of.flight	Total_Injured	Total_Uninjured	Total_Times	Injured Percentage (%)	Non-injured Percentage (%)
Personal	25388.0	52052.0	49448	32.784091	67.215909
Instructional	2891.0	12580.0	10601	18.686575	81.313425
Unknown	11445.0	166487.0	6802	6.432233	93.567767
Aerial Application	997.0	2944.0	4712	25.298148	74.701852
Business	2857.0	6471.0	4018	30.628216	69.371784
Positioning	683.0	2122.0	1646	24.349376	75.650624
Other Work Use	749.0	1878.0	1264	28.511610	71.488390
Ferry	302.0	634.0	812	32.264957	67.735043
Aerial Observation	646.0	912.0	794	41.463415	58.536585
Public Aircraft	457.0	1671.0	720	21.475564	78.524436

Engine.Type

Quick Analysis

- **Reciprocating engines** have a high number of incidents (69,530) with a relatively high injury percentage (30.10%), indicating a moderate level of risk. Turbo Shaft engines have a higher injury rate (34.54%) with fewer incidents (3,609), reflecting a slightly riskier profile compared to reciprocating engines.
- **Turbo Prop engines** have the lowest injury percentage (13.69%), showing that they tend to be safer in terms of injuries despite a moderate number of incidents (3,391). Turbo Fan and Turbo Jet engines have very low injury rates (around 2.47% and 2.89%, respectively), suggesting these engine types are generally safer, despite fewer total incidents.
- **Geared Turbofan** engines show no reported injuries in the dataset, with a 100% non-injury rate. Electric engines and LR engines show higher injury rates (30% and 65.63%, respectively), though their total number of incidents is very low.

In [63]:

```
# Group by 'Engine.Type' and calculate required statistics in one step
Engine_summary = Aviation_df.groupby('Engine.Type').agg(
    Total_Injured=('Total.injured', 'sum'),
    Total_Uninjured=('Total.Uninjured', 'sum'),
    Total_Uses=('Engine.Type', 'size')
)

# Calculate Injured and Non-injured Percentages
Engine_summary['Injured Percentage (%)'] = Engine_summary['Total_Injured'] / (Engine_summary['Total_Injured'] + Engine_su
Engine_summary['Non-injured Percentage (%)'] = Engine_summary['Total_Uninjured'] / (Engine_summary['Total_Injured'] + Eng

# Sort by 'Total_Uses'
```

```
sorted_Engine_summary = Engine_summary.sort_values('Total_Uses', ascending=False)

# Display top 10 results
sorted_Engine_summary.head(10)
```

Out[63]:

	Total_Injured	Total_Uninjured	Total_Uses	Injured Percentage (%)	Non-injured Percentage (%)
Engine.Type					
Reciprocating	32408.0	75246.0	69530	30.103851	69.896149
Turbo Shaft	2563.0	4858.0	3609	34.537124	65.462876
Turbo Prop	2670.0	16835.0	3391	13.688798	86.311202
Turbo Fan	5357.0	211048.0	2481	2.475451	97.524549