Flight Data Analytics

Overview

Flight Data Analytics analyzes aviation accident data to identify potential risks associated with expansion to the aviation industry as well advise on how to mitigate said risks. The analysis leverages accident data to inform decisions on aircraft acquisition, equipment purchase as well as staff training to successfully purchase and operate planes for commercial and private enterprises.

Business Problem

Our company is expanding into aviation and needs to evaluate potential risks associated with managing fleets of airplanes. The goal is to: 1.determine which aircraft are best to purchase 2.Necessary equipment to be purchased to enhance safety 3.Necessary experience needed by staff as well as additional training they should undertake

Data Understanding

The data is sourced from the National Transportation Safety Board (NTSB), covering aviation accidents from 1948 to the end of 2022. It includes information such as: 1.accident severity 2,aircraft type 3.injury statistics 3.weather condition 4.plane make and model

For this particular project we will only analyse data going back six(6) years for actionable insight as requested by management

In [28]:

```
#importing standard libraries

from matplotlib import pyplot as plt
import pandas as pd
import seaborn as sns
```

In [29]:

```
pd.set_option("display.max_columns",500) #This allows me to look at all

data=pd.read_csv(r"C:\Users\User\Desktop\DATA SCIENCE\Phase 1 project\A
```

In [30]:
```
df=data.copy()#Create a copy of the data to use for manipulation
df.head() #Check the first five rows make sure data is succesfully impo
```

Out[30]:

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

In [31]:
```
df.shape #Checking the number of rows and columns
```

Out[31]:
```
(88889, 31)
```

In [32]:
```
df.columns #Check for column names
```

Out[32]:
```
Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Da
te',
       'Location', 'Country', 'Latitude', 'Longitude', 'Airport.Cod
e',
       'Airport.Name', 'Injury.Severity', 'Aircraft.damage',
       'Aircraft.Category', 'Registration.Number', 'Make', 'Model',
       'Amateur.Built', 'Number.of.Engines', 'Engine.Type', 'FAR.Desc
ription',
       'Schedule', 'Purpose.of.flight', 'Air.carrier', 'Total.Fatal.I
njuries',
       'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninj
ured',
       'Weather.Condition', 'Broad.phase.of.flight', 'Report.Status',
       'Publication.Date'],
      dtype='object')
```

In [33]:

```
df.info() #Summary of the data
```

```
<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            50132 non-null  object 
 9   Airport.Name            52704 non-null  object 
 10  Injury.Severity         87889 non-null  object 
 11  Aircraft.damage         85695 non-null  object 
 12  Aircraft.Category       32287 non-null  object 
 13  Registration.Number     87507 non-null  object 
 14  Make                    88826 non-null  object 
 15  Model                   88797 non-null  object 
 16  Amateur.Built           88787 non-null  object 
 17  Number.of.Engines       82805 non-null  float64
 18  Engine.Type             81793 non-null  object 
 19  FAR.Description         32023 non-null  object 
 20  Schedule                12582 non-null  object 
 21  Purpose.of.flight       82697 non-null  object 
 22  Air.carrier             16648 non-null  object 
 23  Total.Fatal.Injuries    77488 non-null  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           82505 non-null  object 
 30  Publication.Date        75118 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

In [34]:

```
df.describe() #Statistical summary of my data frame
```

Out[34]:

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries
count	82805.000000	77488.000000	76379.000000	76956.000000
mean	1.146585	0.647855	0.279881	0.357061
std	0.446510	5.485960	1.544084	2.235625
min	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.000000	0.000000	0.000000
50%	1.000000	0.000000	0.000000	0.000000
75%	1.000000	0.000000	0.000000	0.000000
max	8.000000	349.000000	161.000000	380.000000

In [35]:
```
df.isnull().sum() #Check for null values
```

Out[35]:
```
Event.Id                    0
Investigation.Type          0
Accident.Number             0
Event.Date                  0
Location                   52
Country                   226
Latitude                54507
Longitude               54516
Airport.Code            38757
Airport.Name            36185
Injury.Severity          1000
Aircraft.damage          3194
Aircraft.Category       56602
Registration.Number      1382
Make                       63
Model                      92
Amateur.Built             102
Number.of.Engines        6084
Engine.Type              7096
FAR.Description         56866
Schedule                76307
Purpose.of.flight        6192
Air.carrier             72241
Total.Fatal.Injuries    11401
Total.Serious.Injuries  12510
Total.Minor.Injuries    11933
Total.Uninjured          5912
Weather.Condition        4492
Broad.phase.of.flight   27165
Report.Status            6384
Publication.Date        13771
dtype: int64
```

DATA PREPARATION

Data Cleaning

Data cleaning and wrangling is essential to the data science process. I do these by first checking and dropping all the duplicates in the data frame.

Next I standardize all the column names by removing white space,using underscore as a separator and making all the characters lower case making them easier to call.

I then filter out all the data older than 6 years because of constant innovation and changing technologies in the aviation space

Dropping columns with more than half null values

I impute all numerical columns with zero[0] and all the categorical with "unknown"

Lastly I drop all the non essential columns and finally I drop all rows with null values

In [36]:
```
#Check and drop duplicates
df.duplicated().sum()
```

Out[36]:
```
0
```

In [37]:
```
#Standardize column names by removing white space, lowercase, using und
df.columns=df.columns.str.strip().str.lower().str.replace(" ","_").str.

df.columns
```

Out[37]:
```
Index(['event_id', 'investigation_type', 'accident_number', 'event_da
te',
       'location', 'country', 'latitude', 'longitude', 'airport_cod
e',
       'airport_name', 'injury_severity', 'aircraft_damage',
       'aircraft_category', 'registration_number', 'make', 'model',
       'amateur_built', 'number_of_engines', 'engine_type', 'far_desc
ription',
       'schedule', 'purpose_of_flight', 'air_carrier', 'total_fatal_i
njuries',
       'total_serious_injuries', 'total_minor_injuries', 'total_uninj
ured',
       'weather_condition', 'broad_phase_of_flight', 'report_status',
       'publication_date'],
      dtype='object')
```

In [38]:

```
#Drop data that is more than 6 years old

#Covert event_date to date time format
df["event_date"]=pd.to_datetime(df["event_date"])
df["event_date"].isnull().sum() #check for any null values of thr event

start="2017-01-01" #Define the start date

df=df[df["event_date"]>=start] #Filter the data set

df.head(10) #Check whether its been correctly filtered
```

Out[38]:

	event_id	investigation_type	accident_number	event_date	location
79402	20170110X14448	Accident	GAA17CA108	2017-01-01	Casa Grande, AZ
79403	20170117X42903	Accident	CEN17LA079	2017-01-01	New Braunfels, TX
79404	20170103X14851	Accident	WPR17FA045	2017-01-02	Payson, AZ
79405	20170103X43747	Accident	WPR17LA046	2017-01-03	Paradise, MT
79406	20170105X45917	Accident	WPR17LA048	2017-01-04	Napa, CA
79407	20170105X51011	Accident	CEN17LA068	2017-01-04	Nacogdoches, TX
79408	20170105X81632	Accident	CEN17FA067	2017-01-04	Brookfield, WI
79409	20170105X41106	Accident	WPR17FA047	2017-01-05	San Pedro, CA
79410	20170105X74726	Accident	CEN17FA071	2017-01-05	Gurdon, AR
79411	20170105X85226	Accident	ERA17LA078	2017-01-05	Atlanta, GA

In [39]:

```
df.shape #The new shape of the filtered data
```

Out[39]:

```
(9487, 31)
```

In [40]:

```
df.isnull().sum() #Check the null values of the new data
```

Out[40]:

```
event_id                 0
investigation_type       0
accident_number          0
event_date               0
location                 0
country                  0
latitude              1347
longitude             1347
airport_code          3979
airport_name          4162
injury_severity        559
aircraft_damage        780
aircraft_category      192
registration_number      2
make                     0
model                    0
amateur_built            0
number_of_engines     2019
engine_type           3795
```

In [41]:

```
#Drop columns with more than 50% of missing values
thresh=len(df)*0.5
df=df.loc[:,df.isnull().sum()<=thresh]

df.isnull().sum()
```

Out[41]:

```
event_id                   0
investigation_type         0
accident_number            0
event_date                 0
location                   0
country                    0
latitude                1347
longitude               1347
airport_code            3979
airport_name            4162
injury_severity          559
aircraft_damage          780
aircraft_category        192
registration_number        2
make                       0
model                      0
amateur_built              0
number_of_engines       2019
engine_type             3795
far_description          199
purpose_of_flight       2194
total_fatal_injuries       0
total_serious_injuries     0
total_minor_injuries       0
total_uninjured            0
weather_condition       2320
report_status           4522
publication_date         953
dtype: int64
```

In [42]:
```
#Filling in numerical columns
numcol=["total_fatal_injuries", "total_serious_injuries","total_minor_i
#The numerical columns will be filled with [0]
df[numcol]=df[numcol].fillna(0)
df.isnull().sum()
```

Out[42]:
```
event_id                     0
investigation_type           0
accident_number              0
event_date                   0
location                     0
country                      0
latitude                  1347
longitude                 1347
airport_code              3979
airport_name              4162
injury_severity            559
aircraft_damage            780
aircraft_category          192
registration_number          2
make                         0
model                        0
amateur_built                0
number_of_engines            0
engine_type               3795
far_description            199
purpose_of_flight         2194
total_fatal_injuries         0
total_serious_injuries       0
total_minor_injuries         0
total_uninjured              0
weather_condition         2320
report_status             4522
publication_date           953
dtype: int64
```

In [43]:

```
#Categorical columns
catcol=["location","injury_severity","weather_condition","country","eng
#They will be filled with unknown
df[catcol]=df[catcol].fillna("Unk")

df.isnull().sum()
```

Out[43]:

```
event_id                    0
investigation_type          0
accident_number             0
event_date                  0
location                    0
country                     0
latitude                 1347
longitude                1347
airport_code             3979
airport_name             4162
injury_severity             0
aircraft_damage             0
aircraft_category           0
registration_number         2
make                        0
model                       0
amateur_built               0
number_of_engines           0
engine_type                 0
far_description           199
purpose_of_flight        2194
total_fatal_injuries        0
total_serious_injuries      0
total_minor_injuries        0
total_uninjured             0
weather_condition           0
report_status            4522
publication_date          953
dtype: int64
```

In [44]:

```
#Dropping columns not useful for the analysis"fl
df=df.drop(columns=["airport_code","airport_name","registration_number'
```

In [45]:
```
df.isnull().sum()
```

Out[45]:
```
event_id                  0
investigation_type        0
event_date                0
location                  0
country                   0
injury_severity           0
aircraft_damage           0
aircraft_category         0
make                      0
model                     0
amateur_built             0
number_of_engines         0
engine_type               0
total_fatal_injuries      0
total_serious_injuries    0
total_minor_injuries      0
total_uninjured           0
weather_condition         0
dtype: int64
```

In [46]:
```
 #Drop all other null values
df=df.dropna()
```

In [47]:
```
df.shape
```

Out[47]:
```
(9487, 18)
```

In [48]:
```

#Check our final data set with no null values
df.isnull().sum()
```

Out[48]:
```
event_id                  0
investigation_type        0
event_date                0
location                  0
country                   0
injury_severity           0
aircraft_damage           0
aircraft_category         0
make                      0
model                     0
amateur_built             0
number_of_engines         0
engine_type               0
total_fatal_injuries      0
total_serious_injuries    0
total_minor_injuries      0
total_uninjured           0
weather_condition         0
dtype: int64
```

In [49]:

```
# Convert all names in the 'make' column to lowercase
df['make'] = df['make'].str.lower().str.replace(" ","_")

# Display unique makes to confirm the changes
unique_makes = df['make'].unique()

# Print the first 50 unique makes and total count
print("Unique Aircraft Makes in Lowercase:")
print(unique_makes[:50])  # Display the first 50 unique makes
print(f"Total unique aircraft makes: {len(unique_makes)}")
```

```
Unique Aircraft Makes in Lowercase:
['larson_roger_h' 'quicksilver' 'cessna' 'softex_invest_llc'
 'schosanski_john_h' 'mooney_aircraft_corp.' 'demmer'
 'robinson_helicopter' 'columbia_aircraft_mfg'
 'aircraft_mfg_&_development_co' 'boeing' 'canadair' 'cirrus'
 'christen_industries_inc' 'boeing_company' 'maule' 'fields' 'mooney'
 'piper' 'sharpe_william_l' 'beech' 'piper_aircraft_corporation' 'aer
onca'
 'american_champion_aircraft' 'textron_aviation_inc'
 'american_legend_aircraft_co' 'johnson' 'air_tractor_inc'
 'hawker_beechcraft' 'avro' 'hawker_beechcraft_corp' 'bellanca' 'robi
nson'
 'bombardier_inc' 'bell' 'cirrus_design_corp'
 'grumman_american_corporation' 'eurocopter_deutschland_gmbh' 'ercoup
e'
 'great_lakes' 'vaughan_gerald_r' 'aviat_aircraft_inc' 'zenith' 'coo
k'
 'robinson_michael_e' 's_c_aerostar_s_a' 'bell_helicopter_textron'
 'shell_john' 'saab' 'md_helicopter']
Total unique aircraft makes: 1405
```

In [50]:

```
df.shape
```

Out[50]:

```
(9487, 18)
```

In [51]:

```
df.to_csv(r"C:\Users\User\Desktop\Flight-Data\AviationData_clean.csv",i
```

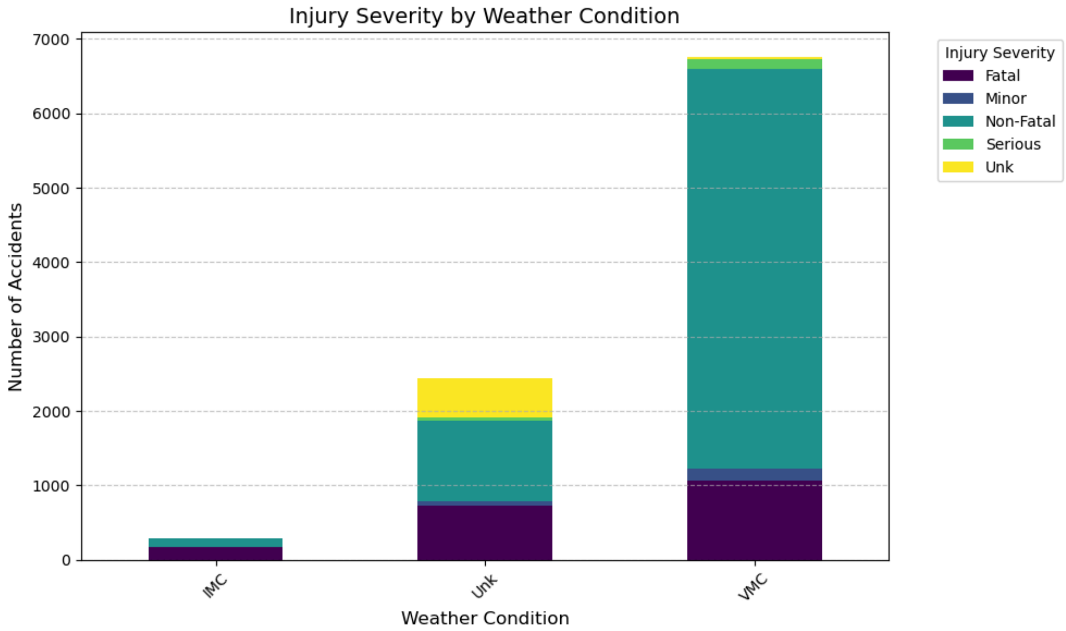
ANALYSIS

1. Analyse injury severity by weather condition

We can see that majority of accidents, even though they are non-fatal, happen during clear skies and weather conditions when pilots rely on visual references and stimuli

In [52]:

```
# Cross-tabulation of weather condition and injury severity
weather_injury = pd.crosstab(df['weather_condition'], df['injury_severi

# Visualize the relationship
weather_injury.plot(kind='bar', stacked=True, figsize=(10, 6), colormap
plt.title('Injury Severity by Weather Condition', fontsize=14)
plt.xlabel('Weather Condition', fontsize=12)
plt.ylabel('Number of Accidents', fontsize=12)
plt.xticks(rotation=45)
plt.legend(title='Injury Severity', bbox_to_anchor=(1.05, 1), loc='uppe
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()

plt.show()
```

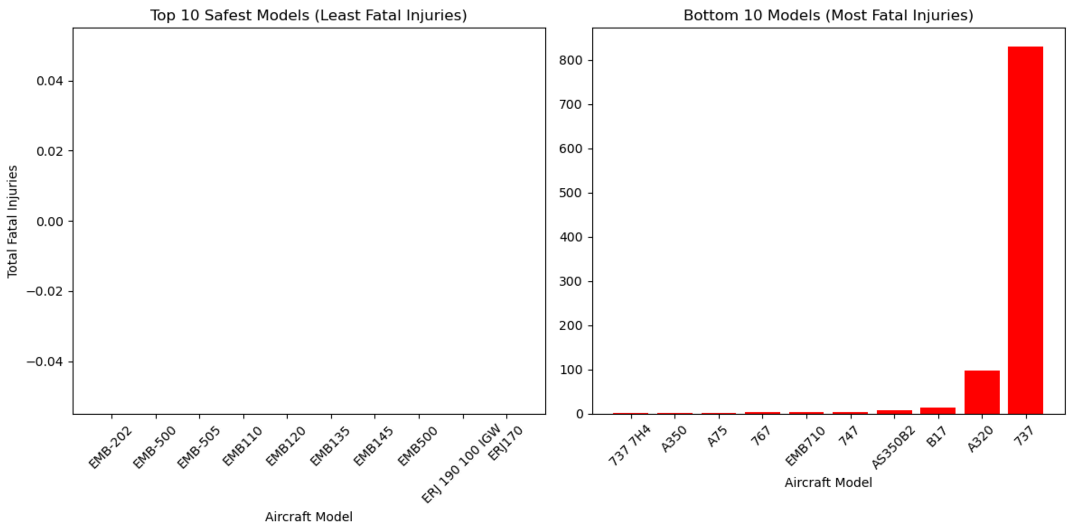


2.Aircraft make & model by fatalities per accidents

Modern aircrafts are all relatively safe due to strict regulations by relevant authorites. Even though we can clearly see the Airbus A320 and Boeing 737 have more accidents than the rest

In [53]:

```
# Aggregate accident and fatality data by make and model
safest_models = df.groupby(['make',"model"]).agg({
    'event_id': 'count',  # Total accidents
    'total_fatal_injuries': 'sum'  # Total fatalities
}).reset_index()

safest_models=safest_models.sort_values(by="total_fatal_injuries",ascer
# safest_models.tail(50)
# "embraer" in safest_models["make"].unique()

# biggest Commercial Plane manufacturer
commercial_planes=safest_models[safest_models["make"].str.lower().isin(
commercial_planes.head()


# Get the top 10 models with the least fatalities
top_10 = commercial_planes.head(10)

# Get the bottom 10 models with the most fatalities
bottom_10 = commercial_planes.tail(10)

# Plot side-by-side bar charts
plt.figure(figsize=(12, 6))

# Plot top 10 models with the least fatalities
plt.subplot(1, 2, 1)
plt.bar(top_10['model'], top_10['total_fatal_injuries'], color='green')
plt.title('Top 10 Safest Models (Least Fatal Injuries)', fontsize=12)
plt.xlabel('Aircraft Model', fontsize=10)
plt.ylabel('Total Fatal Injuries', fontsize=10)
plt.xticks(rotation=45)

# Plot bottom 10 models with the most fatalities
plt.subplot(1, 2, 2)
plt.bar(bottom_10['model'], bottom_10['total_fatal_injuries'], color='r
plt.title('Bottom 10 Models (Most Fatal Injuries)', fontsize=12)
plt.xlabel('Aircraft Model', fontsize=10)
plt.xticks(rotation=45)

# Adjust layout for readability
plt.tight_layout()
plt.show()
```

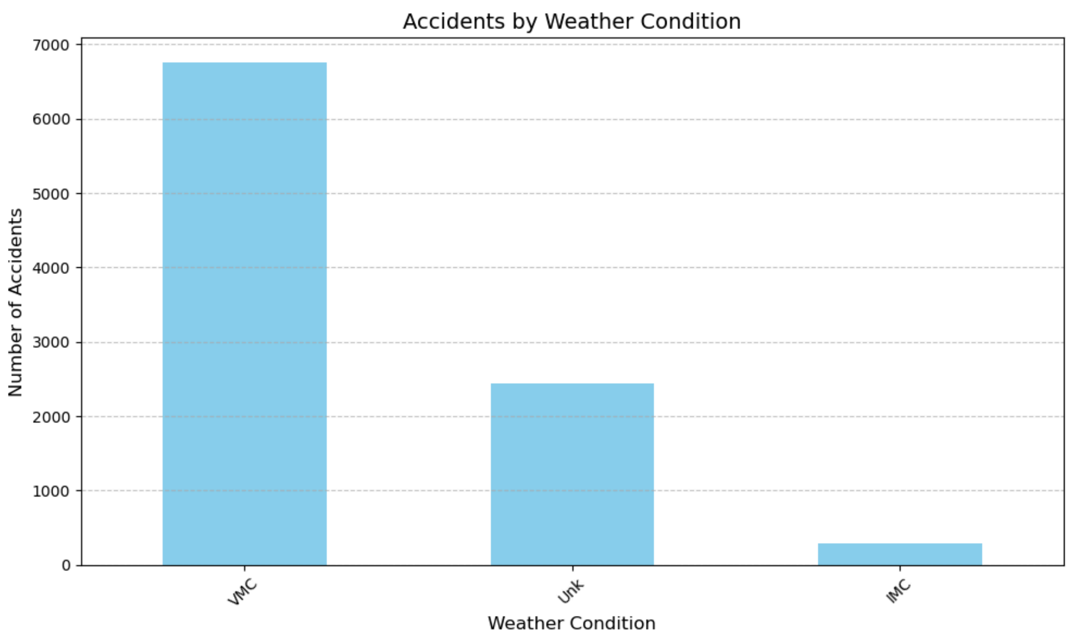


3. Analyse total number of accidents by weather conditions

This graph shows that majority of accidents happen during clear weather conditions while pilots use visual flight rules(VFR)

In [54]:

```
# Count accidents by each weather condition
weather_accidents = df['weather_condition'].value_counts()

# Plot weather accidents
plt.figure(figsize=(10, 6))
weather_accidents.plot(kind='bar', color='skyblue')
plt.title('Accidents by Weather Condition', fontsize=14)
plt.xlabel('Weather Condition', fontsize=12)
plt.ylabel('Number of Accidents', fontsize=12)
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```



CONCLUSION

The analysis conducted leads to the following observations and recommendations

1.Invest in advanced training programs for pilots to enhance navigational skills and advanced situational awareness.

This is because most accidents happen during clear skies/ visual meteorological conditions suggesting that over reliance in visual references leads to errors.

2.Consider other factors such as RELIABILITY,EFFICIENCY,VERSATILITY AND PRICE while purchasing aircrafts instead of accident data.

This is because even though we can clearly see the Airbus A320 and Boeing 737 have more accidents than the rest its crucial to note that it's not a reflection on poor safety. These two are the most widely used planes

3.Adopt advanced navigation and auto pilot systems to enhance safety even clear weather conditions

Most accidents happen during VFR conditions which are deceptively safer but pose unique challenges