Data-Driven Decision Support for Aircraft Procument

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Overview

This project aims to support the company's data-driven decision to procure relatively low-risk airplane models to operate the fleet in the commercial and private enterprise sectors. It analyzes a dataset compiled by the National Transportation Safety board and retrieved from Kaggle.com. Presented recommendations are deduced from descriptive statistics results and backed-up by interactive visualizations modeled using Tableau Public.

Business Problem

Venturing into a new industry avails a company of potential growth opportunities. Diversifying a company's portfolio lowers reliance on a single revenue stream (asset diversification) and optimizes resilience against unfavorable business environments/ factors (Luo, 2022). However, venturing into a highly sensitive sector, such as operating airplanes for commercial and private enterprises, necessitates data-driven decisions, strategic implementation, and formative performance evaluation (Altundag & Wynn, 2024). Purchasing airplane models prone to crashing poses a substantial risk to human life, brand image, competitiveness, profitability, and the company's longevity once it ventures into the new industry.

Data Understanding

The NTSB aviation accident database contains information on crashes and contingency incidents within the U.S., its territories, and across international waters from 1962 to 2023. The dataset was retrieved from Kaggle.com (NTSB, 2023). The dataset is formatted as a .csv file with 31 columns and 88889 rows. The columns are meticulously organized to capture variables of interest in aircraft accidents and incidents. Extracting, analyzing, and visualizing relevant data from the dataset is vital to shedding insight into the safest, low-risk airplane models for a new entrant to the commercial aviation industry.

However, the dataset is enormous, contains some missing values duplicates, and needs to be customized to meet new entrants' needs aiming to purchase and operate airplanes for commercial and private enterprises. For instance, it contains data for airplane crashes across multiple scenarios (purpose of the flight), in which some cases exceed the target scope of the company. For this project, the target variables are categorized into Dimensions and Measures. The Dimension variables include: Event Date, Investigation Type, Aircraft Damage, Location, Make, Model, Weather Condition, and Purpose of Flight. The Measure variables include: The number of Engines, Total Fatal Injuries, Total Minor Injuries, and Total Uninjured passengers. The insights yielded from analyzing these variables and visualizing their respective relationships are deemed appropriate for deducing recommendations to support data-driven decisions by the company to procure a fleet that comprises safe, low-risk airplanes

In [1]:
```
# Importing standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

In [2]:
```
# Loading the dataset and creating the master dataframe
df_master = pd.read_csv("Data/AviationData.csv", encoding='latin1', low_memory=Fals
df_master.shape
```

Out[2]: (88889, 31)

Copying the initialy loaded DataFrame to perfom ETL processes without modifying df_master.

In [3]:
```
df=df_master.copy()
df.shape
```

Out[3]: (88889, 31)

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

Out[4]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitu
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	N
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	N
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.922223	-81.8780
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	N
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	N

5 rows × 31 columns

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                88889 non-null  object 
 1   Investigation.Type      88889 non-null  object 
 2   Accident.Number         88889 non-null  object 
 3   Event.Date              88889 non-null  object 
 4   Location                88837 non-null  object 
 5   Country                 88663 non-null  object 
 6   Latitude                34382 non-null  object 
 7   Longitude               34373 non-null  object 
 8   Airport.Code            50249 non-null  object 
 9   Airport.Name            52790 non-null  object 
 10  Injury.Severity         87889 non-null  object 
 11  Aircraft.damage         85695 non-null  object 
 12  Aircraft.Category       32287 non-null  object 
 13  Registration.Number     87572 non-null  object 
 14  Make                    88826 non-null  object 
 15  Model                   88797 non-null  object 
 16  Amateur.Built           88787 non-null  object 
 17  Number.of.Engines       82805 non-null  float64
 18  Engine.Type             81812 non-null  object 
 19  FAR.Description         32023 non-null  object 
 20  Schedule                12582 non-null  object 
 21  Purpose.of.flight       82697 non-null  object 
 22  Air.carrier             16648 non-null  object 
 23  Total.Fatal.Injuries    77488 non-null  float64
 24  Total.Serious.Injuries  76379 non-null  float64
 25  Total.Minor.Injuries    76956 non-null  float64
 26  Total.Uninjured         82977 non-null  float64
 27  Weather.Condition       84397 non-null  object 
 28  Broad.phase.of.flight   61724 non-null  object 
 29  Report.Status           82508 non-null  object 
 30  Publication.Date        75118 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

It is evident that the columns from 4th index to the 30th index are missing some data values.

In [6]:
```
df.dtypes
```

Out[6]:
```
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
```

The data type for all the variables is either an object or a float. This information reveals the need for data type transformations (to be perfomed later).

In [7]:
```
df.isna().sum()
```

Out[7]:
```
Event.Id                      0
Investigation.Type            0
Accident.Number               0
Event.Date                    0
Location                     52
Country                     226
Latitude                  54507
Longitude                 54516
Airport.Code              38640
Airport.Name              36099
Injury.Severity            1000
Aircraft.damage            3194
Aircraft.Category         56602
Registration.Number        1317
Make                         63
Model                        92
Amateur.Built               102
Number.of.Engines          6084
Engine.Type                7077
FAR.Description           56866
Schedule                  76307
Purpose.of.flight          6192
Air.carrier               72241
Total.Fatal.Injuries      11401
Total.Serious.Injuries    12510
Total.Minor.Injuries      11933
Total.Uninjured            5912
Weather.Condition          4492
Broad.phase.of.flight     27165
Report.Status              6381
Publication.Date          13771
dtype: int64
```

Data Preparation

Digital maturity in leveraging novel data analytics is the key driver for aircraft safety. Manufacturers use these technologies to design safer aircraft (Boyd & Stolzer, 2016). On the other hand, companies operating in the airline sector base their strategic procurement plans on data-supported decisions (Altundag & Wynn, 2024). The progressive scope in which key stakeholders in the airline sector are embracing data analytics is reflected in the cumulative number of aircraft accidents and accidents recorded by the NTSB for each decade. Additionally, structural and material design advancements progressively increase aircraft safety. Thus, the first step to cleaning the data is to convert the `Event.Date` format from an object to the datetime format and slice the DataFrame to capture data for accidents and incidents from 2000 to 2023.

In [8]:
```
# Converting the 'Event.Date' column to a datetime dtype
df['Event.Date'] = pd.to_datetime(df['Event.Date'], errors='coerce')
# Incoporating conditionals to select the period between 2000 and 2023
mask_2000_2023 = (df['Event.Date'].dt.year >= 2000) & (df['Event.Date'].dt.year <=
# Applying the masks
df = df[mask_2000_2023]
```

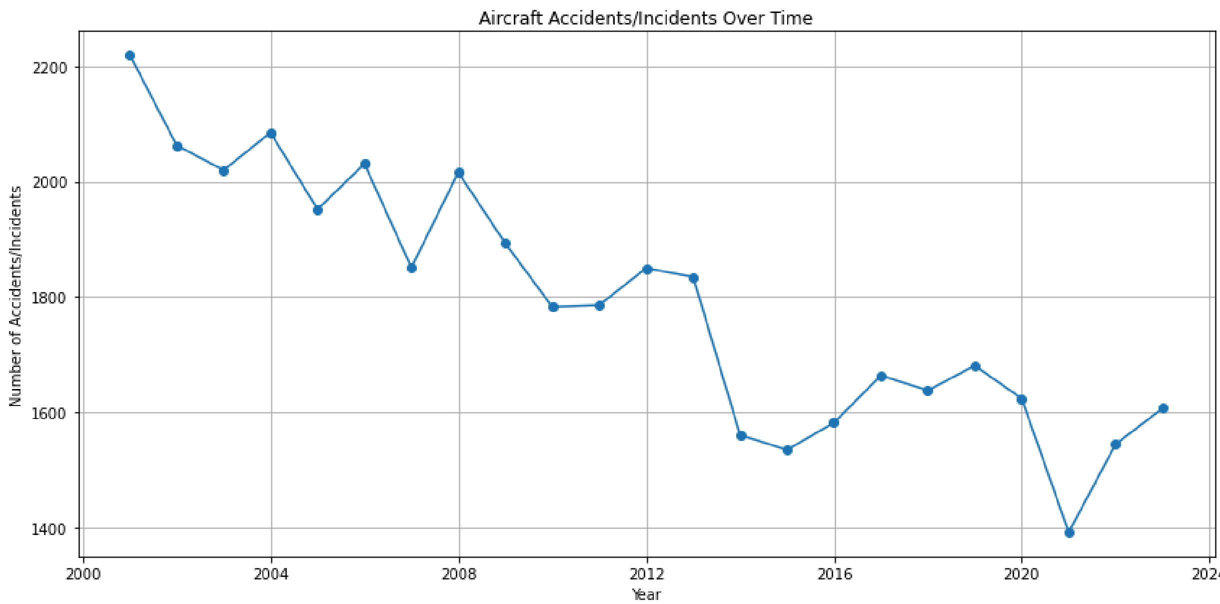
As captured in the time-series plot below, the number of aircraft accidents and incidents has been dropping. The selected period is deemed appropriate because analyzing data for aircraft accidents and incidents before 2000 would comprise the reliability of deduced recommendations for real-world application in the 2020s.

In [9]:
```
# Setting the 'Event.Date' as the index
df.set_index('Event.Date', inplace=True)

# Resampling the data to count incidents per year (year-end)
yearly_counts = df.resample('Y').size()

# Creating the time series line plot
plt.figure(figsize=(12, 6))
plt.plot(yearly_counts.index, yearly_counts.values, marker='o', linestyle='-')

plt.title('Aircraft Accidents/Incidents Over Time')
plt.xlabel('Year')
plt.ylabel('Number of Accidents/Incidents')
plt.grid(True)
plt.tight_layout()
plt.show()
```



The second step is dropping all the columns deemed inappropriate for this project

In [10]:
```
# Dropping columns with data deemed inappropriate per the project's objectives
columns_to_drop = ['Event.Id', 'Latitude', 'Longitude', 'Airport.Code', 'Airport.Na
df.drop(columns = columns_to_drop, inplace=True)
```

In [11]:
```
df.shape
```

Out[11]: (41214, 14)

In [12]:
```
df.dtypes
```

Out[12]:
```
Investigation.Type         object
Location                   object
Country                    object
Aircraft.damage            object
Make                       object
Model                      object
Number.of.Engines         float64
Engine.Type                object
Purpose.of.flight          object
Total.Fatal.Injuries      float64
Total.Serious.Injuries    float64
Total.Minor.Injuries      float64
Total.Uninjured           float64
Weather.Condition          object
dtype: object
```

Droping rows for entries with NaNs except for the float data type columns. The missing values for `Number.of.Engines` are also dropped because the number of engines in an aircraft despite being an interger represent an object and the variable is discrete.

In [13]:
```
df = df.dropna(subset=['Location'])
df = df.dropna(subset=['Aircraft.damage'])
df = df.dropna(subset=['Make'])
df = df.dropna(subset=['Model'])
df = df.dropna(subset=['Number.of.Engines'])
df = df.dropna(subset=['Engine.Type'])
df = df.dropna(subset=['Purpose.of.flight'])
df = df.dropna(subset=['Weather.Condition'])
```

In [14]:
```
df.isna().sum()
```

Out[14]:
```
Investigation.Type            0
Location                      0
Country                       8
Aircraft.damage               0
Make                          0
Model                         0
Number.of.Engines             0
Engine.Type                   0
Purpose.of.flight             0
Total.Fatal.Injuries       9213
Total.Serious.Injuries    10005
Total.Minor.Injuries       9283
Total.Uninjured            4517
Weather.Condition             0
dtype: int64
```

The descriptive statistics for the float data type columns (except Number.of.Engines) are computed to determine the best approach to impute missing values.

In [15]:
```
# Computing the descriptive statistics for float dtype columns
columns_to_check = ['Total.Fatal.Injuries', 'Total.Serious.Injuries', 'Total.Minor.

for col in columns_to_check:
    print(f"Descriptive Statistics for {col}:")
    print(df[col].describe())
```

```
Descriptive Statistics for Total.Fatal.Injuries:
count    20912.000000
mean         0.447972
std          1.111269
min          0.000000
25%          0.000000
50%          0.000000
75%          1.000000
max         88.000000
Name: Total.Fatal.Injuries, dtype: float64
Descriptive Statistics for Total.Serious.Injuries:
count    20120.000000
mean         0.320974
std          0.668653
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          9.000000
Name: Total.Serious.Injuries, dtype: float64
Descriptive Statistics for Total.Minor.Injuries:
count    20842.000000
mean         0.305057
std          0.744264
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max         42.000000
Name: Total.Minor.Injuries, dtype: float64
Descriptive Statistics for Total.Uninjured:
count    25608.000000
mean         1.398899
std          5.919773
min          0.000000
25%          0.000000
50%          1.000000
75%          2.000000
max        386.000000
Name: Total.Uninjured, dtype: float64
```

All four variables exhibit right skewness, meaning most incidents have low injury counts. Since a few incidents have substantially higher counts, the median is more robust to outliers and better represents the typical value in skewed distributions. Thus, imputing missing values with the median for each column is more logical.

In [16]:
```
# Imputing missing values with the median
df.loc[:, 'Total.Fatal.Injuries'] = df['Total.Fatal.Injuries'].fillna(df['Total.Fat
df.loc[:, 'Total.Serious.Injuries'] = df['Total.Serious.Injuries'].fillna(df['Total
df.loc[:, 'Total.Minor.Injuries'] = df['Total.Minor.Injuries'].fillna(df['Total.Min
df.loc[:, 'Total.Uninjured'] = df['Total.Uninjured'].fillna(df['Total.Uninjured'].m
```

In [17]:
```
df.shape
```

Out[17]:
```
(30125, 14)
```

In [18]:
```
df.isna().sum()
```

Out[18]:
```
Investigation.Type       0
Location                 0
Country                  8
Aircraft.damage          0
Make                     0
Model                    0
Number.of.Engines        0
Engine.Type              0
Purpose.of.flight        0
Total.Fatal.Injuries     0
Total.Serious.Injuries   0
Total.Minor.Injuries     0
Total.Uninjured          0
Weather.Condition        0
dtype: int64
```

Although the dataset doesnt have NANs, their could be entries assigned to an unknown variable

Using Lambda functions to drop unknown values for categorical columns

In [19]:
```
df['Aircraft.damage'].value_counts()
```

Out[19]:
```
Substantial    26006
Destroyed       3733
Minor            380
Unknown            6
Name: Aircraft.damage, dtype: int64
```

In [20]:
```
#Using a lambda function to drop entries with unknown
df = df[df['Aircraft.damage'].apply(lambda which_damage: which_damage != 'Unknown')
```

In [21]:
```
df['Engine.Type'].value_counts()
```

Out[21]:
```
Reciprocating    26916
Turbo Prop        1367
Turbo Shaft       1338
Turbo Fan          294
Turbo Jet          145
Unknown             35
None                13
Electric             7
NONE                 2
UNK                  1
LR                   1
Name: Engine.Type, dtype: int64
```

In [22]:
```
#Using a lambda function to drop entries with unknown
df = df[df['Engine.Type'].apply(lambda drop_unknown: (drop_unknown != 'Unknown') &
```

In [23]:
```
df['Purpose.of.flight'].value_counts()
```

Out[23]:
```
Personal                     19838
Instructional                 4332
Aerial Application            1544
Business                       879
Positioning                    773
Other Work Use                 487
Flight Test                    344
Aerial Observation             326
Unknown                        314
Public Aircraft                220
Ferry                          169
Executive/corporate            148
Skydiving                      132
Banner Tow                      94
External Load                   92
Public Aircraft - Federal       86
Public Aircraft - Local         67
Public Aircraft - State         60
Air Race show                   57
Air Race/show                   48
Glider Tow                      35
Firefighting                    22
Air Drop                         8
PUBS                             2
ASHO                             2
PUBL                             1
Name: Purpose.of.flight, dtype: int64
```

In [24]:
```
# Using a Lambda function to select only entries whose purpose of flight are releva
df = df[df['Purpose.of.flight'].apply(lambda niche: niche in ['Aerial Application',
```

In [25]:
```
df.shape
```

Out[25]:
```
(2571, 14)
```

In [26]:
```
df['Weather.Condition'].value_counts()
```

Out[26]:
```
VMC    2376
IMC     191
UNK       2
Unk       2
Name: Weather.Condition, dtype: int64
```

In [27]:
```
#Using a lambda function to drop entries with unknown
df = df[df['Weather.Condition'].apply(lambda drop_unknown: (drop_unknown != 'Unk')
```

In [28]:
```
df['Make'].value_counts()
```

Out[28]:
```
Cessna              265
Air Tractor         220
AIR TRACTOR INC     154
CESSNA              153
Piper               142
                   ...
Siai-Marchetti        1
Stinson               1
Fairchild Merlin      1
Walker                1
ULTRAMAGIC SA         1
Name: Make, Length: 297, dtype: int64
```

Converting all the values in the `Make` column to uppercase

In [29]:
```
df['Make'] = df['Make'].str.upper().str.strip()
```

In [30]:
```
df['Make'].value_counts()
```

Out[30]:
```
CESSNA                   418
AIR TRACTOR              265
PIPER                    231
BELL                     224
AIR TRACTOR INC          156
                        ...
CONSOLIDATED-VULTEE        1
YUNEEC                     1
SIAI MARCHETTI             1
TAYLORCRAFT                1
ULTRAMAGIC SA              1
Name: Make, Length: 233, dtype: int64
```

Since their is another USState.csv is another file attached (Presumed to be utilized in ploting a regional map in Tableau), the `Country` column is sliced to only feature rows whose value is United States

In [31]:
```
# Using a lambda function to select entries for accidents and incidents that happen
df = df[df['Country'].apply(lambda which_country: which_country == 'United States')
```

Spliting the state abbreviation section from the location's values and creating a new column `Abbreviation` to hold them. The created new column will facilitate the establishment of a relationship with the USState.csv dataset when plotting visualizations in Tableau Desktop.

In [32]:
```
# Creating a new column 'Abbreviation' and extracting the Abbreviations for the sta
df['Abbreviation'] = df['Location'].apply(lambda x: x.split(', ')[-1] if isinstance
# Overwriting the 'Location' column with values that dont feature the Abbreviation
df['Location'] = df['Location'].apply(lambda x: x.split(', ')[0] if isinstance(x, s
# Removing the 'Abbreviation' column from the dataframe
abbreviation_col = df.pop('Abbreviation')
# Inserting the 'Abbreviation' column next to the 'Location' column
df.insert(df.columns.get_loc('Location') + 1, 'Abbreviation', abbreviation_col)
```

In [33]:
```
df.head()
```

Out[33]:

Event.Date	Investigation.Type	Location	Abbreviation	Country	Aircraft.damage	Make	Model	Number.of
2000-01-13	Accident	FILLMORE	UT	United States	Substantial	BEECH	K35	
2000-01-18	Accident	BRAWLEY	CA	United States	Substantial	BELL	OH-58C	
2000-01-18	Accident	SOMERSET	KY	United States	Destroyed	BEECH	C-90	
2000-01-20	Accident	PLAINVILLE	CT	United States	Substantial	CESSNA	T310R	
2000-01-25	Accident	RAYVILLE	LA	United States	Substantial	AIR TRACTOR	AT-401	

Checking if there are missing values in the newly created `Abbreviations` folder

In [34]:
```
df['Abbreviation'].isna().sum()
```

Out[34]: 4

In [35]:
```
df = df.dropna(subset=['Abbreviation'])
```

In [36]:
```
df.shape
```

Out[36]: (2534, 15)

Checking for duplicate rows

In [37]:
```
df.duplicated().sum()
```

Out[37]: 16

In [38]:
```
df.drop_duplicates()
```

Out[38]:

	Investigation.Type	Location	Abbreviation	Country	Aircraft.damage	Make	Model	Numbe
Event.Date								
2000-01-13	Accident	FILLMORE	UT	United States	Substantial	BEECH	K35	
2000-01-18	Accident	BRAWLEY	CA	United States	Substantial	BELL	OH-58C	
2000-01-18	Accident	SOMERSET	KY	United States	Destroyed	BEECH	C-90	
2000-01-20	Accident	PLAINVILLE	CT	United States	Substantial	CESSNA	T310R	
2000-01-25	Accident	RAYVILLE	LA	United States	Substantial	AIR TRACTOR	AT-401	
...	...	...	...	...	...	...	...	
2022-08-03	Accident	Melville	LA	United States	Substantial	AIR TRACTOR INC	AT-502B	
2022-08-05	Accident	Maynard	IA	United States	Substantial	ROBINSON HELICOPTER COMPANY	R44 II	
2022-08-07	Accident	Circle	MT	United States	Substantial	AIR TRACTOR INC	AT-301	
2022-08-16	Accident	Millville	MN	United States	Substantial	ROBINSON HELICOPTER CO	R66	
2022-08-25	Accident	Murray	NE	United States	Substantial	AIR TRACTOR INC	AT-602	

2518 rows × 15 columns

In [39]:
```
df.dtypes
```

Out[39]:
```
Investigation.Type          object
Location                    object
Abbreviation                object
Country                     object
Aircraft.damage             object
Make                        object
Model                       object
Number.of.Engines          float64
Engine.Type                 object
Purpose.of.flight           object
Total.Fatal.Injuries       float64
Total.Serious.Injuries     float64
Total.Minor.Injuries       float64
Total.Uninjured            float64
Weather.Condition           object
dtype: object
```

Making necessary transformations for the data type of the variables to their respective appropriate d-types

In [40]:
```
df['Investigation.Type'] = df['Investigation.Type'].astype('category')
df['Aircraft.damage'] = df['Aircraft.damage'].astype('category')
df['Number.of.Engines'] = df['Number.of.Engines'].astype(str)
df['Engine.Type'] = df['Engine.Type'].astype('category')
df['Purpose.of.flight'] = df['Purpose.of.flight'].astype('category')
df['Weather.Condition'] = df['Weather.Condition'].astype('category')
```

In [41]:
```
df.dtypes
```

Out[41]:
```
Investigation.Type        category
Location                    object
Abbreviation                object
Country                     object
Aircraft.damage           category
Make                        object
Model                       object
Number.of.Engines           object
Engine.Type               category
Purpose.of.flight         category
Total.Fatal.Injuries       float64
Total.Serious.Injuries     float64
Total.Minor.Injuries       float64
Total.Uninjured            float64
Weather.Condition         category
dtype: object
```

Importing the cleaned dataset to a new .csv file

In [42]:
```
df.to_csv("bestest_aviation_data.csv", index=False, encoding='latin1')
```

Data Modeling

Loading the .csv file of the cleaned data

In [43]:
```
# Reading the cleaned .csv file and creating a new dataframe
df_clean = pd.read_csv("Data/bestest_aviation_data.csv",encoding='latin1', low_memo
df_clean.head()
```

Out[43]:

	ï»¿Investigation.Type	Location	Abbreviation	Country	Aircraft.damage	Make	Model	Number.of.Engin
0	Accident	FILLMORE	UT	United States	Substantial	BEECH	K35	1
1	Accident	BRAWLEY	CA	United States	Substantial	BELL	OH-58C	1
2	Accident	SOMERSET	KY	United States	Destroyed	BEECH	C-90	2
3	Accident	PLAINVILLE	CT	United States	Substantial	CESSNA	T310R	2
4	Accident	RAYVILLE	LA	United States	Substantial	AIR TRACTOR	AT-401	1

In [44]:
```
df_clean.columns
```

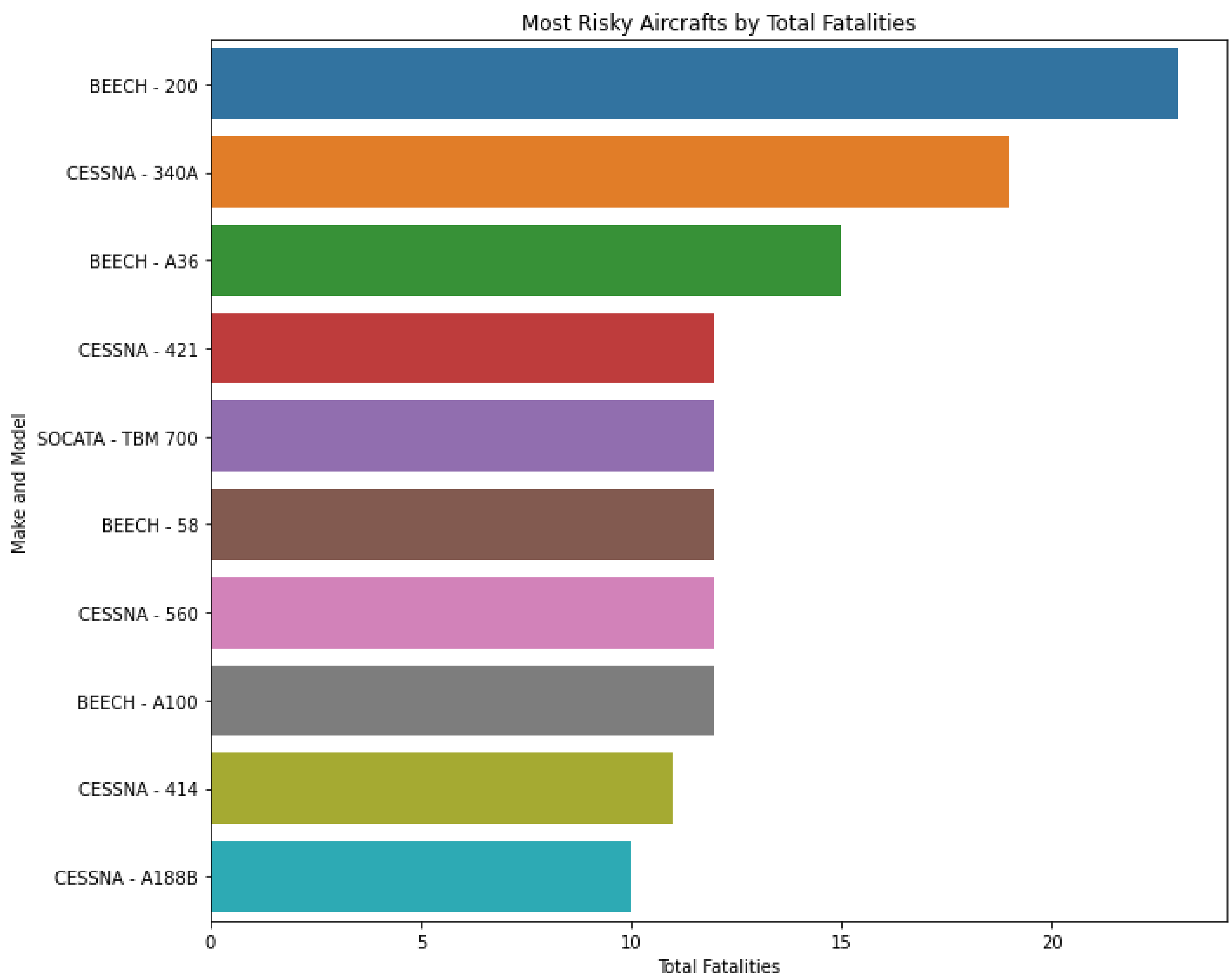
Out[44]:
```
Index(['ï»¿Investigation.Type', 'Location', 'Abbreviation', 'Country',
       'Aircraft.damage', 'Make', 'Model', 'Number.of.Engines', 'Engine.Type',
       'Purpose.of.flight', 'Total.Fatal.Injuries', 'Total.Serious.Injuries',
       'Total.Minor.Injuries', 'Total.Uninjured', 'Weather.Condition'],
      dtype='object')
```

The Least Safe Aircrafts Overall

To gain insight on the least safe aircrafts, I group the `Model` and the `Make` variable and plot a barplot against `Total.Fatal.Injuries`

In [45]:
```
# Groupby 'Make' and 'Model', and sum 'Total.Uninjured'
uninjured_by_make_model = df_clean.groupby(['Make', 'Model'])['Total.Fatal.Injuries
# Creating a list of the Make and Model labels for the y-axis
make_model_labels = [f"{make} - {model}" for make, model in uninjured_by_make_model
# Creating the horizontal bar plot using seaborn
plt.figure(figsize=(10, 8))  # Adjust figure size as needed
sns.barplot(x=uninjured_by_make_model.values, y=make_model_labels, orient='h')

plt.title('Most Risky Aircrafts by Total Fatalities')
plt.xlabel('Total Fatalities')
plt.ylabel('Make and Model')
plt.tight_layout()
plt.show()
```



It is evident the that CESSNA aircraft accidents and incidents are the most fatal.

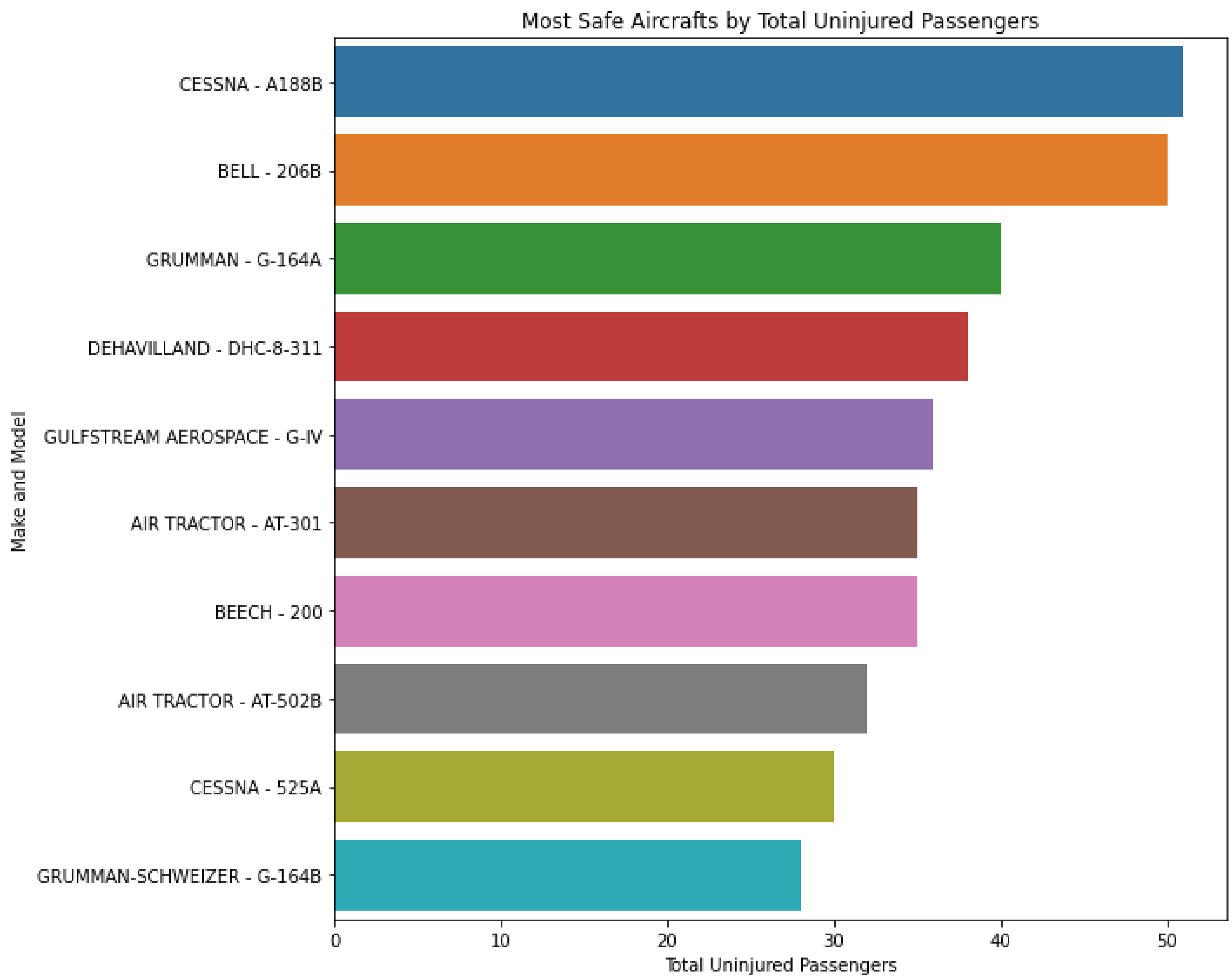
The Most Safe Aircrafts Overall

To gain insight on the safest aircraft model and make, I group the `Model` and the `Make` variable and plot a barplot against `Total.Uninjured`

In [46]:
```
# Group by 'Make' and 'Model', and sum 'Total.Uninjured'
uninjured_by_make_model = df_clean.groupby(['Make', 'Model'])['Total.Uninjured'].su

# Creating a list of the Make and Model labels for the y-axis
make_model_labels = [f"{make} - {model}" for make, model in uninjured_by_make_model

# Creating the horizontal bar plot using seaborn
plt.figure(figsize=(10, 8))  # Adjust figure size as needed
sns.barplot(x=uninjured_by_make_model.values, y=make_model_labels, orient='h')
plt.title('Most Safe Aircrafts by Total Uninjured Passengers')
plt.xlabel('Total Uninjured Passengers')
plt.ylabel('Make and Model')
plt.tight_layout()
plt.show()
```



Determining the safest aircraft models for each of the three civil aviation services the company can venture into. The three categorical values for the `Purpose.of.Flight` columns are plotted in a barplot against uninjured passengers `Total.Uninjured`.

Recommended Aircrafts for Targeted Aviation Services' Niche

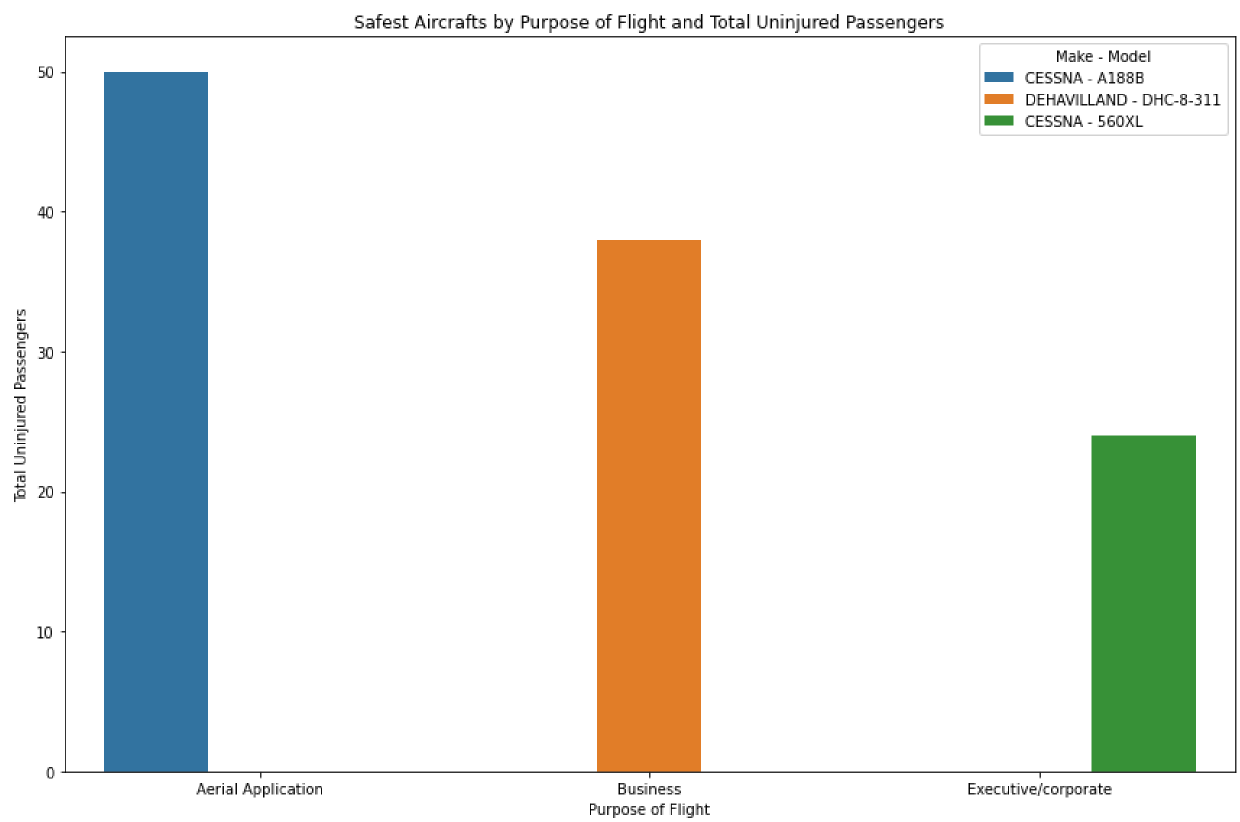
In [47]:
```
# Filtering for the relevant Purpose.of.flight values
df_filtered = df_clean[df_clean['Purpose.of.flight'].isin(['Aerial Application', 'B

# Group by 'Purpose.of.flight', 'Make', and 'Model', and sum 'Total.Uninjured'
uninjured_by_purpose_make_model = df_filtered.groupby(['Purpose.of.flight', 'Make',

# Finding the safest aircraft (highest 'Total.Uninjured') for each purpose
safest_aircraft = uninjured_by_purpose_make_model.loc[uninjured_by_purpose_make_mod

# Creating the "Make - Model" column
safest_aircraft['Make - Model'] = safest_aircraft['Make'] + ' - ' + safest_aircraft

# Creating the bar plot using seaborn
plt.figure(figsize=(12, 8))
sns.barplot(x='Purpose.of.flight', y='Total.Uninjured', hue='Make - Model', data=sa
plt.title('Safest Aircrafts by Purpose of Flight and Total Uninjured Passengers')
plt.xlabel('Purpose of Flight')
plt.ylabel('Total Uninjured Passengers')
plt.legend(title='Make - Model')
plt.tight_layout()
plt.show()
```



Evaluation

The baseline model shed the following insights:

- The BEECH-200 (8-seater), the CESSNA-340A (6-seater), and the BEECH-A36 (6-seater), and the are the top-three most risky aircrafts overall.
- The CESSNA-A188B (1-seater), the BELL-206B (5-seater), and the GRUMMAN-G-164A (1-seater) are the top-three safest aircraft models overall.

Recommendations:

- The CESSNA-560XL (10-seater)is the safest aircraft for Executive/corporate flights.
- The DEHAVILLAND-DHC-8-311 (50-seater) is the safest for business flights.
- The CESSNA-A188B (1-seater) is the safest for Aerial Applications.

The number of engines for these aircraft models.

- BEECH-200: 2 engines
- CESSNA-340A:2 engines
- BEECH-A36:1 engine
- BELL-206B: 1 engine
- GRUMMAN-G-164A: 1 engine
- CESSNA-560XL: 2 engines
- CESSNA-A188B: 1 engine
- DEHAVILLAND-DHC-8-311: 2 engines

Multi-engine aircraft are typically safer than one-engine airplanes (Pilot Institute, 2023). Two-engine designs avail redundancy to propulsion units. Pilots can recalibrate controls and continue flying if one engine stalls or malfunctions. In contrast, such an incident in a single-engine aircraft poses a substantial risk of crashing if the gliding distance falls short of a runway or a relatively flat surface for an emergency landing. Thus, I modified the baseline model to drop row entries whose `Number.of.Engines` is less than 2.

In [48]:
```
df_modified = df_clean.copy()
df_modified.shape
```
Out[48]:
```
(2534, 15)
```

In [49]:
```
df_modified = df_modified[df_modified['Number.of.Engines'].apply(lambda x: x >= 2)]
```

In [50]:
```
df_modified['Number.of.Engines'].value_counts()
```
Out[50]:
```
2.0    369
3.0      7
4.0      3
Name: Number.of.Engines, dtype: int64
```

In [51]:
```
df_modified.shape
```
Out[51]:
```
(379, 15)
```

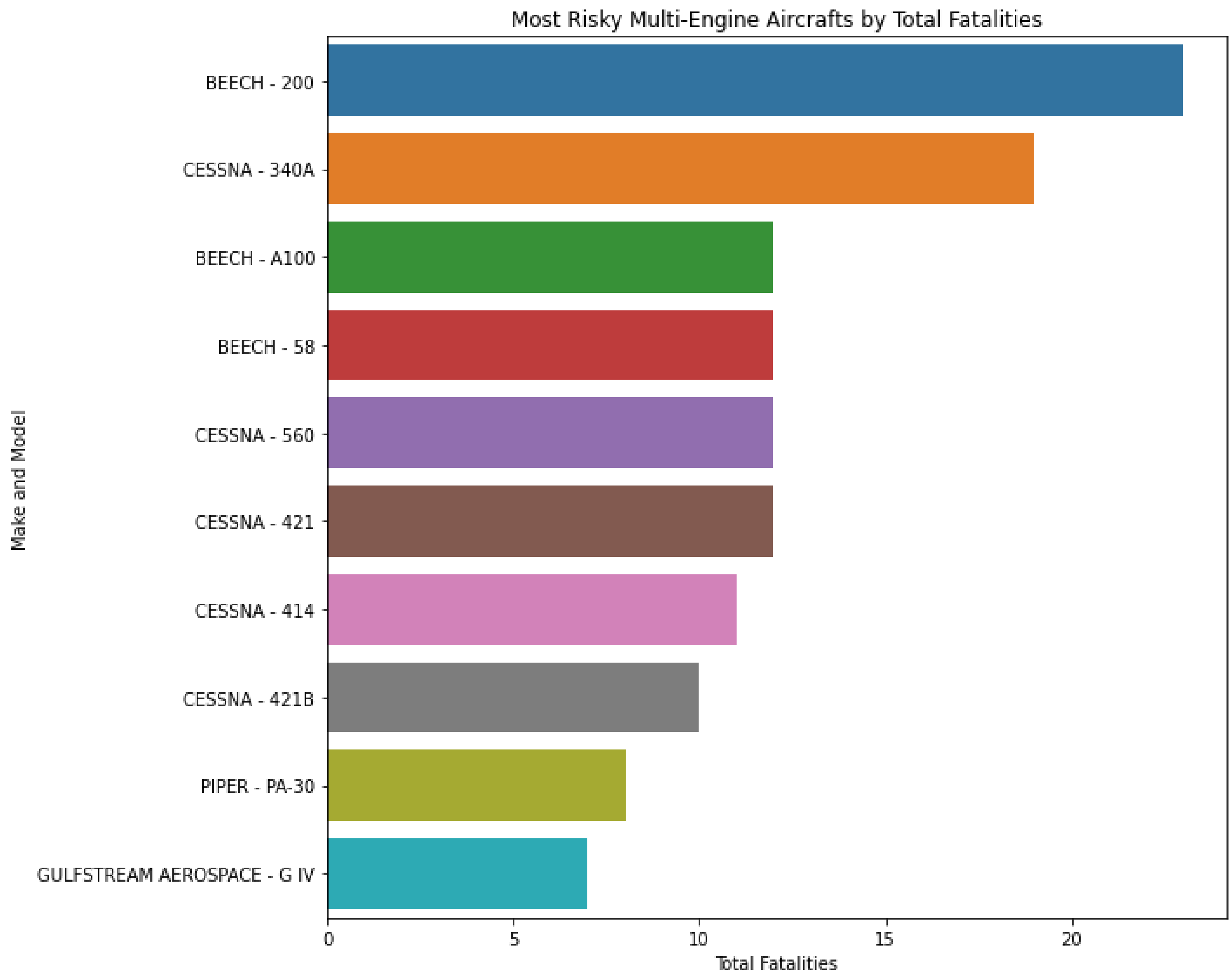
Replotting bar plots to determine the most risky, the safest, and the appropriate airplanes (that have more than one engine) for the company's operations

The Least Safe Multi-Engine Aircrafts

In [52]:
```
# Group by 'Make' and 'Model', and sum 'Total.Uninjured'
uninjured_by_make_model = df_modified.groupby(['Make', 'Model'])['Total.Fatal.Injur

# Creating a list of the Make and Model labels for the y-axis
make_model_labels = [f"{make} - {model}" for make, model in uninjured_by_make_model

# Creating the horizontal bar plot using seaborn
plt.figure(figsize=(10, 8))  # Adjust figure size as needed
sns.barplot(x=uninjured_by_make_model.values, y=make_model_labels, orient='h')
plt.title('Most Risky Multi-Engine Aircrafts by Total Fatalities')
plt.xlabel('Total Fatalities')
plt.ylabel('Make and Model')
plt.tight_layout()
plt.show()
```

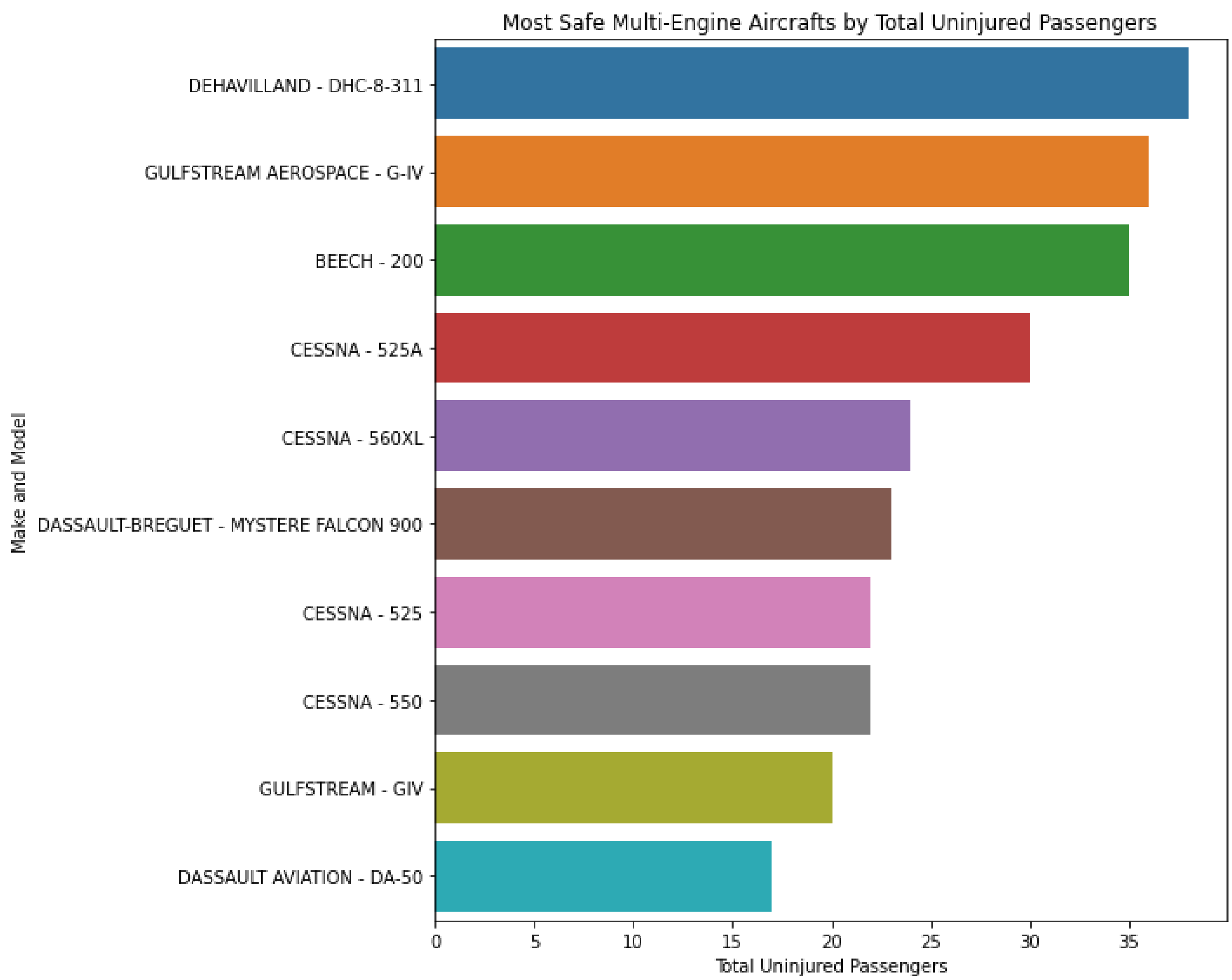


The Most Safe Multi-Engine Aircrafts

In [53]:
```
# Group by 'Make' and 'Model', and sum 'Total.Uninjured'
uninjured_by_make_model = df_modified.groupby(['Make', 'Model'])['Total.Uninjured']

# Creating a list of the Make and Model labels for the y-axis
make_model_labels = [f"{make} - {model}" for make, model in uninjured_by_make_model

# Creating the horizontal bar plot using seaborn
plt.figure(figsize=(10, 8))  # Adjust figure size as needed
sns.barplot(x=uninjured_by_make_model.values, y=make_model_labels, orient='h')
plt.title('Most Safe Multi-Engine Aircrafts by Total Uninjured Passengers')
plt.xlabel('Total Uninjured Passengers')
plt.ylabel('Make and Model')
plt.tight_layout()
plt.show()
```



Recommended Multi-Engine Aircrafts for Targeted Aviation Services' Niche

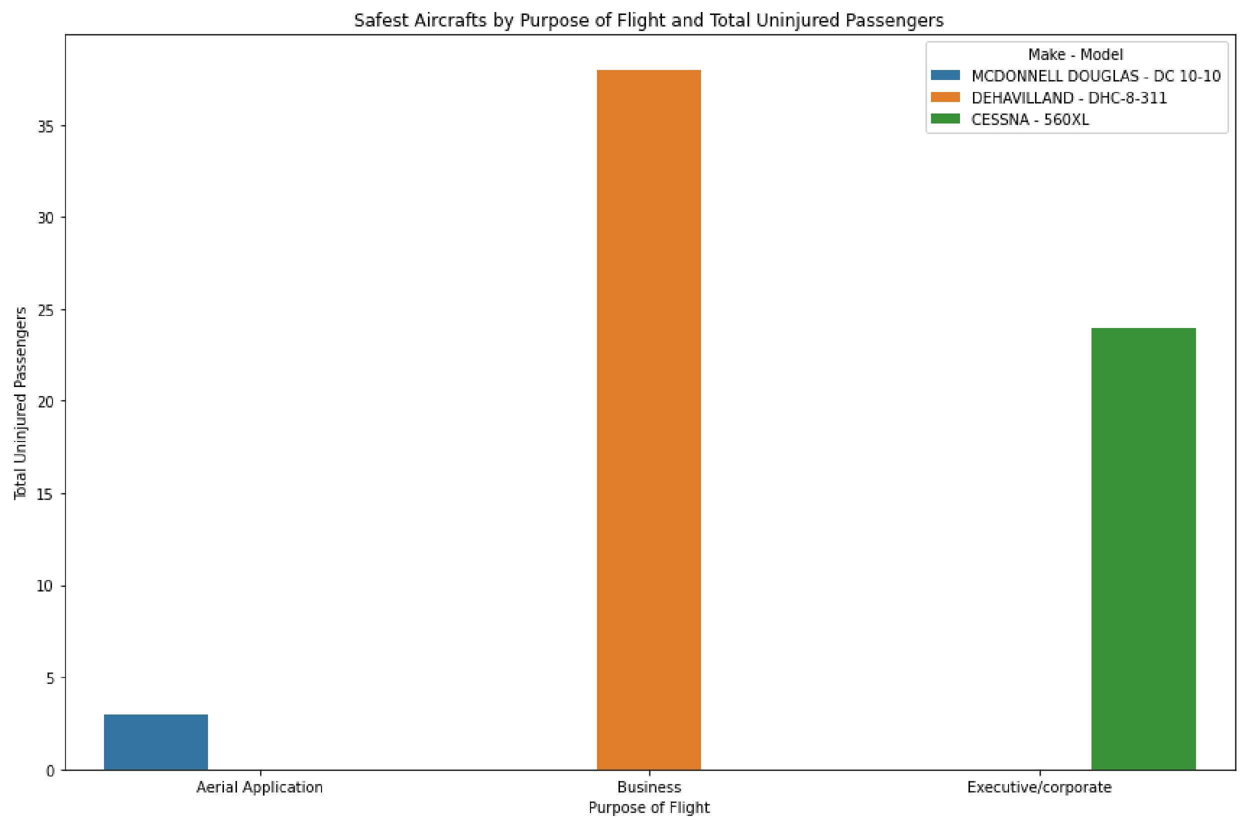
In [54]:
```
# Filtering for the relevant Purpose.of.flight values
df_filtered = df_modified[df_modified['Purpose.of.flight'].isin(['Aerial Applicatio

# Group by 'Purpose.of.flight', 'Make', and 'Model', and sum 'Total.Uninjured'
uninjured_by_purpose_make_model = df_filtered.groupby(['Purpose.of.flight', 'Make',

# Finding the safest aircraft (highest 'Total.Uninjured') for each purpose
safest_aircraft = uninjured_by_purpose_make_model.loc[uninjured_by_purpose_make_mod

# Creating the "Make - Model" column
safest_aircraft['Make - Model'] = safest_aircraft['Make'] + ' - ' + safest_aircraft

# Creating the bar plot using seaborn
plt.figure(figsize=(12, 8))
sns.barplot(x='Purpose.of.flight', y='Total.Uninjured', hue='Make - Model', data=sa
plt.title('Safest Aircrafts by Purpose of Flight and Total Uninjured Passengers')
plt.xlabel('Purpose of Flight')
plt.ylabel('Total Uninjured Passengers')
plt.legend(title='Make - Model')
plt.tight_layout()
plt.show()
```



The modified model shed the following insights:

- The BEECH-200 (13-seater), the CESSNA-340A (6-seater), and the BEECH-A400 (8-seater) are the top-three most risky multi-engine aircrafts overall.
- The DEHAVILLAND DHC-8-311 (50-seater), the GULFSTREAM AEROSPACE-G-IV (10-seater), and the BEECH-200 (13-seater) are the top-three safest multi-engine aircraft models overall.

Recommendations:

- The CESSNA 560XL(10-seater)is the safest multi-engine aircraft for Executive/corporate flights.
- The DEHAVILLAND -DHC-8-311(50-seater) is the safest multi-engine aircraft for business flights.
- The MCDONNELL DOUGLAS-DC 10-10(250-seater) is the safest multi-engine aircraft for Aerial Applications.

The number of engines for these aircraft models.

- BEECH-200: 2 engines
- CESSNA-340A: 2 engines
- BEECH-A400: 2 engines
- GULFSTREAM AEROSPACE-G-IV: 2 engines
- CESSNA 560XL: 2 engines
- DEHAVILLAND DHC-8-311: 2 engines
- MCDONNELL DOUGLAS -DC 10-10: 3 engines

The findings from the results yielded by the baseline model are compared to those yielded by the modified model. After entering the industry, the recommended safest aircraft model for the aviation services the company will offer is based on respective applicability and operational logistics.

Conclusions

The analysis yields three recommendations on the aircraft models the company should procure and operate after entering the commercial aviation industry.

- **The CESSNA-560XL aircraft is recommended for Executive/ Corporate flights:** The baseline and modified model confirm the aircraft is safest for executive and corporate flights.
- **The DEHAVILLAND DHC-8-311 aircraft is recommended for Business Flights:** The baseline and modified model conform the aircraft is safest for business flights.
- **The CESSNA-A188B aircraft is recommended for Aerial Applications:** The modified model proposes the MCDONNELL DOUGLAS-DC 10-10 (a three-engine, 250-seater) aircraft for aerial applications. The proposed alternative by the modified model is rejected because aerial applications typically include agricultural activities such as spraying crop fields. Hence, the single-egine CESSNA-A188B is recommended for aerial applications.

References

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