DIC_Project_Phase_1

October 9, 2024

1 Phase 1

1.1 1: Problem Statement

1.1.1 1.1.1 Problem Statement

This project's goal is to make a detailed analysis on why road accidents are occurring a lot and in what trend, will be helpful in improving road safety measures & make the policy options which can reduce the number of accidents. This research would help to know the impacts of accident severity on the driver attributes, vehicle conditions, surface conditions and environmental conditions.

1.1.2 1.1.2 Potential Contribution & Importance

Road accidents pose a threat to health globally by resulting in significant fatalities and injuries of individuals worldwide. This evaluation plays a role in finding factors that play a vital role in accident prevention. The evidence of this review may support the implementation of measures of safety, improvement of driver education programs, and modification of road systems that can reduce accidents and save lives.

1.2 2: Ask Questions

1.2.1 Bhuvan Thirwani:

Question 1:

How does driving experience, gender, educational level affect the severity of accidents? What is the corelation between total casualties & accident's severity

Hypothesis

There should be no effect of sex of the driver on casualties and accident severity. Higher education must have low casualities and less severity. Higher driving experience must have lower casualities & less severity

Question 2:

Analyzing how the fatality ratio is related with various factors such as light conditions, weather conditions, type of collision & day of the week in traffic accidents. Finding patterns and correlations which can suggest road safety strategies.

Hypothesis

Dark Lighting, Rainy Weather Conditions should have more fatal rate. On Busy days, fatal ratio should be high as outside is overcrowded & Pedestrian should have the highest fatal ratio.

Harshit Malpani: 50608809

Question 1: What vehicles should the authorities focus more on to reduce the cases of road accidents and the severity of the road accidents

Question 2: Does the service period of the vehicle and ownership of the vehicle have any correlation with the accidents

Piyush Gulhane:

Question 1:

Question 2:

1.3 3: Data Retrieval

The dataset has been taken from KAGGLE. For this task, we have uploaded a copy of the dataset to a github repository and downloading the data from the github repository directly to the dataframe

[35]:
```
import pandas as pd
import warnings
import matplotlib.pyplot as plt
warnings.filterwarnings('ignore')
dataset = pd.read_csv('https://raw.githubusercontent.com/hmalpani/RTA-Dataset/
↪main/RTA_Dataset.csv')
```

[36]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12316 entries, 0 to 12315
Data columns (total 32 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   Time                         12316 non-null  object
 1   Day_of_week                  12316 non-null  object
 2   Age_band_of_driver           12316 non-null  object
 3   Sex_of_driver                12316 non-null  object
 4   Educational_level            11575 non-null  object
 5   Vehicle_driver_relation      11737 non-null  object
 6   Driving_experience           11487 non-null  object
 7   Type_of_vehicle              11366 non-null  object
 8   Owner_of_vehicle             11834 non-null  object
```

```
 9   Service_year_of_vehicle      8388 non-null   object
 10  Defect_of_vehicle            7889 non-null   object
 11  Area_accident_occured        12077 non-null  object
 12  Lanes_or_Medians             11931 non-null  object
 13  Road_allignment              12174 non-null  object
 14  Types_of_Junction            11429 non-null  object
 15  Road_surface_type            12144 non-null  object
 16  Road_surface_conditions      12316 non-null  object
 17  Light_conditions             12316 non-null  object
 18  Weather_conditions           12316 non-null  object
 19  Type_of_collision            12161 non-null  object
 20  Number_of_vehicles_involved  12316 non-null  int64
 21  Number_of_casualties         12316 non-null  int64
 22  Vehicle_movement             12008 non-null  object
 23  Casualty_class               12316 non-null  object
 24  Sex_of_casualty              12316 non-null  object
 25  Age_band_of_casualty         12316 non-null  object
 26  Casualty_severity            12316 non-null  object
 27  Work_of_casuality            9118 non-null   object
 28  Fitness_of_casuality         9681 non-null   object
 29  Pedestrian_movement          12316 non-null  object
 30  Cause_of_accident            12316 non-null  object
 31  Accident_severity            12316 non-null  object
dtypes: int64(2), object(30)
memory usage: 3.0+ MB
```

[39]:
```
dataset.head()
```

[39]:
```
       Time Day_of_week Age_band_of_driver Sex_of_driver   Educational_level  \
0  17:02:00      Monday              18-30          Male   Above high school
1  17:02:00      Monday              31-50          Male  Junior high school
2  17:02:00      Monday              18-30          Male  Junior high school
3   1:06:00      Sunday              18-30          Male  Junior high school
4   1:06:00      Sunday              18-30          Male  Junior high school

  Vehicle_driver_relation Driving_experience      Type_of_vehicle  \
0                Employee              1-2yr           Automobile
1                Employee         Above 10yr  Public (> 45 seats)
2                Employee              1-2yr       Lorry (41?100Q)
3                Employee             5-10yr  Public (> 45 seats)
4                Employee              2-5yr                  NaN

  Owner_of_vehicle Service_year_of_vehicle  ... Vehicle_movement  \
0            Owner              Above 10yr  ...   Going straight
1            Owner                 5-10yrs  ...   Going straight
2            Owner                     NaN  ...   Going straight
3     Governmental                     NaN  ...   Going straight
```

```
4           Owner                 5-10yrs  ...   Going straight

    Casualty_class Sex_of_casualty Age_band_of_casualty Casualty_severity  \
0               na              na                   na                na
1               na              na                   na                na
2  Driver or rider            Male                31-50                 3
3       Pedestrian          Female                18-30                 3
4               na              na                   na                na

  Work_of_casuality Fitness_of_casuality Pedestrian_movement  \
0               NaN                  NaN    Not a Pedestrian
1               NaN                  NaN    Not a Pedestrian
2            Driver                  NaN    Not a Pedestrian
3            Driver               Normal    Not a Pedestrian
4               NaN                  NaN    Not a Pedestrian

            Cause_of_accident Accident_severity
0              Moving Backward    Slight Injury
1                   Overtaking    Slight Injury
2   Changing lane to the left   Serious Injury
3  Changing lane to the right    Slight Injury
4                   Overtaking    Slight Injury

[5 rows x 32 columns]
```

1.4 4: Data Cleaning

1.4.1 1) Remove Duplicate Values:

Removing duplicate values is an essential step of data cleaning for any data science project. It helps in reducing the bias where certain data points are represented multiple times. If the duplicate values are not removed, it can skew the results and therefore lead to incorrect conclusions

[43]:
```python
# Remove duplicates
cleaned_dataset = dataset.drop_duplicates()
```

1.4.2 2) Validation

[46]:
```python
# Remove entries with 'Number_of_vehicles_involved' = 0
cleaned_dataset = cleaned_dataset[cleaned_dataset['Number_of_vehicles_involved']␣
↪!= 0]
```

1.4.3 3) Detection and Removal of Outliers

[49]:
```python
# code for outliers handling

numerical_columns = ['Number_of_vehicles_involved', 'Number_of_casualties']
for column in numerical_columns:
```

```
    if not pd.api.types.is_numeric_dtype(cleaned_dataset[column]):
        print(f"Column '{column}' should be numeric but contains non-numeric␣
↪data.")

def detect_outliers(column):
    Q1 = cleaned_dataset[column].quantile(0.05)
    Q3 = cleaned_dataset[column].quantile(0.95)
    IQR = Q3 - Q1
    outliers = cleaned_dataset[(cleaned_dataset[column] < (Q1 - 1.5 * IQR)) |␣
↪(cleaned_dataset[column] > (Q3 + 1.5 * IQR))]
    return outliers

for column in numerical_columns:
    outliers = detect_outliers(column)
    if not outliers.empty:
        print(f"Outliers detected in column '{column}':\n", outliers.shape)

def remove_outliers(df, column):
    Q1 = cleaned_dataset[column].quantile(0.05)
    Q3 = cleaned_dataset[column].quantile(0.95)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return cleaned_dataset[(cleaned_dataset[column] >= lower_bound) &␣
↪(cleaned_dataset[column] <= upper_bound)]

print("Shape before removing outliers:", cleaned_dataset.shape)
# Remove outliers from both columns
cleaned_dataset = remove_outliers(cleaned_dataset, 'Number_of_vehicles_involved')
cleaned_dataset = remove_outliers(cleaned_dataset, 'Number_of_casualties')

# Check the shape of the DataFrame after removal
print("Shape after removing outliers:", cleaned_dataset.shape)
```

```
Outliers detected in column 'Number_of_vehicles_involved':
 (7, 32)
Shape before removing outliers: (12316, 32)
Shape after removing outliers: (12309, 32)
```

1.4.4 4) Handling Missing Values:

In this step of Data Cleaning, we either remove or impute the missing values in the dataset

[52]:
```
# Find the number of missing values
missing_value_count = cleaned_dataset.isnull().sum()
missing_value_count
```

[52]:
```
Time                             0
Day_of_week                      0
Age_band_of_driver               0
Sex_of_driver                    0
Educational_level              741
Vehicle_driver_relation        579
Driving_experience             829
Type_of_vehicle                950
Owner_of_vehicle               482
Service_year_of_vehicle       3923
Defect_of_vehicle             4427
Area_accident_occured          239
Lanes_or_Medians               385
Road_allignment                142
Types_of_Junction              887
Road_surface_type              172
Road_surface_conditions          0
Light_conditions                 0
Weather_conditions               0
Type_of_collision              155
Number_of_vehicles_involved      0
Number_of_casualties             0
Vehicle_movement               306
Casualty_class                   0
Sex_of_casualty                  0
Age_band_of_casualty             0
Casualty_severity                0
Work_of_casuality             3197
Fitness_of_casuality          2634
Pedestrian_movement              0
Cause_of_accident                0
Accident_severity                0
dtype: int64
```

[54]:
```
dataset_columns = cleaned_dataset.columns.tolist()
missing_values_columns = missing_value_count[missing_value_count > 0].index.
 ↪tolist()
print(missing_values_columns)
```

```
['Educational_level', 'Vehicle_driver_relation', 'Driving_experience',
'Type_of_vehicle', 'Owner_of_vehicle', 'Service_year_of_vehicle',
'Defect_of_vehicle', 'Area_accident_occured', 'Lanes_or_Medians',
'Road_allignment', 'Types_of_Junction', 'Road_surface_type',
'Type_of_collision', 'Vehicle_movement', 'Work_of_casuality',
'Fitness_of_casuality']
```

[56]:
```
# Replace missing values
cleaned_dataset['Educational_level'].fillna(cleaned_dataset['Educational_level'].
↪mode()[0], inplace=True)
cleaned_dataset['Vehicle_driver_relation'].fillna('Unknown', inplace=True)
cleaned_dataset['Driving_experience'].
↪fillna(cleaned_dataset['Driving_experience'].mode()[0], inplace=True)
cleaned_dataset['Type_of_vehicle'].fillna('Unknown', inplace=True)
cleaned_dataset['Owner_of_vehicle'].fillna('Unknown', inplace=True)
cleaned_dataset['Service_year_of_vehicle'].fillna('Unknown', inplace=True)
cleaned_dataset['Defect_of_vehicle'].fillna('No defect', inplace=True)
cleaned_dataset['Area_accident_occured'].fillna('Unknown', inplace=True)
cleaned_dataset['Lanes_or_Medians'].fillna('Unknown', inplace=True)
cleaned_dataset['Road_allignment'].fillna('Unknown', inplace=True)
cleaned_dataset['Types_of_Junction'].fillna('Unknown', inplace=True)
cleaned_dataset['Road_surface_type'].fillna('Unknown', inplace=True)
cleaned_dataset['Type_of_collision'].fillna('Unknown', inplace=True)
cleaned_dataset['Vehicle_movement'].fillna('Unknown', inplace=True)
cleaned_dataset['Work_of_casuality'].fillna('Unknown', inplace=True)
cleaned_dataset['Fitness_of_casuality'].fillna('Unknown', inplace=True)
```

1.4.5 5) Correcting Errors:

In this data cleaning, we identify and fix the errors or incosistencies present in the data

[59]:
```
cleaned_dataset['Type_of_vehicle'] = cleaned_dataset['Type_of_vehicle'].
↪replace('Lorry (41?100Q)', 'Lorry (41 - 100 Q)')
cleaned_dataset['Type_of_vehicle'] = cleaned_dataset['Type_of_vehicle'].
↪replace('Lorry (11?40Q)', 'Lorry (11 - 40 Q)')
cleaned_dataset['Type_of_vehicle'] = cleaned_dataset['Type_of_vehicle'].
↪replace('Public (13?45 seats)', 'Public (13 - 45 seats)')
cleaned_dataset['Area_accident_occured'] =␣
↪cleaned_dataset['Area_accident_occured'].replace('  Recreational areas',␣
↪'Recreational areas')
cleaned_dataset['Area_accident_occured'] =␣
↪cleaned_dataset['Area_accident_occured'].replace('  Market areas', 'Market␣
↪areas')
cleaned_dataset['Area_accident_occured'] =␣
↪cleaned_dataset['Area_accident_occured'].replace(' Church areas', 'Church␣
↪areas')
cleaned_dataset['Area_accident_occured'] =␣
↪cleaned_dataset['Area_accident_occured'].replace(' Hospital areas', 'Hospital␣
↪areas')
cleaned_dataset['Area_accident_occured'] =␣
↪cleaned_dataset['Area_accident_occured'].replace(' Industrial areas',␣
↪'Industrial areas')
```

```
cleaned_dataset['Area_accident_occured'] =␣
↪cleaned_dataset['Area_accident_occured'].replace(' Outside rural areas',␣
↪'Outside rural areas')
cleaned_dataset['Area_accident_occured'] =␣
↪cleaned_dataset['Area_accident_occured'].replace('Rural village areasOffice␣
↪areas', 'Rural Office areas')
cleaned_dataset['Road_allignment'] = cleaned_dataset['Road_allignment'].
↪replace('Tangent road with mountainous terrain and', 'Tangent road with␣
↪mountainous terrain')
cleaned_dataset['Fitness_of_casuality'] =␣
↪cleaned_dataset['Fitness_of_casuality'].replace('NormalNormal', 'Normal')
cleaned_dataset['Casualty_severity'] = cleaned_dataset['Casualty_severity'].
↪replace('na', 'Unknown')
```

1.4.6 6) Standardize the Data

a) Convert all the entries in `Time` column to a consistent format.
b) Convert `Over 51` to `51 and Over` in the `Age_band_of_driver` column

[62]:
```
# Standardize the 'Time' column
cleaned_dataset['Time'] = pd.to_datetime(cleaned_dataset['Time'], format='%H:%M:
↪%S').dt.time
# Make 'Over 51' to '51 and Over' for Driver Age band
cleaned_dataset['Age_band_of_driver'] = cleaned_dataset['Age_band_of_driver'].
↪replace('Over 51', '51 and Over')
```

1.4.7 7) Parsing the data

Convert all the text in the dataset to lowercase to ensure consistency. This helps in avoiding the situations where same words with different cases are considered different

[65]:
```
# Make all the characters to lowercase
cleaned_dataset = cleaned_dataset.map(lambda x: x.lower() if isinstance(x, str)␣
↪else x)
```

1.4.8 8) Feature Engineering

[68]:
```
print(cleaned_dataset['Time'].head())
cleaned_dataset['Hour'] = pd.to_datetime(cleaned_dataset['Time'], format='%H:%M:
↪%S').dt.hour
Time_of_dat = ['Night', 'Morning', 'Noon', 'Evening']

def categorize_time_of_day(hour):
    if 5 <= hour < 12:
        return 2
    elif 12 <= hour < 17:
        return 3
```

```
    elif 17 <= hour < 21:
        return 4
    else:
        return 1


cleaned_dataset['Time_of_day'] = cleaned_dataset['Hour'].
 ↪apply(categorize_time_of_day)

print("Data head after categorizing and encoding Time_of_day:\n")
cleaned_dataset[['Time', 'Hour', 'Time_of_day']].head()
```

```
0    17:02:00
1    17:02:00
2    17:02:00
3    01:06:00
4    01:06:00
Name: Time, dtype: object
Data head after categorizing and encoding Time_of_day:
```

[68]:

	Time	Hour	Time_of_day
0	17:02:00	17	4
1	17:02:00	17	4
2	17:02:00	17	4
3	01:06:00	1	1
4	01:06:00	1	1

9) One Hot Encoding

[71]:

```
from sklearn.preprocessing import OneHotEncoder

encoding_dict = {
    'Day_of_week': 'ordinal',
    'Age_band_of_driver': 'ordinal',
    'Sex_of_driver': 'one_hot',
    'Educational_level': 'ordinal',
    'Vehicle_driver_relation': 'one_hot',
    'Driving_experience': 'ordinal',
    'Type_of_vehicle': 'one_hot',
    'Owner_of_vehicle': 'one_hot',
    'Service_year_of_vehicle': 'ordinal',
    'Defect_of_vehicle': 'one_hot',
    'Area_accident_occured': 'one_hot',
    'Lanes_or_Medians': 'one_hot',
    'Road_allignment': 'one_hot',
    'Types_of_Junction': 'one_hot',
    'Road_surface_type': 'one_hot',
```

```
    'Road_surface_conditions': 'ordinal',
    'Light_conditions': 'one_hot',
    'Weather_conditions': 'one_hot',
    'Type_of_collision': 'one_hot',
    'Vehicle_movement': 'one_hot',
    'Casualty_class': 'one_hot',
    'Sex_of_casualty': 'one_hot',
    'Age_band_of_casualty': 'ordinal',
    'Casualty_severity': 'ordinal',
    'Work_of_casuality': 'one_hot',
    'Fitness_of_casuality': 'one_hot',
    'Pedestrian_movement': 'one_hot',
    'Cause_of_accident': 'one_hot',
    'Accident_severity': 'ordinal'
}

ordinal_mappings = {
    'Day_of_week': {
        'Monday': 0, 'Tuesday': 1, 'Wednesday': 2, 'Thursday': 3,
        'Friday': 4, 'Saturday': 5, 'Sunday': 6, 'Unknown': -1
    },
    'Age_band_of_driver': {
        'Under 18': 0, '18-30': 1, '31-50': 2, 'Over 51': 3, 'Unknown': -1
    },
    'Educational_level': {
        'Illiterate': 0, 'Writing & reading': 1, 'Elementary school': 2,
        'Junior high school': 3, 'High school': 4, 'Above high school': 5,
        'Unknown': -1
    },
    'Driving_experience': {
        'No Licence': 0, 'Below 1yr': 1, '1-2yr': 2, '2-5yr': 3, '5-10yr': 4,
        'Above 10yr': 5, 'unknown': -1
    },
    'Service_year_of_vehicle': {
        'Below 1yr': 0, '1-2yr': 1, '2-5yrs': 2, '5-10yrs': 3,
        'Above 10yr': 4, 'Unknown': -1
    },
    'Road_surface_conditions': {
        'Dry': 0, 'Wet or damp': 1, 'Snow': 2, 'Flood over 3cm. deep': 3,␣
↪'Unknown': -1
    },
    'Age_band_of_casualty': {
        'Under 18': 0, '18-30': 1, '31-50': 2, 'Over 51': 3, '5': 4, 'na': -1,␣
↪'Unknown': -1
    },
    'Casualty_severity': {
        '3': 0, '2': 1, '1': 2, 'na': -1, 'Unknown': -1
```

```
    },
    'Accident_severity': {
        'Slight Injury': 0, 'Serious Injury': 1, 'Fatal injury': 2, 'Unknown': -1
    }
}

def apply_onehot_encoding(df, encoding_dict, ordinal_mappings):
    one_hot_encoder = OneHotEncoder(sparse_output=False, drop='first')

    for column, encoding_type in encoding_dict.items():
        if encoding_type == 'one_hot':
            one_hot_encoded_df = pd.get_dummies(df[column], prefix=column,␣
↪drop_first=True)
            df = pd.concat([df, one_hot_encoded_df], axis=1)
    return df

cleaned_dataset = apply_onehot_encoding(cleaned_dataset, encoding_dict,␣
↪ordinal_mappings)

cleaned_dataset.head()
```

[71]:

```
       Time Day_of_week Age_band_of_driver Sex_of_driver   Educational_level  \
0  17:02:00      monday              18-30          male   above high school
1  17:02:00      monday              31-50          male  junior high school
2  17:02:00      monday              18-30          male  junior high school
3  01:06:00      sunday              18-30          male  junior high school
4  01:06:00      sunday              18-30          male  junior high school

  Vehicle_driver_relation Driving_experience      Type_of_vehicle  \
0                employee              1-2yr           automobile
1                employee         above 10yr  public (> 45 seats)
2                employee              1-2yr    lorry (41 - 100 q)
3                employee             5-10yr  public (> 45 seats)
4                employee              2-5yr              unknown

  Owner_of_vehicle Service_year_of_vehicle  ...  \
0            owner              above 10yr  ...
1            owner                 5-10yrs  ...
2            owner                 unknown  ...
3     governmental                 unknown  ...
4            owner                 5-10yrs  ...

  Cause_of_accident_no distancing Cause_of_accident_no priority to pedestrian  \
0                           False                                       False
1                           False                                       False
2                           False                                       False
3                           False                                       False
```

```
4                            False                                        False

  Cause_of_accident_no priority to vehicle Cause_of_accident_other  \
0                                    False                   False
1                                    False                   False
2                                    False                   False
3                                    False                   False
4                                    False                   False

  Cause_of_accident_overloading Cause_of_accident_overspeed  \
0                         False                       False
1                         False                       False
2                         False                       False
3                         False                       False
4                         False                       False

  Cause_of_accident_overtaking Cause_of_accident_overturning  \
0                        False                         False
1                         True                         False
2                        False                         False
3                        False                         False
4                         True                         False

  Cause_of_accident_turnover Cause_of_accident_unknown
0                      False                     False
1                      False                     False
2                      False                     False
3                      False                     False
4                      False                     False

[5 rows x 175 columns]
```

10) Ordinal Encoding

[74]:
```python
def apply_ordinal_encoding(df, encoding_dict, ordinal_mappings):
    for column, encoding_type in encoding_dict.items():
        if encoding_type == 'ordinal':
            # Apply ordinal encoding using a mapping dictionary
            if column in ordinal_mappings:
                df[f"{column}_ordinal"] = df[column].
 ↪map(ordinal_mappings[column])
            else:
                print(f"No ordinal mapping provided for column: {column}")
    return df

cleaned_dataset = apply_ordinal_encoding(cleaned_dataset, encoding_dict,␣
 ↪ordinal_mappings)
```

```
cleaned_dataset.head()
```

[74]:
```
       Time Day_of_week Age_band_of_driver Sex_of_driver   Educational_level  \
0  17:02:00      monday              18-30          male   above high school
1  17:02:00      monday              31-50          male  junior high school
2  17:02:00      monday              18-30          male  junior high school
3  01:06:00      sunday              18-30          male  junior high school
4  01:06:00      sunday              18-30          male  junior high school

  Vehicle_driver_relation Driving_experience      Type_of_vehicle  \
0                employee              1-2yr           automobile
1                employee         above 10yr  public (> 45 seats)
2                employee              1-2yr   lorry (41 - 100 q)
3                employee             5-10yr  public (> 45 seats)
4                employee              2-5yr              unknown

  Owner_of_vehicle Service_year_of_vehicle  ... Cause_of_accident_unknown  \
0            owner              above 10yr  ...                     False
1            owner                 5-10yrs  ...                     False
2            owner                 unknown  ...                     False
3     governmental                 unknown  ...                     False
4            owner                 5-10yrs  ...                     False

  Day_of_week_ordinal Age_band_of_driver_ordinal Educational_level_ordinal  \
0                 NaN                        1.0                       NaN
1                 NaN                        2.0                       NaN
2                 NaN                        1.0                       NaN
3                 NaN                        1.0                       NaN
4                 NaN                        1.0                       NaN

  Driving_experience_ordinal Service_year_of_vehicle_ordinal  \
0                        2.0                             NaN
1                        NaN                             3.0
2                        2.0                             NaN
3                        4.0                             NaN
4                        3.0                             3.0

  Road_surface_conditions_ordinal Age_band_of_casualty_ordinal  \
0                             NaN                         -1.0
1                             NaN                         -1.0
2                             NaN                          2.0
3                             NaN                          1.0
4                             NaN                         -1.0

  Casualty_severity_ordinal Accident_severity_ordinal
0                       NaN                       NaN
```

```
1                          NaN                        NaN
2                          0.0                        NaN
3                          0.0                        NaN
4                          NaN                        NaN

[5 rows x 184 columns]
```

1.5 5: Exploratory Data Analysis (EDA)

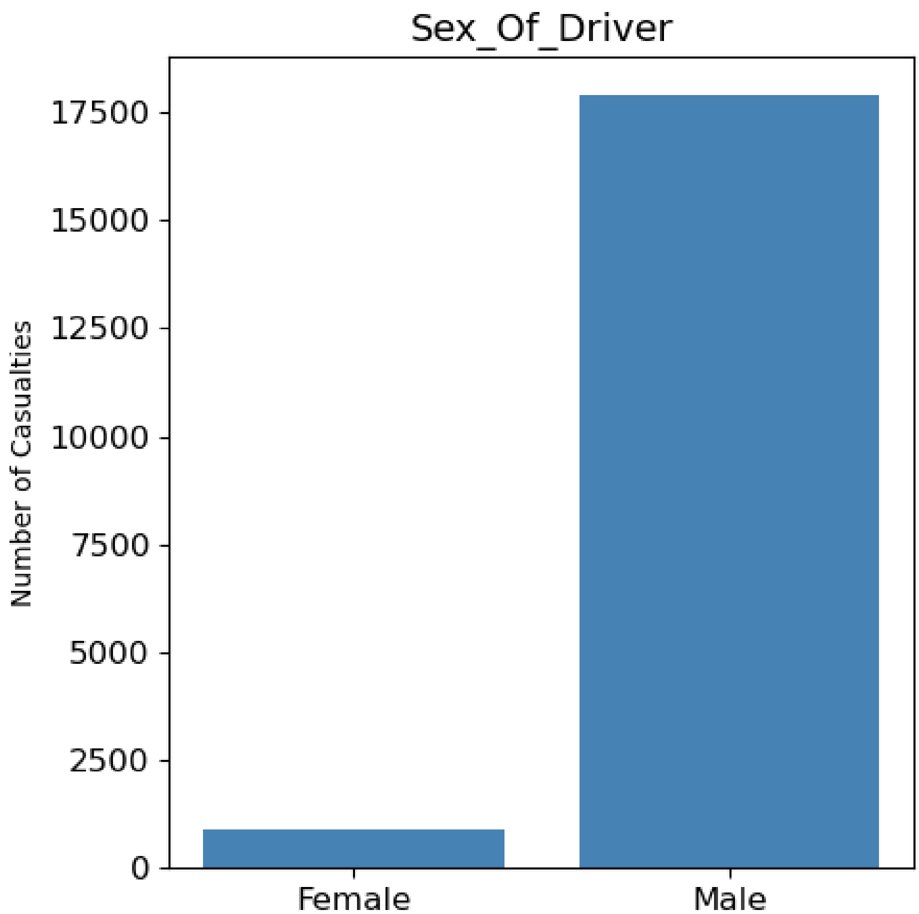
1.5.1 Bhuvan Thirwani:

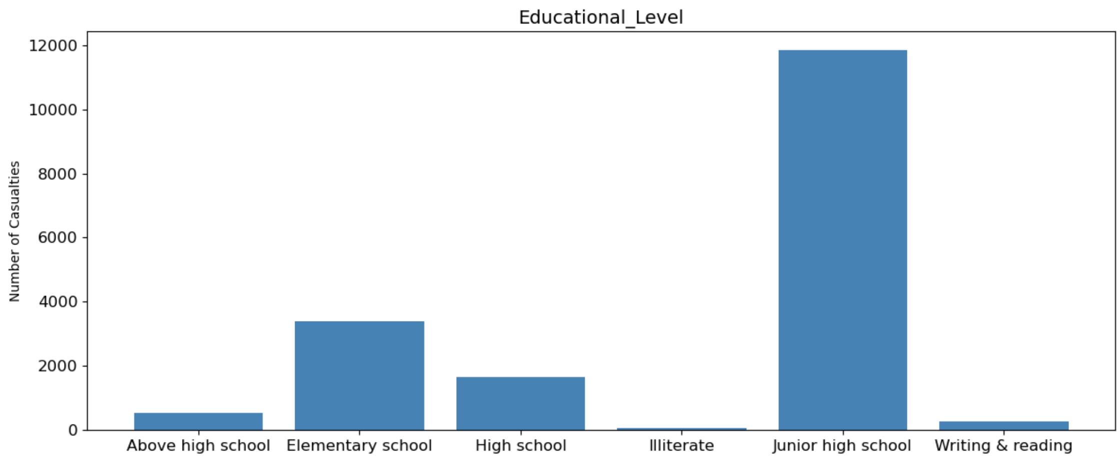
1.5.2 Question 1:

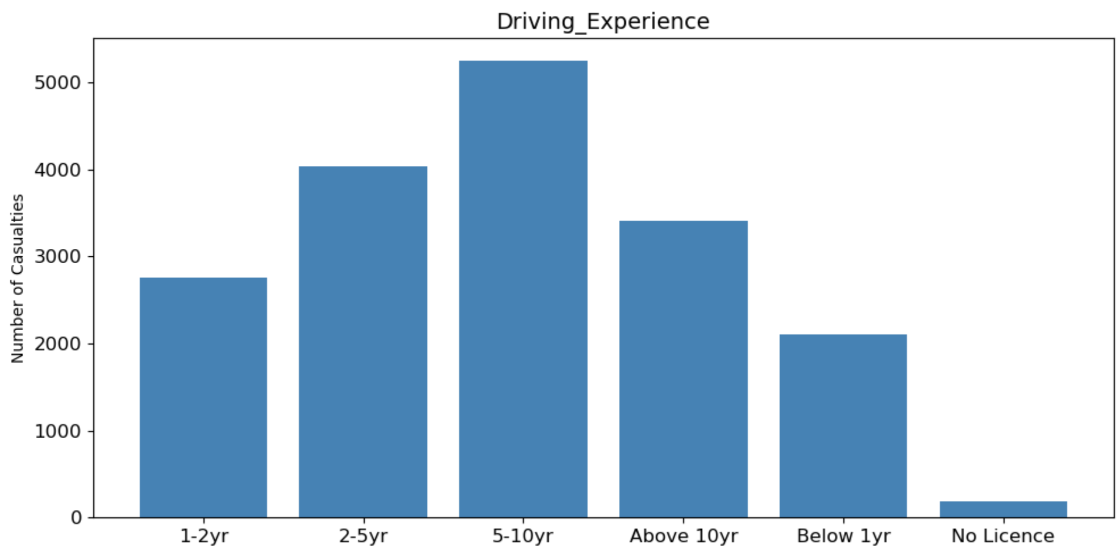
How does driving experience, gender, educational level affect the severity of accidents? What is the corelation between total casualties & accident's severity? ### Hypothesis #### There should be no effect of sex of the driver on casualties and accident severity. Higher education must have low casualities and less severity. Higher driving experience must have lower casualities & less severity

[79]:
```
df=dataset
plt.figure(figsize=(5, 5))
col = 'Sex_of_driver'
df_known = df[~df[col].str.lower().isin(['unknown'])]
plot_data = df_known.groupby(col)['Number_of_casualties'].sum().reset_index()
plt.bar(plot_data[col], plot_data['Number_of_casualties'], color='steelblue')
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.title(col.title(), fontsize=14)
plt.xlabel('')
plt.ylabel('Number of Casualties')
plt.tight_layout()
plt.show()

plt.figure(figsize=(12, 5))
col = 'Educational_level'
df_known = df[~df[col].str.lower().isin(['unknown'])]
plot_data = df_known.groupby(col)['Number_of_casualties'].sum().reset_index()
plt.bar(plot_data[col], plot_data['Number_of_casualties'], color='steelblue')
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.title(col.title(), fontsize=14)
plt.xlabel('')
plt.ylabel('Number of Casualties')
plt.tight_layout()
plt.show()

plt.figure(figsize=(10, 5))
col = 'Driving_experience'
```

```
df_known = df[~df[col].str.lower().isin(['unknown'])]
plot_data = df_known.groupby(col)['Number_of_casualties'].sum().reset_index()
plt.bar(plot_data[col], plot_data['Number_of_casualties'], color='steelblue')
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.title(col.title(), fontsize=14)
plt.xlabel('')
plt.ylabel('Number of Casualties')
plt.tight_layout()
plt.show()
```







1.5.3 Outcomes and Insights

Driving Experience

- **Observation:** The bar chart shows that drivers with 5-10 years of experience are involved in the most accidents, while those without a license have the fewest.
- **Hypothesis Testing:** Contrary to the hypothesis, higher driving experience does not necessarily correlate with fewer casualties or less severity. This suggests that other factors might influence accident outcomes.

Educational Level

- **Observation:** The majority of drivers involved in accidents have a junior high school education. Higher education levels seem to have fewer casualties.

- **Hypothesis Testing:** This supports the hypothesis that higher education correlates with fewer casualties, possibly due to better risk assessment and decision-making skills.

Sex of Driver

- **Observation:** A significantly higher number of male drivers are involved in accidents compared to female drivers.
- **Hypothesis Testing:** The data challenges the hypothesis that sex has no effect on casualties and accident severity. Male drivers appear more frequently in accident data, suggesting gender may play a role.

1.5.4 Feature Engineering

- **Observation:** Almost all the categorical variables have a biased group length.
- **Learning:** We will be using Oversampling methods for making the groups rows count comparable for each column

1.6 Question 2:

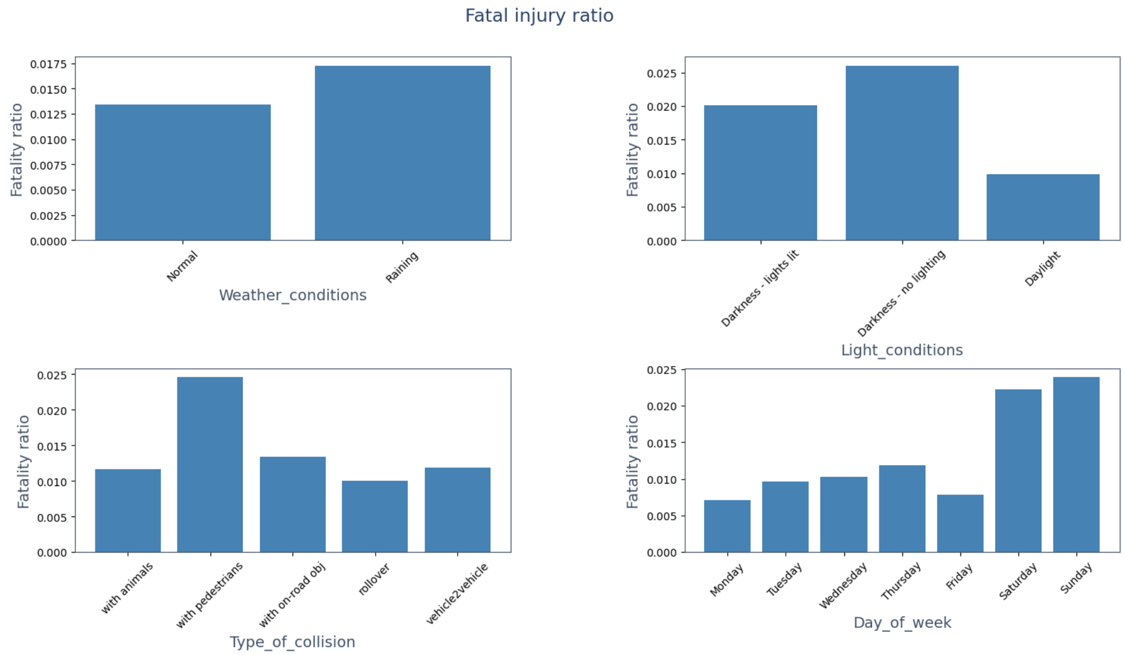
1.6.1 Analyzing how the fatality ratio is related with various factors such as light conditions, weather conditions, type of collision & day of the week in traffic accidents. Finding patterns and correlations which can suggest road safety strategies.

1.6.2 Hypothesis

Dark Lighting, Rainy Weather Conditions should have more fatal rate. On Busy days, fatal ratio should be high as outside is overcrowded & Pedestrian should have the highest fatal ratio.

[83]:
```
df=dataset
def calculate_fatility_ratio(column, df=dataset, sort=False):
    df = df[df[column] != 'Unknown']
    _df = df.groupby(['Accident_severity', column]).Time.count().reset_index()
    rowlist = [row for row in _df[column]]
    time_sum = []
    for row in rowlist:
        time_sum.append(_df.loc[_df[column] == row].Time.sum())

    _df['time_sum'] = time_sum
    _df['fatal_ratio'] = _df['Time'] / _df['time_sum']
    df_with_fatal_ratio = _df.loc[_df.Accident_severity == 'Fatal injury']
    if sort:
        df_with_fatal_ratio = df_with_fatal_ratio.sort_values(by='fatal_ratio')
    return df_with_fatal_ratio

df_with_fatal_ratio = calculate_fatility_ratio('Type_of_collision', df,␣
 ↪sort=True)

def plot_fatal_graphs(ax, column, red_list, df, order=None, custom_labels=None):
```

```python
    fatal_data = calculate_fatility_ratio(column, df)

    if order is not None:
        fatal_data[column] = pd.Categorical(fatal_data[column],␣
↪categories=order, ordered=True)
        fatal_data = fatal_data.sort_values(column)

    x_labels = fatal_data[column]
    y_values = fatal_data['fatal_ratio']

    bars = ax.bar(x_labels, y_values, color='steelblue')

    ax.set_xticks(range(len(x_labels)))
    ax.set_xticklabels(x_labels, rotation=45)

    if custom_labels is not None:
        ax.set_xticks(range(len(custom_labels)))
        ax.set_xticklabels(custom_labels, rotation=45)
    else:
        ax.set_xticks(range(len(x_labels)))
        ax.set_xticklabels(x_labels, rotation=45)

    ax.set_xlabel(column, fontsize=14, color='#425169')
    ax.set_ylabel('Fatality ratio', fontsize=14, color='#425169')
    ax.spines['bottom'].set_color('#425169')
    ax.spines['left'].set_color('#425169')
    ax.spines['top'].set_color('#425169')
    ax.spines['right'].set_color('#425169')

fig, axs = plt.subplots(2, 2, figsize=(15, 8))
plt.suptitle("Fatal injury ratio", fontsize=17, color='#2c4369')

day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday',␣
↪'Sunday']

plot_fatal_graphs(axs[0, 0], 'Weather_conditions', [1], df)
plot_fatal_graphs(axs[0, 1], 'Light_conditions', [1], df)
plot_fatal_graphs(axs[1, 0], 'Type_of_collision', [1], df, custom_labels=['with␣
↪animals', 'with pedestrians', 'with on-road obj', 'rollover',␣
↪'vehicle2vehicle'])
plot_fatal_graphs(axs[1, 1], 'Day_of_week', [-1, -2], df, order=day_order)

plt.subplots_adjust(left=0.1, right=1, bottom=0.1, top=0.9, wspace=0.4, hspace=0.
↪7)
plt.show()
```



Insights from Visualizations

Fatal Injury Ratio for different categories   Number of Vehicles Involved:

- Accidents involving fewer vehicles tend to have higher fatality ratios.

Light Conditions:

- Darkness with no lighting has a high fatality ratio which indicates poor visibility can be a risk factor.

Weather Conditions:

- Rainy conditions correlate with higher fatality ratios compared to normal weather.

Type of Collision:

- Collisions with pedestrians and vehicle with vehicle have the highest fatality ratios.

Day of Week:

- Saturdays and Sundays shows higher fatality ratios which suggests weekends have more severe accidents.

Recommendations for Feature Engineering

Feature Selection and Transformation

- **Select Relevant Features:** We should prioritize features like Light_conditions, number of vehicles involved and Type_of_collision due to their strong correlation with fatality ratios.

- **Create New Features:** Develop a composite feature for risk assessment combining Light_conditions and Weather_conditions to capture environmental risk factors.

Conclusion

Our Hypothesis is 100% correct.

[ ]:
```

```