Final Project Submission

Please fill out:

- Student name: Elizabeth Kiilu
- Student pace: Part Time
- Scheduled project review date/time: 21/7/2025
- Instructor name: Christine Kirimi
- Blog post URL:

INTRODUCTION

African Airways Co. wants to venture into the airplanes business within its region.The vision is to purchase and operate airplanes for commercial and private clients.The company has taken a data driven appoach to make critical decisions for the set-up and onward operation of this new venture, based on assessment of risk factors associated with operating equipment (airplane) and selection of the most risk-averse and profitable model of airplane to launch this business.

This analysis aims at bringing out assessed data that has been modelled to: 1- 2 -Highlight the risks associated with selected airplanes that can be deployed. 3 - Actionable insights to help make decisions for the new business.

1. Accessing and Assessing the Aviation data

In [57]:

```
# Importing the necessary libraries

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

In [58]:

```
#reading our data

df= pd.read_csv('Aviation_Data.csv')
df.head()
```

```
C:\Users\kgn70877\anaconda3\envs\learn-env\lib\site-packages\IPython\core\interactive
shell.py:3145: DtypeWarning: Columns (6,7,28) have mixed types.Specify dtype option o
n import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

Out[58]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.9222
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN

5 rows × 31 columns

In [59]:

```
# To understand the columns type and check for null values

df.info()
```

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

*After assessing the data and given the objective of our analysis, I deemed the following columns uneccesary for the study or had lots of null values hence to be dropped to allow for clarity while analysing data. The columns incude : Event Id, Event date, accident number,latitude, longitude, FAR.Description, Report.Status, Airport.code , Airport.name,schedule, Air.carrier

In [60]:
```
# Removing unnecessary columns with reference to the objective of our analysis and co

df.columns = df.columns.str.strip()
drop_cols =['Event.Id','Events.Date','Longitude','Latitude','Publication.Date','Regis

df = df.drop(columns=[col for col in drop_cols if col in df.columns])
df.shape #moved from 31 to 17 columns
```

Out[60]:
```
(90348, 17)
```

2. Exploring Data Analysis of our remaining columns

In [61]:
```
# filling critical columns with '0' value to allow for usability of the data

col_injury = ['Total.Fatal.Injuries', 'Total.Serious.Injuries','Total.Minor.Injuries

df[col_injury]= df[col_injury].fillna(0)
```

In [62]:
```
# To check distinct values in the Injury.Severity column

df['Injury.Severity'].unique()# only Fatal injury has counts attached to it . require
```

Out[62]:
```
array(['Fatal(2)', 'Fatal(4)', 'Fatal(3)', 'Fatal(1)', 'Non-Fatal',
       'Incident', 'Fatal(8)', 'Fatal(78)', 'Fatal(7)', 'Fatal(6)',
       'Fatal(5)', 'Fatal(153)', 'Fatal(12)', 'Fatal(14)', 'Fatal(23)',
       'Fatal(10)', 'Fatal(11)', 'Fatal(9)', 'Fatal(17)', 'Fatal(13)',
       'Fatal(29)', 'Fatal(70)', 'Unavailable', 'Fatal(135)', 'Fatal(31)',
       'Fatal(256)', 'Fatal(25)', 'Fatal(82)', 'Fatal(156)', 'Fatal(28)',
       'Fatal(18)', 'Fatal(43)', 'Fatal(15)', 'Fatal(270)', 'Fatal(144)',
       'Fatal(174)', 'Fatal(111)', 'Fatal(131)', 'Fatal(20)', 'Fatal(73)',
       'Fatal(27)', 'Fatal(34)', 'Fatal(87)', 'Fatal(30)', 'Fatal(16)',
       'Fatal(47)', 'Fatal(56)', 'Fatal(37)', 'Fatal(132)', 'Fatal(68)',
       'Fatal(54)', 'Fatal(52)', 'Fatal(65)', 'Fatal(72)', 'Fatal(160)',
       'Fatal(189)', 'Fatal(123)', 'Fatal(33)', 'Fatal(110)',
       'Fatal(230)', 'Fatal(97)', 'Fatal(349)', 'Fatal(125)', 'Fatal(35)',
       'Fatal(228)', 'Fatal(75)', 'Fatal(104)', 'Fatal(229)', 'Fatal(80)',
       'Fatal(217)', 'Fatal(169)', 'Fatal(88)', 'Fatal(19)', 'Fatal(60)',
       'Fatal(113)', 'Fatal(143)', 'Fatal(83)', 'Fatal(24)', 'Fatal(44)',
       'Fatal(64)', 'Fatal(92)', 'Fatal(118)', 'Fatal(265)', 'Fatal(26)',
       'Fatal(138)', 'Fatal(206)', 'Fatal(71)', 'Fatal(21)', 'Fatal(46)',
       'Fatal(102)', 'Fatal(115)', 'Fatal(141)', 'Fatal(55)',
       'Fatal(121)', 'Fatal(45)', 'Fatal(145)', 'Fatal(117)',
       'Fatal(107)', 'Fatal(124)', 'Fatal(49)', 'Fatal(154)', 'Fatal(96)',
       'Fatal(114)', 'Fatal(199)', 'Fatal(89)', 'Fatal(57)', 'Fatal', nan,
       'Minor', 'Serious'], dtype=object)
```

In [63]:
```
#To separate the counts in fatal from the status string 'Fatal' by creating a column

df['Severity_Counts'] = df['Injury.Severity'].str.extract(r'Fatal\((\d+)\)').astype(
df['Severity_Counts'] = df['Severity_Counts'].fillna(0)
```

In [64]:
```
# Other critical columns that do not have numerical values but have the 'NAN', we ca

fill_cols = ['Purpose.of.flight', 'Weather.Condition', 'Broad.phase.of.flight','Airc
df[fill_cols] = df[fill_cols].fillna("Unknown")
```

In [65]:
```
# to finally check our dataset again before analysis
df.info()
# we now have no null values and our data is ready for analysis
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 18 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Investigation.Type      90348 non-null  object
 1   Country                 90348 non-null  object
 2   Injury.Severity         90348 non-null  object
 3   Aircraft.damage         90348 non-null  object
 4   Aircraft.Category       90348 non-null  object
 5   Make                    90348 non-null  object
 6   Model                   90348 non-null  object
 7   Amateur.Built           90348 non-null  object
 8   Number.of.Engines       90348 non-null  float64
 9   Engine.Type             90348 non-null  object
 10  Purpose.of.flight       90348 non-null  object
 11  Total.Fatal.Injuries    90348 non-null  float64
 12  Total.Serious.Injuries  90348 non-null  float64
 13  Total.Minor.Injuries    90348 non-null  float64
 14  Total.Uninjured         90348 non-null  float64
 15  Weather.Condition       90348 non-null  object
 16  Broad.phase.of.flight   90348 non-null  object
 17  Severity_Counts         90348 non-null  float64
dtypes: float64(6), object(12)
memory usage: 12.4+ MB
```

3.Conducting Data Analysis

A) Assessing aircraft types and associated high risk factors(Catastrophic)

In [66]:
```
#Combining Aircraft make and model (combining the two to have the specific aircraft)
df['Aircraft_Type'] = df['Make'].astype(str) + ' ' + df['Model'].astype(str) # combi

# Exploring the total Fatal and Serious injuries by adding a total catastrophic  inju

df['Total.catastrophic. Injuries']=(df['Total.Fatal.Injuries'] +df['Total.Serious.In
```

In [67]:
```
#Making assessments from a comibination of factors associated with catastrophic injur

catastrophic_incidence_factors=  df.groupby(['Aircraft_Type','Broad.phase.of.flight',
catastrophic_incidence_factors.head(10)# showing top 10 catastrophic incidences by Ai
```

Out[67]:

	Aircraft_Type	Broad.phase.of.flight	Amateur.Built	Investigation.Type	Purpose.of.flight	Total.catas
0	BOEING 737	Unknown	No	Accident	Unknown	
1	Boeing 737-200	Unknown	No	Accident	Unknown	
2	BOEING 777 - 206	Unknown	No	Accident	Unknown	

	Aircraft_Type	Broad.phase.of.flight	Amateur.Built	Investigation.Type	Purpose.of.flight	Total.catas
3	Boeing MD-82	Unknown	No	Accident	Unknown	
4	AIRBUS A321	Unknown	No	Accident	Unknown	
5	Tupolev TU-154	Unknown	No	Accident	Unknown	
6	Boeing 747-168	Unknown	No	Accident	Unknown	
7	AIRBUS A330	Unknown	No	Accident	Unknown	
8	Boeing 747-121	Unknown	No	Accident	Unknown	
9	Airbus Industrie A300B4-605R	Takeoff	No	Accident	Unknown	

B) Assessing aircraft types and associated minor risks

In [68]:
```
#Making assessments from a comibination of factors associated with minor injuries
minor_incidence_factors=  df.groupby(['Aircraft_Type','Broad.phase.of.flight','Amateu

minor_incidence_factors.head(10)# showing top 10 minor incidences by Aircraft type
```

Out[68]:

	Aircraft_Type	Broad.phase.of.flight	Amateur.Built	Investigation.Type	Purpose.of.flight	Total.Mino
0	Boeing 747-2B6B	Unknown	Yes	Incident	Unknown	
1	Mcdonnell Douglas MD-11	Unknown	No	Accident	Unknown	
2	Boeing 747-122	Cruise	No	Accident	Unknown	
3	Mcdonnell Douglas DC-10-10	Cruise	No	Accident	Unknown	
4	Piper PA-28-140	Takeoff	No	Accident	Personal	
5	Mcdonnell Douglas MD-11	Cruise	No	Accident	Unknown	
6	Mcdonnell Douglas MD-82	Unknown	No	Accident	Unknown	
7	Cessna 208B	Unknown	No	Accident	Unknown	
8	BOEING 737	Unknown	No	Accident	Unknown	

	Aircraft_Type	Broad.phase.of.flight	Amateur.Built	Investigation.Type	Purpose.of.flight	Total.Mino
9	Boeing 737-824	Cruise	No	Accident	Unknown	

C) Assessing aircraft types with associated low risk factors

In [69]:

```
#Making assessments from a comibination of factors associated with uninjuries

lowrisk_incidence_factors=  df.groupby(['Aircraft_Type','Broad.phase.of.flight','Amat

lowrisk_incidence_factors.head(10)# showing top 10 incidences no injuries by Aircraft
```

Out[69]:

	Aircraft_Type	Broad.phase.of.flight	Amateur.Built	Investigation.Type	Purpose.of.flight	Total.Uninj
0	BOEING 737	Unknown	No	Incident	Unknown	14:
1	BOEING 737	Unknown	No	Accident	Unknown	6
2	BOEING 777	Unknown	No	Incident	Unknown	5
3	BOEING 777	Unknown	No	Accident	Unknown	2
4	BOEING 767	Unknown	No	Incident	Unknown	2
5	BOEING 767	Unknown	No	Accident	Unknown	2
6	Boeing 737	Unknown	No	Accident	Unknown	2
7	AIRBUS A320	Unknown	No	Incident	Unknown	1
8	BOEING 787	Unknown	No	Incident	Unknown	1
9	Boeing 747-400	Unknown	No	Accident	Unknown	1

High Risk Fatalities Aircraft

4.Combining analysis for assessment

In [70]:

```
# From the data given, the following aircrafts had the highest value counts meaning,


most_common_operated_aircraft =df['Aircraft_Type'].value_counts().reset_index()
most_common_operated_aircraft.columns = ['Aircraft Type', 'Total Number']
most_common_operated_aircraft.index.name = 'Index'
most_common_operated_aircraft.head(10)
```

Out[70]:

Index	Aircraft Type	Total Number
0	Cessna 152	2168
1	Unknown Unknown	1504
2	Cessna 172	1254

	Aircraft Type	Total Number
Index		
3	Cessna 172N	996
4	Piper PA-28-140	812
5	Cessna 150	716
6	Cessna 172M	667
7	Cessna 172P	597
8	Piper PA-18	539
9	Cessna 150M	539

In [71]:

```
#selecting top 5 of most common operated aircrafts, ommiting the unknown type as indi
most_common_selected_aircrafts =['Cessna 152','Cessna 172','Cessna 172N','Piper PA-28

# creating a dataframe
most_common_selected_flights_df = df[df['Aircraft_Type'].isin (most_common_selected_a

# Tracking the safety records of the most common operated flights selected
safety_record_most_common_aircraft= most_common_selected_flights_df.groupby(['Aircraf
'Total.Uninjured']].sum().reset_index()

safety_record_most_common_aircraft
```

Out[71]:

	Aircraft_Type	Investigation.Type	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Tota
0	Cessna 150	Accident	78.0	104.0	182.0	
1	Cessna 150	Incident	0.0	0.0	2.0	
2	Cessna 152	Accident	349.0	168.0	404.0	
3	Cessna 152	Incident	0.0	0.0	1.0	
4	Cessna 172	Accident	231.0	192.0	325.0	
5	Cessna 172	Incident	0.0	0.0	0.0	
6	Cessna 172N	Accident	365.0	150.0	320.0	
7	Cessna 172N	Incident	0.0	0.0	0.0	
8	Piper PA-28-140	Accident	284.0	219.0	374.0	
9	Piper PA-28-140	Incident	0.0	0.0	0.0	

In [72]:

```
# checking most common operated aircraft track record by investigation type = 'Accide

common_aircraft_accident_safety_record = most_common_selected_flights_df[most_common_
].groupby(['Aircraft_Type', 'Investigation.Type'])[['Total.Fatal.Injuries', 'Total.Se
].sum().reset_index()

common_aircraft_accident_safety_record
```

Out[72]:

	Aircraft_Type	Investigation.Type	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Tota
0	Cessna 150	Accident	78.0	104.0	182.0	
1	Cessna 152	Accident	349.0	168.0	404.0	
2	Cessna 172	Accident	231.0	192.0	325.0	
3	Cessna 172N	Accident	365.0	150.0	320.0	
4	Piper PA-28-140	Accident	284.0	219.0	374.0	

In [73]:

```
# checking most common operated aircraft track record by investigation type = 'Incide

common_aircraft_incident_safety_record = most_common_selected_flights_df[most_common_
].groupby(['Aircraft_Type', 'Investigation.Type'])[['Total.Fatal.Injuries', 'Total.Se
].sum().reset_index()

common_aircraft_incident_safety_record
```

Out[73]:

	Aircraft_Type	Investigation.Type	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Tota
0	Cessna 150	Incident	0.0	0.0	2.0	
1	Cessna 152	Incident	0.0	0.0	1.0	
2	Cessna 172	Incident	0.0	0.0	0.0	
3	Cessna 172N	Incident	0.0	0.0	0.0	
4	Piper PA-28-140	Incident	0.0	0.0	0.0	

In [74]:

```
#Ratio of incidences that have occured in most common operated flight to uninjured in

total_incidences_mostcommon = most_common_selected_flights_df[['Total.Fatal.Injuries
]].sum().sum()
total_uninjured_mostcommon = most_common_selected_flights_df['Total.Uninjured'].sum()


Safety_Percentage =100-(total_incidences_mostcommon/total_uninjured_mostcommon)*100

print(f"Total Uninjured: {total_uninjured_mostcommon}")
print(f"Total Injury Incidents: {total_incidences_mostcommon}")
print(f"Safety Percentage (Injured / Uinjured): {Safety_Percentage:.2f} %")
```

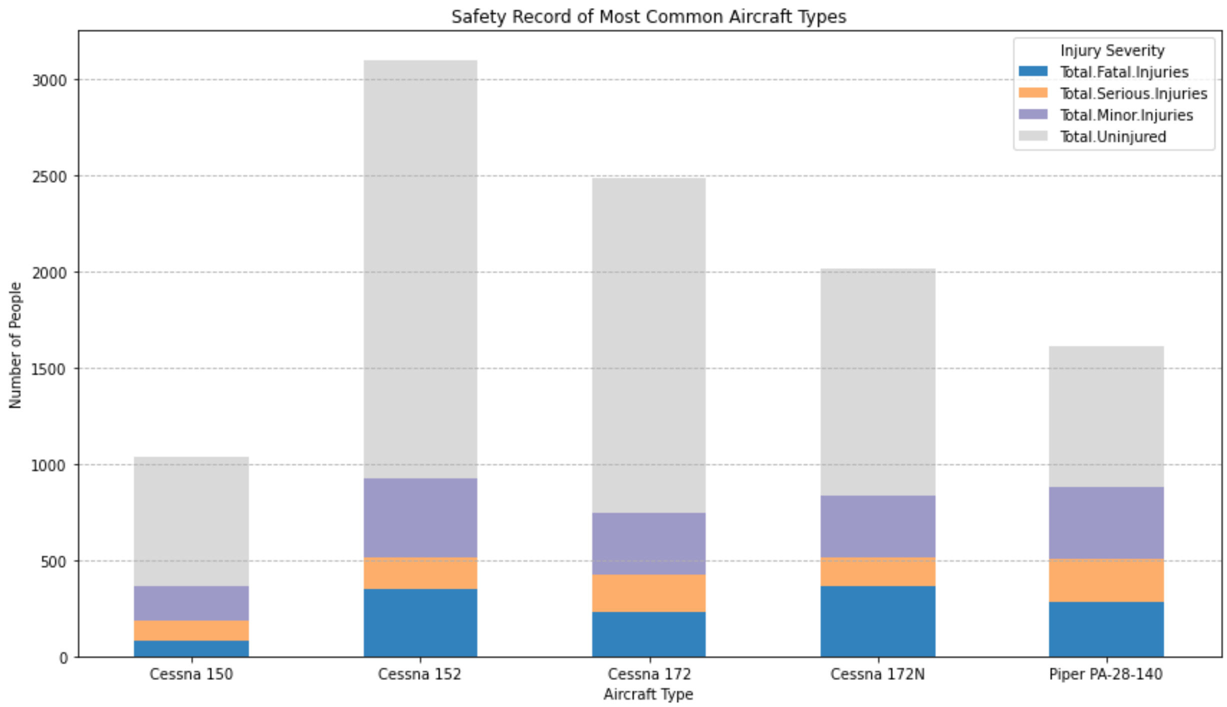
```
Total Uninjured: 6499.0
Total Injury Incidents: 3748.0
Safety Percentage (Injured / Uinjured): 42.33 %
```

In [75]:
```
# Pivoting for easier plotting (sum across all Investigation Types per Aircraft Type)
pivot_df = safety_record_most_common_aircraft.groupby('Aircraft_Type')[['Total.Fatal.
'Total.Uninjured']].sum()

# Plotting
pivot_df.plot(kind='bar', stacked=True, figsize=(12, 7), colormap='tab20c')

plt.title('Safety Record of Most Common Aircraft Types')
plt.xlabel('Aircraft Type')
plt.ylabel('Number of People')
plt.xticks(rotation=360)
plt.legend(title='Injury Severity')
plt.tight_layout()
plt.grid(axis='y', linestyle='--')

plt.show()
```



In [76]:
```
#Track record of top 5 flights with known lowrisk factors

selected_lowrisk_aircraft =lowrisk_incidence_factors['Aircraft_Type'].head(10).tolist
selected_lowrisk_aircraft_df= df[df['Aircraft_Type'].isin (selected_lowrisk_aircraft)

#Assessing lowrisk incident aircraft type safety record
lowrisk_safety_record=selected_lowrisk_aircraft_df.groupby(['Aircraft_Type','Investig
'Total.Uninjured']].sum().reset_index()

lowrisk_safety_record
```

Out[76]:

	Aircraft_Type	Investigation.Type	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	To
0	AIRBUS A320	Accident	170.0	4.0	9.0	
1	AIRBUS A320	Incident	0.0	6.0	0.0	
2	BOEING 737	Accident	1348.0	350.0	75.0	

	Aircraft_Type	Investigation.Type	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	To
3	BOEING 737	Incident	0.0	30.0	1.0	
4	BOEING 767	Accident	0.0	60.0	16.0	
5	BOEING 767	Incident	0.0	0.0	0.0	
6	BOEING 777	Accident	0.0	23.0	17.0	
7	BOEING 777	Incident	0.0	0.0	1.0	
8	BOEING 787	Accident	0.0	1.0	2.0	
9	BOEING 787	Incident	0.0	4.0	0.0	
10	Boeing 737	Accident	0.0	8.0	15.0	
11	Boeing 737	Incident	0.0	0.0	0.0	
12	Boeing 747-400	Accident	83.0	43.0	40.0	
13	Boeing 747-400	Incident	0.0	0.0	0.0	

In [77]:

```
# checking lowrisk track record for Aircraft_Type by investigation type = 'Accident'

lowrisk_accident_safety_record = selected_lowrisk_aircraft_df[selected_lowrisk_aircra
].groupby(['Aircraft_Type', 'Investigation.Type'])[['Total.Fatal.Injuries', 'Total.Se
].sum().reset_index()

lowrisk_accident_safety_record
```

Out[77]:

	Aircraft_Type	Investigation.Type	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Tota
0	AIRBUS A320	Accident	170.0	4.0	9.0	
1	BOEING 737	Accident	1348.0	350.0	75.0	
2	BOEING 767	Accident	0.0	60.0	16.0	
3	BOEING 777	Accident	0.0	23.0	17.0	
4	BOEING 787	Accident	0.0	1.0	2.0	
5	Boeing 737	Accident	0.0	8.0	15.0	
6	Boeing 747-400	Accident	83.0	43.0	40.0	

In [78]:

```
# checking Fatal track record for Aircraft_Type by investigation type = 'Incident'

lowrisk_incident_safety_record  = selected_lowrisk_aircraft_df[selected_lowrisk_aircr
].groupby(['Aircraft_Type', 'Investigation.Type'])[['Total.Fatal.Injuries', 'Total.Se
].sum().reset_index()

lowrisk_incident_safety_record
```

Out[78]:

	Aircraft_Type	Investigation.Type	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Tota

	Aircraft_Type	Investigation.Type	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Tota
0	AIRBUS A320	Incident	0.0	6.0	0.0	
1	BOEING 737	Incident	0.0	30.0	1.0	
2	BOEING 767	Incident	0.0	0.0	0.0	
3	BOEING 777	Incident	0.0	0.0	1.0	
4	BOEING 787	Incident	0.0	4.0	0.0	
5	Boeing 737	Incident	0.0	0.0	0.0	
6	Boeing 747-400	Incident	0.0	0.0	0.0	

In [79]:

```
#Ratio of incidences that have occured in most common operated flight to uninjured ir

total_incidences_lowrisk =selected_lowrisk_aircraft_df[['Total.Fatal.Injuries','Total
]].sum().sum()
total_uninjured_lowrisk =selected_lowrisk_aircraft_df['Total.Uninjured'].sum()


lowrisk_safety_ratio = 100-(total_incidences_lowrisk/total_uninjured_lowrisk)*100

print(f"Total Uninjured: {total_uninjured_mostcommon}")
print(f"Total Injury Incidents: {total_incidences_mostcommon}")
print(f"Safety Percentage (Injured / Uinjured): {lowrisk_safety_ratio:.2f} %")
```

```
Total Uninjured: 6499.0
Total Injury Incidents: 3748.0
Safety Percentage (Injured / Uinjured): 95.27 %
```

In [80]:

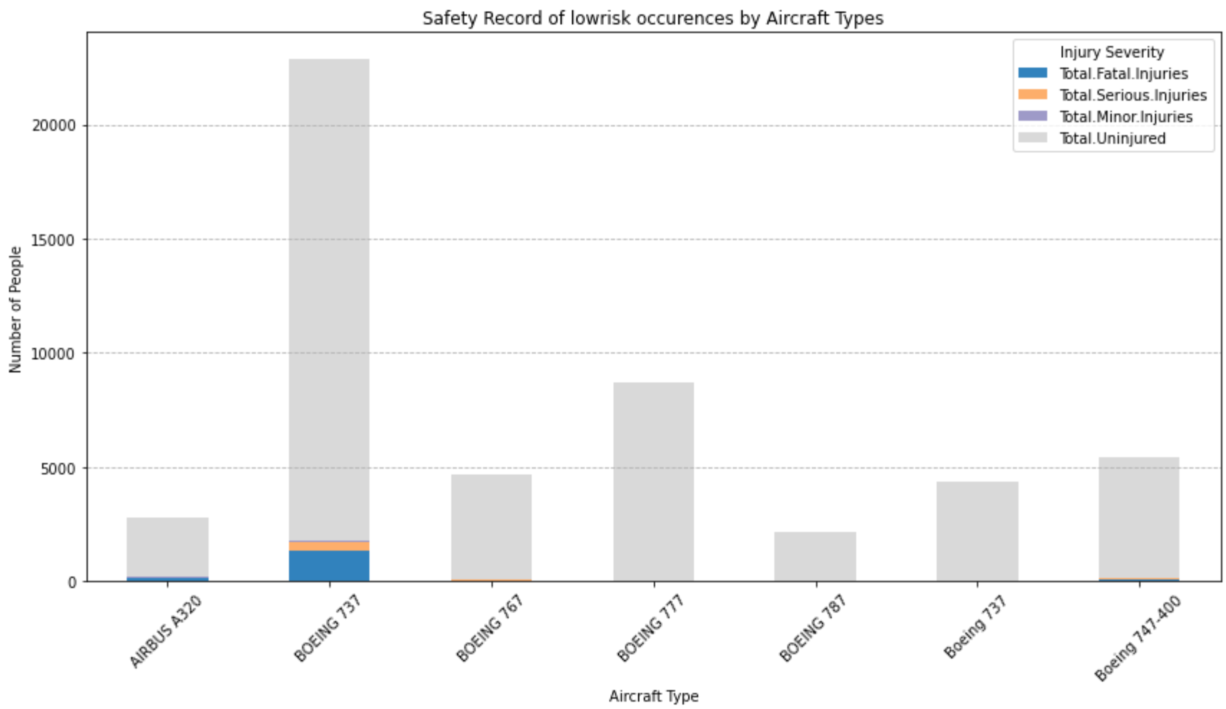
```
# Pivoting for easier plotting (sum across all Investigation Types per Aircraft Type)

lowrisk_df = lowrisk_safety_record.groupby('Aircraft_Type')[['Total.Fatal.Injuries',
'Total.Uninjured']].sum()

# Plotting
lowrisk_df.plot(kind='bar', stacked=True, figsize=(12, 7), colormap='tab20c')

plt.title('Safety Record of lowrisk occurences by Aircraft Types')
plt.xlabel('Aircraft Type')
plt.ylabel('Number of People')
plt.xticks(rotation=45)
plt.legend(title='Injury Severity')
plt.tight_layout()
plt.grid(axis='y', linestyle='--')

plt.show()
```



SUMMARY ANALYSIS ON MOST COMMON AIRCRAFT OPERATED AND THE LOW RISK AIRCRAFT OPERATED

1. MOST COMMON AIRCRAFTS OPERATED

If African Airways Co. would like to consider the most common aircraft operated as their choice of flight based on information assessed: a)Most common aircraft selected have lower numbers of passangers, maybe due to the flights being smaller b)further analysis should be done to know why they are common. It could be that they are cheaper to acquire c) The safety percentage for these aircraft is however low at 42%

If African Airways Co.rather consi der the low risk aircraft operated as their choice of flight based on information assessed: a) They appear to move large volumes of passangers b)The safety record is quite impressive at95.27%

In [81]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Investigation.Type      90348 non-null  object
 1   Country                 90348 non-null  object
 2   Injury.Severity         90348 non-null  object
 3   Aircraft.damage         90348 non-null  object
 4   Aircraft.Category       90348 non-null  object
 5   Make                    90348 non-null  object
 6   Model                   90348 non-null  object
 7   Amateur.Built           90348 non-null  object
 8   Number.of.Engines       90348 non-null  float64
 9   Engine.Type             90348 non-null  object
 10  Purpose.of.flight       90348 non-null  object
 11  Total.Fatal.Injuries    90348 non-null  float64
```

```
 12  Total.Serious.Injuries        90348 non-null  float64
 13  Total.Minor.Injuries          90348 non-null  float64
 14  Total.Uninjured               90348 non-null  float64
 15  Weather.Condition             90348 non-null  object
 16  Broad.phase.of.flight         90348 non-null  object
 17  Severity_Counts               90348 non-null  float64
 18  Aircraft_Type                 90348 non-null  object
 19  Total.catastrophic. Injuries  90348 non-null  float64
dtypes: float64(7), object(13)
memory usage: 13.8+ MB
```

In [82]:

```
# For purpose of use in Tableau, given the changed information from the original data

df.to_csv("cleaned_aviation_data.csv", index=False)
```