Tamilnadu_road_accident_2021

January 3, 2024

1 Road Accidents in Tamil Nadu: A Deep Dive into the 2021 Statistics

1.1 Introduction

My research is inspired by a article titled "Road Accidents Killed 1.55 Lakh In India In 2021, Highest Ever: Report." Intrigued by this claim, I embarked on an exploration to understand why 2021 is considered the deadliest year despite the fact that 2017 witnessed a higher overall number of accidents. Unraveling the intricacies behind this assertion became the focal point of my investigation.

In delving into this nationwide concern, I have chosen to narrow my focus to the state of Tamil Nadu as it is my home state and i want to know better. The objective is to discern the unique factors contributing to the alarming statistics of road accidents in the year 2021 within this specific region. Through a detailed analysis of road safety measures, traffic regulations, and other relevant variables

1.2 Aim and objective

The aim is not only to understand the issue but also to contribute significantly to the national discourse on road safety in India. By specifically analyzing Tamil Nadu, my research seeks to fill an important gap in the understanding of regional variations in accident patterns. This focus allows me to explore and facilitate the identification of targeted interventions for the state.

My research endeavors to provide insights that go beyond statistical analysis. It aspires to be a catalyst for positive change, offering actionable recommendations to inform policy decisions. Additionally, it aims to enhance road safety measures and potentially mitigate accidents in Tamil Nadu. This approach sets my contribution apart as a groundbreaking and community-focused effort, striving to make a tangible impact on the road safety landscape.

1.3 Install Requirements

[ ]:
```
!pip install numpy
!pip install pandas
!pip install matplotlib
!pip install seaborn
!pip install beautifulsoup4
!pip install requests
!pip install geopandas
```

```
!pip install Pillow
```

```
Requirement already satisfied: numpy in c:\users\sumo\anaconda3\lib\site-
packages (1.24.3)
Requirement already satisfied: pandas in c:\users\sumo\anaconda3\lib\site-
packages (2.0.3)
Requirement already satisfied: python-dateutil>=2.8.2 in
c:\users\sumo\anaconda3\lib\site-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in c:\users\sumo\anaconda3\lib\site-
packages (from pandas) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in
c:\users\sumo\anaconda3\lib\site-packages (from pandas) (2023.3)
Requirement already satisfied: numpy>=1.21.0 in
c:\users\sumo\anaconda3\lib\site-packages (from pandas) (1.24.3)
Requirement already satisfied: six>=1.5 in c:\users\sumo\anaconda3\lib\site-
packages (from python-dateutil>=2.8.2->pandas) (1.16.0)
Requirement already satisfied: matplotlib in c:\users\sumo\anaconda3\lib\site-
packages (3.7.2)
Requirement already satisfied: contourpy>=1.0.1 in
c:\users\sumo\anaconda3\lib\site-packages (from matplotlib) (1.0.5)
Requirement already satisfied: cycler>=0.10 in c:\users\sumo\anaconda3\lib\site-
packages (from matplotlib) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
c:\users\sumo\anaconda3\lib\site-packages (from matplotlib) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
c:\users\sumo\anaconda3\lib\site-packages (from matplotlib) (1.4.4)
Requirement already satisfied: numpy>=1.20 in c:\users\sumo\anaconda3\lib\site-
packages (from matplotlib) (1.24.3)
Requirement already satisfied: packaging>=20.0 in
c:\users\sumo\anaconda3\lib\site-packages (from matplotlib) (23.1)
Requirement already satisfied: pillow>=6.2.0 in
c:\users\sumo\anaconda3\lib\site-packages (from matplotlib) (10.0.1)
Requirement already satisfied: pyparsing<3.1,>=2.3.1 in
c:\users\sumo\anaconda3\lib\site-packages (from matplotlib) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in
c:\users\sumo\anaconda3\lib\site-packages (from matplotlib) (2.8.2)
Requirement already satisfied: six>=1.5 in c:\users\sumo\anaconda3\lib\site-
packages (from python-dateutil>=2.7->matplotlib) (1.16.0)
Requirement already satisfied: seaborn in c:\users\sumo\anaconda3\lib\site-
packages (0.12.2)
Requirement already satisfied: numpy!=1.24.0,>=1.17 in
c:\users\sumo\anaconda3\lib\site-packages (from seaborn) (1.24.3)
Requirement already satisfied: pandas>=0.25 in c:\users\sumo\anaconda3\lib\site-
packages (from seaborn) (2.0.3)
Requirement already satisfied: matplotlib!=3.6.1,>=3.1 in
c:\users\sumo\anaconda3\lib\site-packages (from seaborn) (3.7.2)
Requirement already satisfied: contourpy>=1.0.1 in
c:\users\sumo\anaconda3\lib\site-packages (from
```

```
matplotlib!=3.6.1,>=3.1->seaborn) (1.0.5)
Requirement already satisfied: cycler>=0.10 in c:\users\sumo\anaconda3\lib\site-
packages (from matplotlib!=3.6.1,>=3.1->seaborn) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
c:\users\sumo\anaconda3\lib\site-packages (from
matplotlib!=3.6.1,>=3.1->seaborn) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
c:\users\sumo\anaconda3\lib\site-packages (from
matplotlib!=3.6.1,>=3.1->seaborn) (1.4.4)
Requirement already satisfied: packaging>=20.0 in
c:\users\sumo\anaconda3\lib\site-packages (from
matplotlib!=3.6.1,>=3.1->seaborn) (23.1)
Requirement already satisfied: pillow>=6.2.0 in
c:\users\sumo\anaconda3\lib\site-packages (from
matplotlib!=3.6.1,>=3.1->seaborn) (10.0.1)
Requirement already satisfied: pyparsing<3.1,>=2.3.1 in
c:\users\sumo\anaconda3\lib\site-packages (from
matplotlib!=3.6.1,>=3.1->seaborn) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in
c:\users\sumo\anaconda3\lib\site-packages (from
matplotlib!=3.6.1,>=3.1->seaborn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in c:\users\sumo\anaconda3\lib\site-
packages (from pandas>=0.25->seaborn) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in
c:\users\sumo\anaconda3\lib\site-packages (from pandas>=0.25->seaborn) (2023.3)
Requirement already satisfied: six>=1.5 in c:\users\sumo\anaconda3\lib\site-
packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=3.1->seaborn) (1.16.0)
Requirement already satisfied: beautifulsoup4 in
c:\users\sumo\anaconda3\lib\site-packages (4.12.2)
Requirement already satisfied: soupsieve>1.2 in
c:\users\sumo\anaconda3\lib\site-packages (from beautifulsoup4) (2.4)
Requirement already satisfied: requests in c:\users\sumo\anaconda3\lib\site-
packages (2.31.0)
Requirement already satisfied: charset-normalizer<4,>=2 in
c:\users\sumo\anaconda3\lib\site-packages (from requests) (2.0.4)
Requirement already satisfied: idna<4,>=2.5 in c:\users\sumo\anaconda3\lib\site-
packages (from requests) (3.4)
Requirement already satisfied: urllib3<3,>=1.21.1 in
c:\users\sumo\anaconda3\lib\site-packages (from requests) (1.26.16)
Requirement already satisfied: certifi>=2017.4.17 in
c:\users\sumo\anaconda3\lib\site-packages (from requests) (2023.11.17)
```

1.4 Import Requirements

[10]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
```

```
import matplotlib.pyplot as plt
import geopandas as gpd
import bs4
from wordcloud import WordCloud, STOPWORDS
from PIL import Image
```

1.5 Acquire a Dataset

To support this investigation, I will acquire the necessary datasets from the Open City Portal India and data.gov.in.This dataset will form the basis for a thorough analysis of road accidents in Tamil Nadu, providing the essential information needed for a comprehensive study.

I am using 6 files, below is the descrpitoin of the files 1. india 2017-2021.csv – road accident data of India between 2017-2021 1. india_2021.csv – road accident data of India in 2021 (state-wise) 1. accident_reason.csv – road accident causes of Tamil Nadu in 2021 1. 2021 tamil nadu data.csv – Tamil Nadu road accident data in 2021 (district-wise) 1. time_of_occurrence.csv – road accidents in India in 2021 by time of occurrence (state-wise) 1. tn-newly-registered-2008-21.csv – Tamil Nadu vehicle registration data from 2008-2021

1.6 Preparing Datasets

[11]:
```
import pandas as pd

try:
    df = pd.read_csv("Datasets/india 2017-2021.csv")
except FileNotFoundError:
    print("Error: File 'india 2017-2021.csv' not found.")
except pd.errors.EmptyDataError:
    print("Error: File 'india 2017-2021.csv' is empty.")
except pd.errors.ParserError:
    print("Error: Unable to parse data from file 'india 2017-2021.csv'. Check␣
 ↪the file format.")

try:
    df1 = pd.read_csv("Datasets/india_2021.csv")
except FileNotFoundError:
    print("Error: File 'india_2021.csv' not found.")
except pd.errors.EmptyDataError:
    print("Error: File 'india_2021.csv' is empty.")
except pd.errors.ParserError:
    print("Error: Unable to parse data from file 'india_2021.csv'. Check the␣
 ↪file format.")

try:
    df2 = pd.read_csv("Datasets/accident_reason.csv")
except FileNotFoundError:
    print("Error: File 'accident_reason.csv' not found.")
except pd.errors.EmptyDataError:
```

```
    print("Error: File 'accident_reason.csv' is empty.")
except pd.errors.ParserError:
    print("Error: Unable to parse data from file 'accident_reason.csv'. Check␣
 ↪the file format.")

try:
    df3 = pd.read_csv("Datasets/2021 tamil nadu data.csv")
except FileNotFoundError:
    print("Error: File '2021 tamil nadu data.csv' not found.")
except pd.errors.EmptyDataError:
    print("Error: File '2021 tamil nadu data.csv' is empty.")
except pd.errors.ParserError:
    print("Error: Unable to parse data from file '2021 tamil nadu data.csv'.␣
 ↪Check the file format.")

try:
    df4 = pd.read_csv('Datasets/time_of_occurrence.csv')
except FileNotFoundError:
    print("Error: File 'time_of_occurrence.csv' not found.")
except pd.errors.EmptyDataError:
    print("Error: File 'time_of_occurrence.csv' is empty.")
except pd.errors.ParserError:
    print("Error: Unable to parse data from file 'time_of_occurrence.csv'.␣
 ↪Check the file format.")

try:
    df5 = pd.read_csv("Datasets/tn-newly-registered-2008-21.csv")
except FileNotFoundError:
    print("Error: File 'tn-newly-registered-2008-21.csv' not found.")
except pd.errors.EmptyDataError:
    print("Error: File 'tn-newly-registered-2008-21.csv' is empty.")
except pd.errors.ParserError:
    print("Error: Unable to parse data from file 'tn-newly-registered-2008-21.
 ↪csv'. Check the file format.")
```

1.6.1 Why are these datasets are appropriate

The datasets provide detailed information about road accidents in India, but more importantly, they offer specific insights into the situation in Tamil Nadu. This granularity allows for a focused and in-depth analysis of the region that i am particularly interested in.

1.6.2 How the data format is suitable for analysis

The datasets have been downloaded in CSV format from the website. Once acquired, the CSV file is processed into a Pandas DataFrame, a versatile open-source tool for data analysis and manipulation. This choice aligns seamlessly with the analytical requirements of this project.

1.6.3 Ethics of use of data

The datasets have been sourced from the opencity urban data portal and data.gov.in , and their license and terms and conditions can be found in the link below. open portal data.gov.in

It is important to note that the license agreement intended to allow users to freely share, modify and use this database while maintaining this same freedom for others.

In conclusion, the datasets sourced from the opencity urban data portal adhere to an open and collaborative approach, as outlined in the provided license agreement.

1.7 Project Background

1.7.1 why this field is of interest

I selected the road accident data in Tamil Nadu for this project due to my familiarity with the state. Despite being well-acquainted with Tamil Nadu, there is a lack of specific knowledge regarding the locations and times of accidents. My motivation is rooted in the desire to identify these details, not only to enhance my understanding but also to contribute to the safety of my friends and loved ones. This project serves as a personal exploration into road safety within my state, aiming to gather valuable insights and promote awareness.The choice of the year 2021 is deliberate, aligning with the time I obtained my license and coinciding with what is considered one of the deadliest years for accidents. This period also represents the post-lockdown phase , offering insights into changes in road safety behavior as people resumed outdoor activities.

1.7.2 Previous Exploration of this topic

While extensive explorations have been conducted in previous years, particularly before the onset of the COVID-19 pandemic, these studies were often focused on the entirety of India. In my current research, I aim to shift the focus exclusively to Tamil Nadu, examining its unique contribution to the overall road safety landscape in India.

1.7.3 Scope of Work

I start by investigating and visualizing the trends of road accidents in both India and Tamil Nadu from 2017 to 2021, identifying patterns and changes over the years. Then, I dive deep into Tamil Nadu in 2021, focusing on:

Fatal and non-fatal road accidents.

Gender-wise analysis of road accidents.

Identification of causes behind road accidents.

Vehicle-wise breakdown of road accidents.

Time-of-day analysis for road accidents.

Creation of a word cloud to visually showcase key themes and insights.

This comprehensive approach aims to provide a detailed understanding of the road safety landscape in Tamil Nadu in 2021, contributing valuable insights for informed decision-making and future interventions.

1.7.4 Steps in analytical data processing pipeline

Retrieve necessary data from the website.

Organize the retrieved data into a structured dataframe.

Implement data cleaning procedures to enhance data quality.

Utilize the cleaned data to derive valuable insights through visualization.

Formulate conclusions based on the analysis for a comprehensive understanding of the data.

1.8 Technical exploration of datasets

1.8.1 Data cleaning

For my data science project, I've acquired five datasets that require thorough cleaning before visualization. The data cleaning process is essential to ensure the reliability and accuracy of the datasets for subsequent analysis and visualization. The key tasks involved in data cleaning include handling missing values, addressing duplicates, managing inconsistencies, detecting and handling outliers, correcting typos and spelling errors, dealing with inaccurate data, normalizing and scaling numerical features, handling categorical data, ensuring data integrity, and documenting the entire process for transparency and reproducibility. The goal is to prepare the datasets in a clean and structured format, making them suitable for effective visualization and subsequent analysis in my data science project.

DataFrame

[12]:
```
df.head()
```

[12]:

	Year	Total Number of Fatalities	Total Number of People Injured
0	2017	147913	470975
1	2018	151417	469418
2	2019	151113	451361
3	2020	131714	348279
4	2021	153972	384448

[13]:
```
df.isna().sum()
```

[13]:
```
Year                              0
Total Number of Fatalities        0
Total Number of People Injured    0
dtype: int64
```

[14]:
```
df.describe()
```

[14]:

	Year	Total Number of Fatalities	Total Number of People Injured
count	5.000000	5.000000	5.000000
mean	2019.000000	147225.800000	424896.200000
std	1.581139	8934.146277	55479.916057
min	2017.000000	131714.000000	348279.000000
25%	2018.000000	147913.000000	384448.000000

```
50%    2019.000000            151113.000000                     451361.000000
75%    2020.000000            151417.000000                     469418.000000
max    2021.000000            153972.000000                     470975.000000
```

Dataframe 1

[15]:
```
df1.head()
```

[15]:
```
  Category      State/UT/City  \
0    State     Andhra Pradesh
1    State  Arunachal Pradesh
2    State              Assam
3    State              Bihar
4    State       Chhattisgarh

   Rural Area(Near School/College/Educational Institution) - Male  \
0                                                207
1                                                  6
2                                                285
3                                                115
4                                                143

   Rural Area(Near School/College/Educational Institution) - Female  \
0                                                 47
1                                                  1
2                                                 39
3                                                 23
4                                                 24

   Rural Area(Near School/College/Educational Institution) - Transgender  \
0                                                  0
1                                                  0
2                                                  0
3                                                  0
4                                                  0

   Rural Area(Near School/College/Educational Institution) - Total  \
0                                                254
1                                                  7
2                                                324
3                                                138
4                                                167

   Rural Area (Near Residential Area) - Male  \
0                                       1338
1                                         21
2                                        733
3                                        233
```

```
4                                   1049

   Rural Area (Near Residential Area) - Female  \
0                                         238
1                                           0
2                                         122
3                                          48
4                                         152

   Rural Area (Near Residential Area) - Transgender  \
0                                                 0
1                                                 0
2                                                 0
3                                                 0
4                                                 0

   Rural Area (Near Residential Area) - Total  …  \
0                                        1576  …
1                                          21  …
2                                         855  …
3                                         281  …
4                                        1201  …

   Urban Area (Others) - Transgender  Urban Area (Others) - Total  \
0                                  0                          627
1                                  0                           33
2                                  0                           19
3                                  0                         1158
4                                  0                          774

   Urban Area (Sub Total) - Male  Urban Area (Sub Total) - Female  \
0                           1461                              336
1                             54                               10
2                           1305                              219
3                           4881                             1303
4                           1371                              191

   Urban Area (Sub Total) - Transgender  Urban Area (Sub Total) - Total  \
0                                     0                            1797
1                                     0                              64
2                                     0                            1524
3                                     0                            6184
4                                     0                            1562

   Grand Total - Male  Grand Total - Female  Grand Total - Transgender  \
0                7009                  1177                          0
1                 153                    20                          0
```

```
2              2600                 414                       0
3              6137                1523                       0
4              4773                 640                       0

   Grand Total - Total
0                 8186
1                  173
2                 3014
3                 7660
4                 5413

[5 rows x 66 columns]
```

[16]:
```
df1.isna().sum()
```

[16]:
```
Category                                                                0
State/UT/City                                                           0
Rural Area(Near School/College/Educational Institution) - Male          0
Rural Area(Near School/College/Educational Institution) - Female        0
Rural Area(Near School/College/Educational Institution) - Transgender   0
                                                                       ..
Urban Area (Sub Total) - Total                                          0
Grand Total - Male                                                      0
Grand Total - Female                                                    0
Grand Total - Transgender                                               0
Grand Total - Total                                                     0
Length: 66, dtype: int64
```

[17]:
```
df1.describe()
```

[17]:
```
       Rural Area(Near School/College/Educational Institution) - Male  \
count                                          93.000000
mean                                          171.258065
std                                           769.637929
min                                             0.000000
25%                                             0.000000
50%                                             2.000000
75%                                            25.000000
max                                          5253.000000

       Rural Area(Near School/College/Educational Institution) - Female  \
count                                          93.000000
mean                                           31.193548
std                                           139.816359
min                                             0.000000
25%                                             0.000000
50%                                             0.000000
```

```
75%                                                          9.000000
max                                                        953.000000

       Rural Area(Near School/College/Educational Institution) - Transgender  \
count                                               93.0
mean                                                 0.0
std                                                  0.0
min                                                  0.0
25%                                                  0.0
50%                                                  0.0
75%                                                  0.0
max                                                  0.0

       Rural Area(Near School/College/Educational Institution) - Total  \
count                                          93.000000
mean                                          202.451613
std                                           909.381844
min                                             0.000000
25%                                             0.000000
50%                                             2.000000
75%                                            31.000000
max                                          6206.000000

       Rural Area (Near Residential Area) - Male  \
count                                  93.000000
mean                                  780.591398
std                                  3466.585484
min                                     0.000000
25%                                     0.000000
50%                                    16.000000
75%                                   138.000000
max                                 23799.000000

       Rural Area (Near Residential Area) - Female  \
count                                    93.000000
mean                                    119.548387
std                                     532.327284
min                                       0.000000
25%                                       0.000000
50%                                       1.000000
75%                                      27.000000
max                                    3646.000000

       Rural Area (Near Residential Area) - Transgender  \
count                                               93.0
mean                                                 0.0
std                                                  0.0
```

```
min                                                    0.0
25%                                                    0.0
50%                                                    0.0
75%                                                    0.0
max                                                    0.0

       Rural Area (Near Residential Area) - Total  \
count                                   93.000000
mean                                   900.139785
std                                   3998.653302
min                                      0.000000
25%                                      0.000000
50%                                     17.000000
75%                                    165.000000
max                                  27445.000000

       Rural Area (Near Religious Place) - Male  \
count                                 93.000000
mean                                 115.967742
std                                  521.925666
min                                    0.000000
25%                                    0.000000
50%                                    0.000000
75%                                   13.000000
max                                 3561.000000

       Rural Area (Near Religious Place) - Female  …  \
count                                   93.000000  …
mean                                    21.301075  …
std                                     96.098544  …
min                                      0.000000  …
25%                                      0.000000  …
50%                                      0.000000  …
75%                                      3.000000  …
max                                    653.000000  …

       Urban Area (Others) - Transgender  Urban Area (Others) - Total  \
count                          93.000000                    93.000000
mean                            0.086022                   660.440860
std                             0.318144                  2636.833569
min                             0.000000                     0.000000
25%                             0.000000                     4.000000
50%                             0.000000                    38.000000
75%                             0.000000                   199.000000
max                             2.000000                 18399.000000

       Urban Area (Sub Total) - Male  Urban Area (Sub Total) - Female  \
```

```
count                93.00000                          93.000000
mean               1802.11828                         312.258065
std                7166.73005                        1251.342765
min                   0.00000                           0.000000
25%                  74.00000                          11.000000
50%                 147.00000                          22.000000
75%                1070.00000                         101.000000
max               49483.00000                        8560.000000

       Urban Area (Sub Total) - Transgender  Urban Area (Sub Total) - Total  \
count                             93.000000                       93.000000
mean                               0.139785                     2114.516129
std                                0.479841                     8417.091677
min                                0.000000                        0.000000
25%                                0.000000                       91.000000
50%                                0.000000                      184.000000
75%                                0.000000                     1172.000000
max                                3.000000                    58046.000000

       Grand Total - Male  Grand Total - Female  Grand Total - Transgender  \
count           93.000000             93.000000                  93.000000
mean          4580.473118            727.215054                   0.204301
std          19492.764892           3092.942956                   0.774023
min              1.000000              0.000000                   0.000000
25%            116.000000             17.000000                   0.000000
50%            196.000000             35.000000                   0.000000
75%           1088.000000            149.000000                   0.000000
max         134374.000000          21243.000000                   5.000000

       Grand Total - Total
count            93.000000
mean           5307.892473
std           22584.894518
min               1.000000
25%             131.000000
50%             226.000000
75%            1172.000000
max          155622.000000

[8 rows x 64 columns]
```

Dataframe 2

[18]:
```
df2.head()
```

[18]:
```
   _id       State/UT/City  \
0    1      ANDHRA PRADESH
1    2   ARUNACHAL PRADESH
```

```
2   3             ASSAM
3   4             BIHAR
4   5      CHHATTISGARH

   Dangerous or Careless Driving/ Overtaking etc Cases  \
0                                               2185
1                                                 65
2                                                886
3                                               5039
4                                               3536

   Dangerous or Careless Driving/ Overtaking etc Injured  \
0                                               2271
1                                                 59
2                                                833
3                                               4134
4                                               3258

   Dangerous or Careless Driving/ Overtaking etc Died  Overspeeding Cases  \
0                                                755               16631
1                                                 40                 120
2                                                347                4303
3                                               4071                2886
4                                               1750                6378

   Overspeeding Injured  Overspeeding Died  \
0                 16188               6371
1                   127                 74
2                  3237               1946
3                  2348               2284
4                  5603               2723

   Driving under Influence of Drug/Alcohol Cases  \
0                                            119
1                                              3
2                                            288
3                                             51
4                                            145

   Driving under Influence of Drug/Alcohol Injured  …  \
0                                               64  …
1                                                6  …
2                                              201  …
3                                               53  …
4                                              159  …

   Vehicles Parking at Road Shoulders Died  Causes Not Known Cases  \
```

```
0                                    18.0                    121.0
1                                     0.0                      9.0
2                                    45.0                     42.0
3                                    95.0                     20.0
4                                    71.0                    455.0

   Causes Not Known Injured  Causes Not Known Died  Other Causes Cases  \
0                     119.0                   32.0              2129.0
1                       4.0                    7.0                38.0
2                       0.0                   10.0                89.0
3                      12.0                   22.0               101.0
4                     220.0                  258.0              1163.0

   Other Causes Injured  Other Causes Died  Total Road Accidents Cases  \
0                1957.0              817.0                     21556.0
1                  37.0               28.0                       261.0
2                  95.0               21.0                      7069.0
3                  70.0               77.0                      9553.0
4                 917.0              445.0                     12395.0

   Total Road Accidents Injured  Total Road Accidents Died
0                       21040.0                     8186.0
1                         266.0                      173.0
2                        5420.0                     3014.0
3                        7946.0                     7660.0
4                       10682.0                     5413.0

[5 rows x 44 columns]
```

[19]:
```
df2.isna().sum()
```

[19]:
```
_id                                                 0
State/UT/City                                       0
Dangerous or Careless Driving/ Overtaking etc Cases      0
Dangerous or Careless Driving/ Overtaking etc Injured    0
Dangerous or Careless Driving/ Overtaking etc Died       0
Overspeeding Cases                                  0
Overspeeding Injured                                0
Overspeeding Died                                   0
Driving under Influence of Drug/Alcohol Cases       0
Driving under Influence of Drug/Alcohol Injured     0
Driving under Influence of Drug/Alcohol Died        0
Physical Fatigue of Drivers Cases                   0
Physical Fatigue of Drivers Injured                 0
Physical Fatigue of Drivers Died                    0
Defect in Mechanical Condition of Vehicle Cases     0
Defect in Mechanical Condition of Vehicle Injured   0
```

```
Defect in Mechanical Condition of Vehicle Died          0
Animal Crossing Cases                                   0
Animal Crossing Injured                                 0
Animal Crossing Died                                    0
Weather Condition (Total) Cases                         0
Weather Condition (Total) Injured                       0
Weather Condition (Total) Died                          0
Weather Condition (Poor Visibility) Cases               0
Weather Condition (Poor Visibility) Injured             0
Weather Condition (Poor Visibility) Died                0
Weather Condition (Other Causes) Cases                  0
Weather Condition (Other Causes) Injured                0
Weather Condition (Other Causes) Died                   0
Lack of Road Infrastructure Cases                       1
Lack of Road Infrastructure Injured                     1
Lack of Road Infrastructure Died                        1
Vehicles Parking at Road Shoulders Cases                1
Vehicles Parking at Road Shoulders Injured              1
Vehicles Parking at Road Shoulders Died                 1
Causes Not Known Cases                                  1
Causes Not Known Injured                                1
Causes Not Known Died                                   1
Other Causes Cases                                      1
Other Causes Injured                                    1
Other Causes Died                                       1
Total Road Accidents Cases                              1
Total Road Accidents Injured                            1
Total Road Accidents Died                               1
dtype: int64
```

[20]:
```
df2.dropna(inplace=True)
```

[21]:
```
df2.describe()
```

[21]:
```
             _id  Dangerous or Careless Driving/ Overtaking etc Cases  \
count  92.000000                                        92.000000
mean   47.086957                                      2564.434783
std    27.125533                                     10864.043050
min     1.000000                                         0.000000
25%    23.750000                                        38.250000
50%    47.500000                                       144.500000
75%    70.250000                                      1182.000000
max    93.000000                                    100835.000000

       Dangerous or Careless Driving/ Overtaking etc Injured  \
count                                          92.000000
mean                                         2259.891304
```

```
std                                                  9589.162177
min                                                     0.000000
25%                                                    26.000000
50%                                                   121.500000
75%                                                   957.250000
max                                                 89276.000000

       Dangerous or Careless Driving/ Overtaking etc Died  Overspeeding Cases  \
count                                           92.000000           92.000000
mean                                          1016.043478         5925.673913
std                                           4588.699588        25098.930572
min                                              0.000000            0.000000
25%                                             14.750000          172.500000
50%                                             58.500000          591.000000
75%                                            353.750000         2742.000000
max                                          42184.000000       233314.000000

       Overspeeding Injured  Overspeeding Died  \
count             92.000000          92.000000
mean            5559.173913        2053.586957
std            23779.551634        9112.330644
min                0.000000           0.000000
25%              116.000000          60.000000
50%              418.500000         128.000000
75%             1698.500000         613.000000
max           219850.000000       85709.000000

       Driving under Influence of Drug/Alcohol Cases  \
count                                      92.000000
mean                                      192.500000
std                                       836.721894
min                                         0.000000
25%                                         2.000000
50%                                        12.000000
75%                                        99.250000
max                                      7607.000000

       Driving under Influence of Drug/Alcohol Injured  \
count                                        92.000000
mean                                        175.608696
std                                         795.537512
min                                           0.000000
25%                                           1.000000
50%                                           7.000000
75%                                          65.750000
max                                        7127.000000
```

```
       Driving under Influence of Drug/Alcohol Died  …  \
count                                     92.000000  …
mean                                      69.500000  …
std                                      317.030643  …
min                                        0.000000  …
25%                                        0.000000  …
50%                                        3.000000  …
75%                                       28.250000  …
max                                     2910.000000  …

       Vehicles Parking at Road Shoulders Died  Causes Not Known Cases  \
count                                92.000000               92.000000
mean                                 30.652174              152.565217
std                                 141.868956              585.385161
min                                   0.000000                0.000000
25%                                   0.000000                0.000000
50%                                   0.000000                0.500000
75%                                   9.000000               43.000000
max                                1320.000000             5256.000000

       Causes Not Known Injured  Causes Not Known Died  Other Causes Cases  \
count                 92.000000              92.000000           92.000000
mean                 130.826087              66.804348          515.239130
std                  507.593993             290.368854         2025.500521
min                    0.000000               0.000000            0.000000
25%                    0.000000               0.000000            0.000000
50%                    0.000000               0.000000            5.500000
75%                   34.500000              21.250000          146.250000
max                 4516.000000            2673.000000        18202.000000

       Other Causes Injured  Other Causes Died  Total Road Accidents Cases  \
count             92.000000          92.000000                   92.000000
mean             467.543478         176.913043                 9968.652174
std             1804.687781         772.423682                41821.795063
min                0.000000           0.000000                    4.000000
25%                0.000000           0.000000                  351.000000
50%                4.000000           2.500000                 1041.500000
75%              171.750000          61.500000                 4722.000000
max            16156.000000        7092.000000               391239.000000

       Total Road Accidents Injured  Total Road Accidents Died
count                     92.000000                  92.000000
mean                    9117.543478                3674.043478
std                    38515.322827               16269.436349
min                        6.000000                   1.000000
25%                      265.250000                 130.750000
50%                      826.500000                 225.000000
```

```
75%                       3540.500000                  1067.000000
max                     359203.000000                153185.000000

[8 rows x 43 columns]
```

Dataframe 3

[22]:
```
df3.head()
```

[22]:
```
   _id  S.No.              District  2020- Fatal  2021- Fatal  \
0    1    1.0          Chennai City          885          975
1    2    2.0       Coimbatore City          187          232
2    3    3.0          Madurai City          158          152
3    4    4.0            Salem City          151          147
4    5    5.0  Thiruchirapalli City          127          126

   2020- Non-fatal  2021- Non-fatal  Total - 2020  Total - 2021  \
0             3502             4059          4387        5034.0
1              520              634           707         866.0
2              372              466           530         618.0
3              473              537           624         684.0
4              271              273           398         399.0

   Death by Lorries - 2021  Death by Buses-2021  Death by Cars/Jeeps 2021  \
0                      156                   69                       181
1                       34                   19                        48
2                       12                   16                        29
3                       28                   13                        35
4                       13                   17                        30

   Death by Three-wheelers - 2021  Death by Two-wheelers 2021  \
0                              35                         464
1                               9                         103
2                               8                          65
3                               1                          59
4                               3                          43

   Death by Others 2021  Total Deaths 2021
0                    93                998
1                    21                234
2                    24                154
3                    13                149
4                    24                130
```

[23]:
```
df3.isna().sum()
```

[23]:
```
_id                                0
S.No.                              1
```

```
District                           0
2020- Fatal                        0
2021- Fatal                        0
2020- Non-fatal                    0
2021- Non-fatal                    0
Total - 2020                       0
Total - 2021                       1
Death by Lorries - 2021            0
Death by Buses-2021                0
Death by Cars/Jeeps 2021           0
Death by Three-wheelers - 2021     0
Death by Two-wheelers 2021         0
Death by Others 2021               0
Total Deaths 2021                  0
dtype: int64
```

[24]:
```
df3.dropna(inplace=True)
```

[25]:
```
df3.describe()
```

[25]:
```
             _id       S.No.  2020- Fatal  2021- Fatal  2020- Non-fatal  \
count  44.000000  44.000000   44.000000    44.000000        44.000000
mean   22.500000  22.500000  315.181818   335.159091       817.636364
std    12.845233  12.845233  181.594139   187.515822       579.234784
min     1.000000   1.000000    1.000000     1.000000         2.000000
25%    11.750000  11.750000  177.500000   219.500000       515.000000
50%    22.500000  22.500000  291.000000   313.000000       649.500000
75%    33.250000  33.250000  445.500000   491.000000      1044.250000
max    44.000000  44.000000  885.000000   975.000000      3502.000000

       2021- Non-fatal  Total - 2020  Total - 2021  Death by Lorries - 2021  \
count        44.000000     44.000000      44.00000                44.000000
mean        930.340909   1132.818182    1265.50000                49.818182
std         656.003259    744.427305     826.69188                33.372648
min           0.000000      3.000000       1.00000                 1.000000
25%         570.000000    713.000000     791.50000                25.750000
50%         809.500000    987.500000    1109.00000                41.000000
75%        1169.250000   1496.500000    1682.25000                67.750000
max        4059.000000   4387.000000    5034.00000               156.000000

       Death by Buses-2021  Death by Cars/Jeeps 2021  \
count            44.000000                 44.000000
mean             22.522727                 84.727273
std              13.311105                 52.605758
min               0.000000                  0.000000
25%              14.500000                 36.750000
50%              20.500000                 80.500000
```

```
75%              29.000000                   123.500000
max              69.000000                   199.000000

       Death by Three-wheelers - 2021  Death by Two-wheelers 2021  \
count                       44.000000                   44.000000
mean                         6.977273                  147.568182
std                          6.090361                   85.686122
min                          0.000000                    0.000000
25%                          3.000000                   90.250000
50%                          6.000000                  144.500000
75%                          9.000000                  204.500000
max                         35.000000                  464.000000

       Death by Others 2021  Total Deaths 2021
count             44.000000          44.000000
mean              38.022727         349.636364
std               25.619296         194.968941
min                0.000000           1.000000
25%               24.000000         225.750000
50%               33.000000         326.000000
75%               49.250000         514.750000
max              106.000000         998.000000
```

Dataframe 4

[26]:
```
df4.head()
```

[26]:
```
          States/UTs  06-900hrs - Day  09-1200hrs - Day  12-1500hrs - Day  \
0     Andhra Pradesh           2337.0            3324.0            3416.0
1  Arunachal Pradesh             23.0              48.0              46.0
2              Assam            881.0            1350.0            1145.0
3              Bihar           1413.0            1525.0            1363.0
4       Chhattisgarh            837.0            1853.0            1940.0

   15-1800hrs - Day  18-2100hrs - Night  21-2400hrs - Night  \
0            4125.0              4522.0              1925.0
1              36.0                43.0                31.0
2            1412.0              1145.0               423.0
3            1508.0              1497.0               648.0
4            2732.0              3110.0              1219.0

   00-300hrs - Night  03-600hrs - Night  Unknown Time  Total Accidents
0              775.0             1126.0           6.0            21556
1               22.0               20.0          14.0              283
2              455.0              472.0         128.0             7411
3              242.0              658.0         699.0             9553
4              375.0              309.0           0.0            12375
```

[27]:
```
df4.isna().sum()
```

[27]:
```
States/UTs              0
06-900hrs - Day         1
09-1200hrs - Day        1
12-1500hrs - Day        1
15-1800hrs - Day        1
18-2100hrs - Night      1
21-2400hrs - Night      1
00-300hrs - Night       1
03-600hrs - Night       1
Unknown Time            1
Total Accidents         0
dtype: int64
```

[28]:
```
df4.dropna(inplace=True)
```

[29]:
```
df4.describe()
```

[29]:
```
       06-900hrs - Day  09-1200hrs - Day  12-1500hrs - Day  15-1800hrs - Day  \
count        37.000000         37.000000         37.000000         37.000000
mean       2344.324324       3318.216216       3412.918919       3971.189189
std        7103.257653      10053.878232      10346.883660      12041.301083
min           0.000000          2.000000          0.000000          1.000000
25%          45.000000         48.000000         50.000000         68.000000
50%         616.000000        764.000000        702.000000        879.000000
75%        2120.000000       2967.000000       3416.000000       4028.000000
max       43370.000000      61387.000000      63139.000000      73467.000000

       18-2100hrs - Night  21-2400hrs - Night  00-300hrs - Night  \
count            37.00000           37.000000          37.000000
mean           4604.27027         2221.189189        1063.891892
std           14003.38772         6731.734380        3227.389716
min               0.00000            1.000000           0.000000
25%              80.00000           39.000000          22.000000
50%            1041.00000          423.000000         277.000000
75%            4238.00000         1925.000000         775.000000
max           85179.00000        41092.000000       19682.000000

       03-600hrs - Night  Unknown Time  Total Accidents
count          37.000000     37.000000        37.000000
mean         1087.567568    270.054054     22293.621622
std          3299.615336    844.975113     67531.572043
min             0.000000      0.000000         4.000000
25%            14.000000      0.000000       366.000000
50%           309.000000     14.000000      5452.000000
75%           843.000000    182.000000     20951.000000
```

```
max          20120.000000   4996.000000    412432.000000
```

Dataframe 5

[30]:
```
df5.head()
```

[30]:
```
  Type of Vehicle Category of Vehicle  2008-2009  2009-2010  2010-2011  \
0       Transport           AMBULANCE        663        412        421
1       Transport                AUTO      12547      23140      52923
2       Transport           MOTOR CAB      11940      13731      21560
3       Transport            MAXI CAB       6478       7163      12176
4       Transport            OMNIBUS         179        214        354

   2011-2012  2012-2013  2013-2014  2014-2015  2015-2016  2016-2017  \
0        407        604        642        686        481        928
1      10377      17092      19459      22572      20444      26630
2      21769      15754      12510      11275      16218      21393
3      12811      13329      10050       8090       8275       9367
4        288        398        151         66        174        282

   2017-2018  2018-2019  2019-2020  2020-2021
0        599        214        604      809.0
1      27286      38429      40909     7395.0
2      17376      16433      13397     2677.0
3       4211       3834       3103      115.0
4        130        103         41       16.0
```

[31]:
```
df5.isna().sum()
```

[31]:
```
Type of Vehicle        1
Category of Vehicle    0
2008-2009              0
2009-2010              0
2010-2011              0
2011-2012              0
2012-2013              0
2013-2014              0
2014-2015              0
2015-2016              0
2016-2017              0
2017-2018              0
2018-2019              0
2019-2020              0
2020-2021              1
dtype: int64
```

[32]:
```
df5.dropna(inplace=True)
```

[33]:
```
df5.describe()
```

[33]:
```
         2008-2009     2009-2010     2010-2011     2011-2012     2012-2013  \
count     33.00000  3.300000e+01  3.300000e+01  3.300000e+01  3.300000e+01
mean   59386.69697  7.091800e+04  9.554664e+04  1.075039e+05  1.103586e+05
std   181912.09078  2.168232e+05  2.855118e+05  3.322140e+05  3.382431e+05
min        6.00000  0.000000e+00  0.000000e+00  0.000000e+00  1.000000e+00
25%      663.00000  4.120000e+02  4.210000e+02  4.070000e+02  3.980000e+02
50%     3450.00000  3.706000e+03  3.907000e+03  3.547000e+03  3.981000e+03
75%    11940.00000  1.387200e+04  2.156000e+04  1.960400e+04  1.709200e+04
max   893514.00000  1.067358e+06  1.409165e+06  1.635422e+06  1.681526e+06

         2013-2014     2014-2015     2015-2016     2016-2017     2017-2018  \
count  3.300000e+01  3.300000e+01  3.300000e+01  3.300000e+01  3.300000e+01
mean   9.888345e+04  1.003035e+05  1.021017e+05  1.154919e+05  1.171745e+05
std    3.072242e+05  3.114022e+05  3.140721e+05  3.590950e+05  3.628030e+05
min    0.000000e+00  1.000000e+00  3.000000e+00  0.000000e+00  1.000000e+00
25%    1.960000e+02  1.920000e+02  1.740000e+02  1.640000e+02  1.300000e+02
50%    2.640000e+03  2.915000e+03  3.298000e+03  3.533000e+03  3.193000e+03
75%    1.330300e+04  1.127500e+04  1.621800e+04  2.139300e+04  1.742300e+04
max    1.532844e+06  1.563429e+06  1.584589e+06  1.789931e+06  1.822593e+06

         2018-2019     2019-2020     2020-2021
count  3.300000e+01  3.300000e+01  3.300000e+01
mean   1.292594e+05  1.166622e+05  8.955758e+04
std    4.141890e+05  3.856089e+05  3.088721e+05
min    0.000000e+00  0.000000e+00  0.000000e+00
25%    7.800000e+01  1.800000e+01  0.000000e+00
50%    2.389000e+03  1.703000e+03  1.510000e+02
75%    2.283100e+04  2.340900e+04  2.106500e+04
max    1.990274e+06  1.786646e+06  1.420947e+06
```

Setting Up GeoDataFrame for Map Visualization

[34]:
```python
import geopandas as gpd

india_states = gpd.read_file('India_State_Shapefile/India_State_Boundary.shp')

#columns of the GeoDataFrame
print(india_states.columns)
```

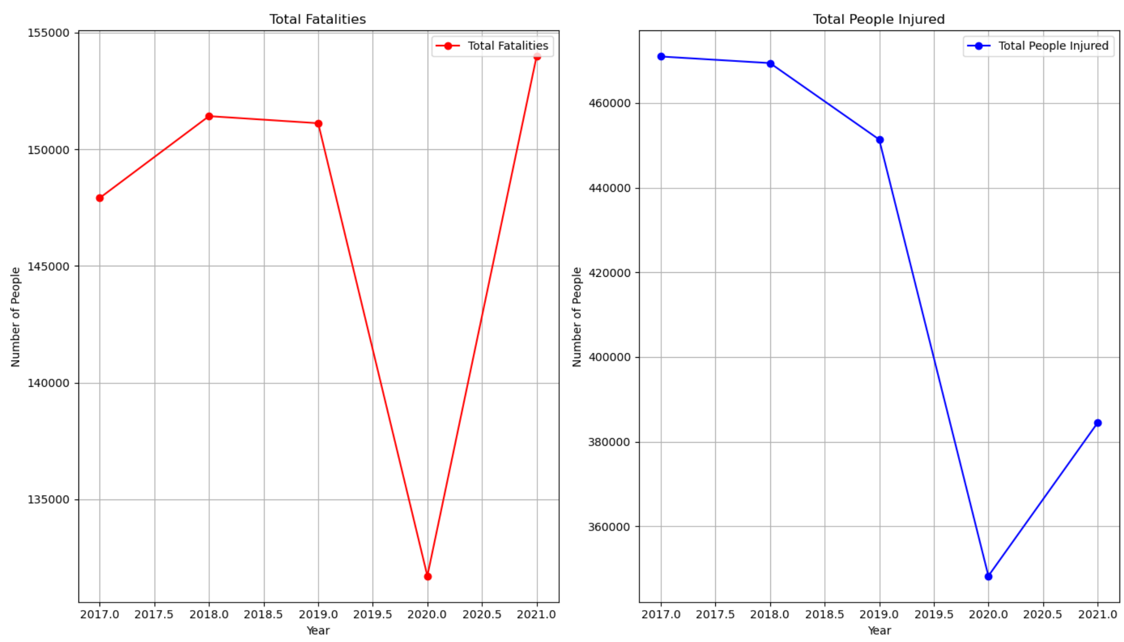
```
Index(['Name', 'Type', 'geometry'], dtype='object')
```

1.8.2 Analysis of data

A Five-Year Analysis (2017-2021) Unveils Alarming Trends with 2021 Emerging as the Deadliest Year

[35]:

```
fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(14, 8))

# Line plot for Total Fatalities
axes[0].plot(df['Year'], df['Total Number of Fatalities'], label='Total␣
 ↪Fatalities', marker='o', color='red')
axes[0].set_title('Total Fatalities')
axes[0].set_xlabel('Year')
axes[0].set_ylabel('Number of People')
axes[0].legend()
axes[0].grid(True)

# Line plot for Total People Injured
axes[1].plot(df['Year'], df['Total Number of People Injured'], label='Total␣
 ↪People Injured', marker='o', color='blue')
axes[1].set_title('Total People Injured')
axes[1].set_xlabel('Year')
axes[1].set_ylabel('Number of People')
axes[1].legend()
axes[1].grid(True)


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



To start off, examining the trend depicted in the two line plots, it becomes apparent why 2021 is considered the deadliest year. Although 2017 recorded a high number of injuries, the corresponding death toll was lower compared to 2021.

In 2021, the statistics reveal a grim reality, with over 1.55 lakh lives lost in road crashes across India. This translates to an average of 426 deaths per day or 18 deaths every hour, marking the highest death figures recorded in any calendar year, as per official data.

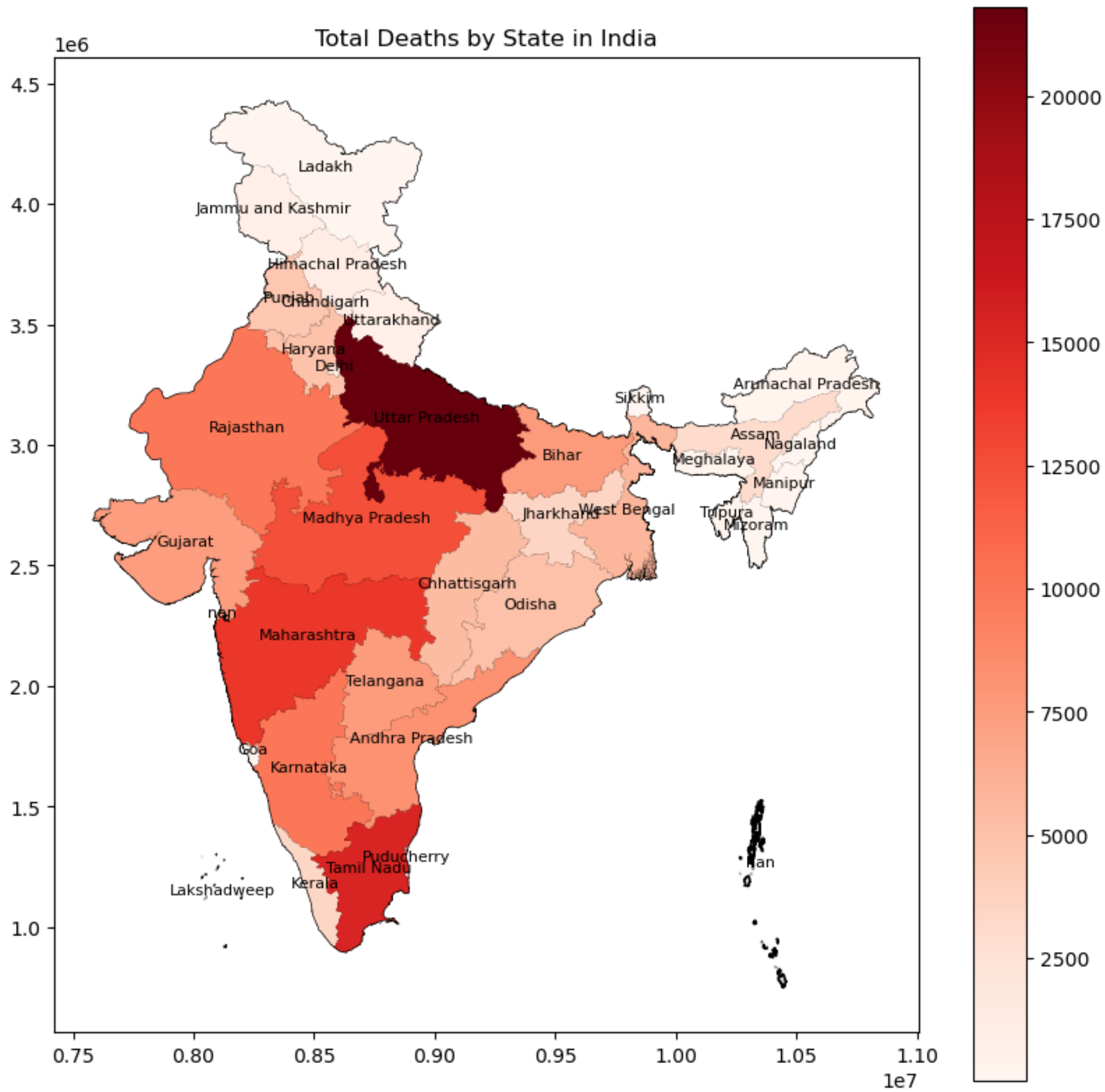
Contrastingly, the data from 2017 indicates 4.45 lakh accidents, 1.50 lakh deaths, and 4.56 lakh injuries, showcasing a different scenario and emphasizing the concerning rise in fatalities over the years.

SOURCE FROM NDTV

Road Accident Deaths in India by State (2021) Lets start with an overview of total road accident deaths in India in 2021 breakdown by each state.

[36]:
```python
import geopandas as gpd
import matplotlib.pyplot as plt

# Load the India states shapefile
india_states = gpd.read_file('India_State_Shapefile/India_State_Boundary.shp')

state_df = df1[df1['Category'] == 'State']
groupby_columns = ['Category', 'State/UT/City']

state_totals = df1.groupby(groupby_columns)['Grand Total - Total'].sum().
    ↪reset_index()

india_states['Name'] = india_states['Name'].str.strip()
state_totals['State/UT/City'] = state_totals['State/UT/City'].str.strip()

name_corrections = {

    'Telengana': 'Telangana',
    'Ladakh UT': 'Ladakh',
    'Jammu and Kashmir' : 'Jammu and Kashmir',
    'Chhattishgarh': 'Chhattisgarh',
    'Tamilnadu': 'Tamil Nadu'
}

india_states = india_states.to_crs(epsg=3395)
india_states['Name'] = india_states['Name'].replace(name_corrections)

merged_data = india_states.merge(state_totals, how='left', left_on='Name',␣
    ↪right_on='State/UT/City')

#a map plot
fig, ax = plt.subplots(1, 1, figsize=(10, 10))
india_states.plot(ax=ax, color='lightgrey', edgecolor='black')
merged_data.plot(ax=ax, column='Grand Total - Total', cmap='Reds', legend=True)
```

```
for x, y, label in zip(merged_data.geometry.centroid.x, merged_data.geometry.
    ↪centroid.y, merged_data['State/UT/City']):
    ax.text(x, y, label, fontsize=8, ha='center', color='black')
plt.title('Total Deaths by State in India')
plt.show()
```

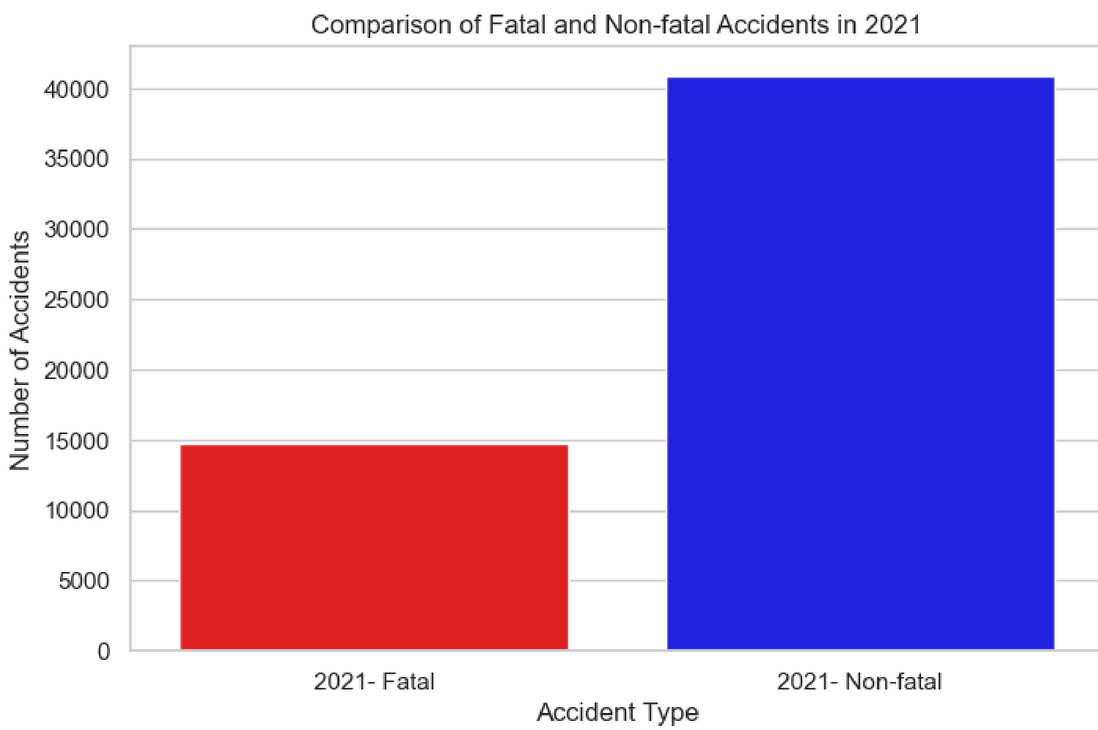


The map illustrates the distribution of road accident deaths across states in 2021. Among all the states, Tamil Nadu recorded the second-highest number of fatalities, following Uttar Pradesh. The intensity of the red color on the map corresponds to the severity of fatalities, with deeper shades indicating higher numbers of deaths in 2021.

Now, we are delving into an in-depth investigation of Tamil Nadu to understand where things went wrong and how it ranked as the second-highest in road accident fatalities in India.

Road Accident Analysis in Tamil Nadu (2021) Let's start by examining how many injuries and deaths occurred in India due to road accidents.

[37]:
```
subset_df = df3[['2021- Fatal', '2021- Non-fatal']]

sns.set(style="whitegrid")
plt.figure(figsize=(8, 5))
sns.barplot(x=subset_df.columns, y=subset_df.sum(), palette=['red', 'blue'])

plt.title('Comparison of Fatal and Non-fatal Accidents in 2021')
plt.xlabel('Accident Type')
plt.ylabel('Number of Accidents')
plt.show()
```

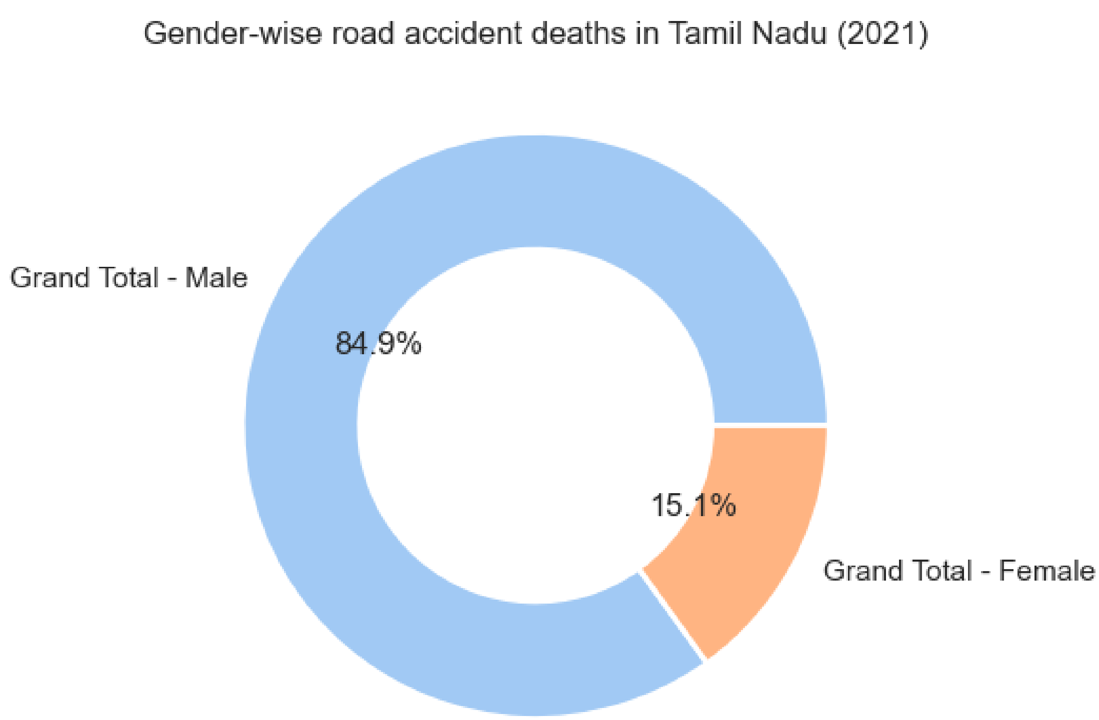


This analysis offers a foundational overview of the road accident data for Tamil Nadu in 2021, elucidating the comprehensive figures of accidents and delineating the incidence of fatal and non-fatal incidents. From the graphical representation, it is evident that among the 40,935 reported accidents, 14,747 resulted in fatalities.

Gender-wise Analysis in Tamil Nadu (2021) Next, As of 2021, Tamil Nadu's population is estimated to be 83.9 million, making it the most populous state in South India. we can now explore the gender distribution of individuals involved in accidents within this demographic.

[38]:

```
tamilnadu_data = df1[(df1['Category'] == 'State') & (df1['State/UT/City'] ==␣
↪'Tamil Nadu')]

# Extract gender columns
gender_columns = ['Grand Total - Male', 'Grand Total - Female']
tamilnadu_gender_data = tamilnadu_data[['State/UT/City'] + gender_columns]

# Melt the DataFrame for visualization
tamilnadu_gender_melted = pd.melt(tamilnadu_gender_data, id_vars=['State/UT/
↪City'], value_vars=gender_columns,
                                  var_name='Gender', value_name='Total Count')

sns.set(style="whitegrid")

plt.figure(figsize=(5, 5))
plt.pie(tamilnadu_gender_melted['Total Count'],␣
↪labels=tamilnadu_gender_melted['Gender'], autopct='%1.1f%%',
        wedgeprops=dict(width=0.4, edgecolor='w', linewidth=2), colors=sns.
↪color_palette("pastel"))


plt.title('Gender-wise road accident deaths in Tamil Nadu (2021)')
plt.show()
```

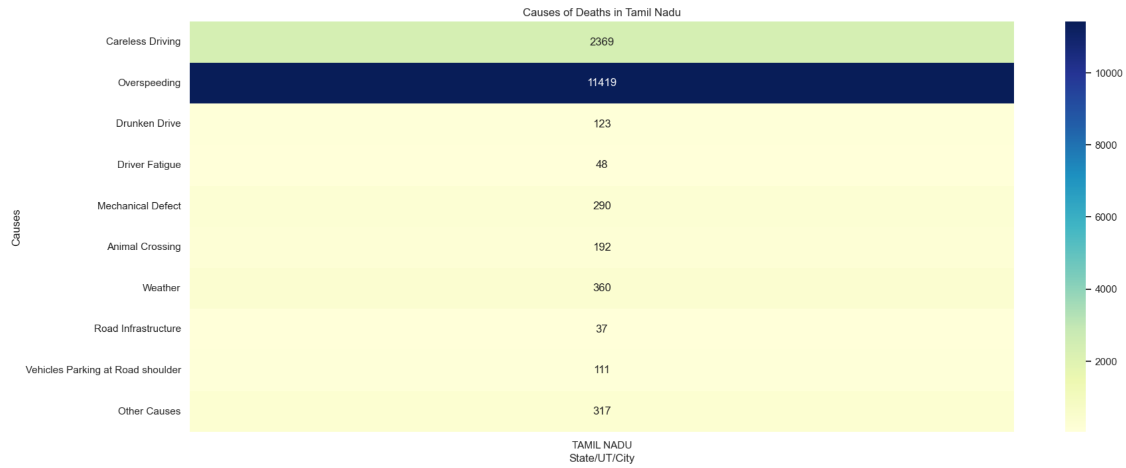


In terms of gender-specific road accidents in Tamil Nadu for the year 2021, the data reveals a notable disparity. Among the 40,935 reported incidents, approximately 85% involve males, while females account for around 15% cases.

Cause-wise Analysis in Tamil Nadu (2021) Now, we can explore the leading causes of road accidents in Tamil Nadu in 2021 with highlighting major contributing factors.

[40]:
```
# Filter data for Tamil Nadu
tamil_nadu_data = df2[df2['State/UT/City'] == 'TAMIL NADU']

causes_columns = [
    'Dangerous or Careless Driving/ Overtaking etc Died',
    'Overspeeding Died',
    'Driving under Influence of Drug/Alcohol Died',
    'Physical Fatigue of Drivers Died',
    'Defect in Mechanical Condition of Vehicle Died',
    'Animal Crossing Died',
    'Weather Condition (Total) Died',
    'Lack of Road Infrastructure Died',
    'Vehicles Parking at Road Shoulders Died',
    'Other Causes Died'
]


died_data = tamil_nadu_data[['State/UT/City'] + causes_columns].copy()
died_data.set_index('State/UT/City', inplace=True)

column_mapping = {
    'Dangerous or Careless Driving/ Overtaking etc Died': 'Careless Driving',
    'Overspeeding Died': 'Overspeeding',
    'Driving under Influence of Drug/Alcohol Died': 'Drunken Drive',
    'Physical Fatigue of Drivers Died': 'Driver Fatigue',
    'Defect in Mechanical Condition of Vehicle Died': 'Mechanical Defect',
    'Animal Crossing Died': 'Animal Crossing',
    'Weather Condition (Total) Died': 'Weather',
    'Lack of Road Infrastructure Died': 'Road Infrastructure',
    'Vehicles Parking at Road Shoulders Died': 'Vehicles Parking at Road␣
↪shoulder',
    'Other Causes Died': 'Other Causes'
}

died_data.rename(columns=column_mapping, inplace=True)

plt.figure(figsize=(20, 8))
sns.heatmap(died_data.T, cmap='YlGnBu', annot=True, fmt='g')
```

```
plt.title('Causes of Deaths in Tamil Nadu')
plt.xlabel('State/UT/City')
plt.ylabel('Causes')
plt.show()
```

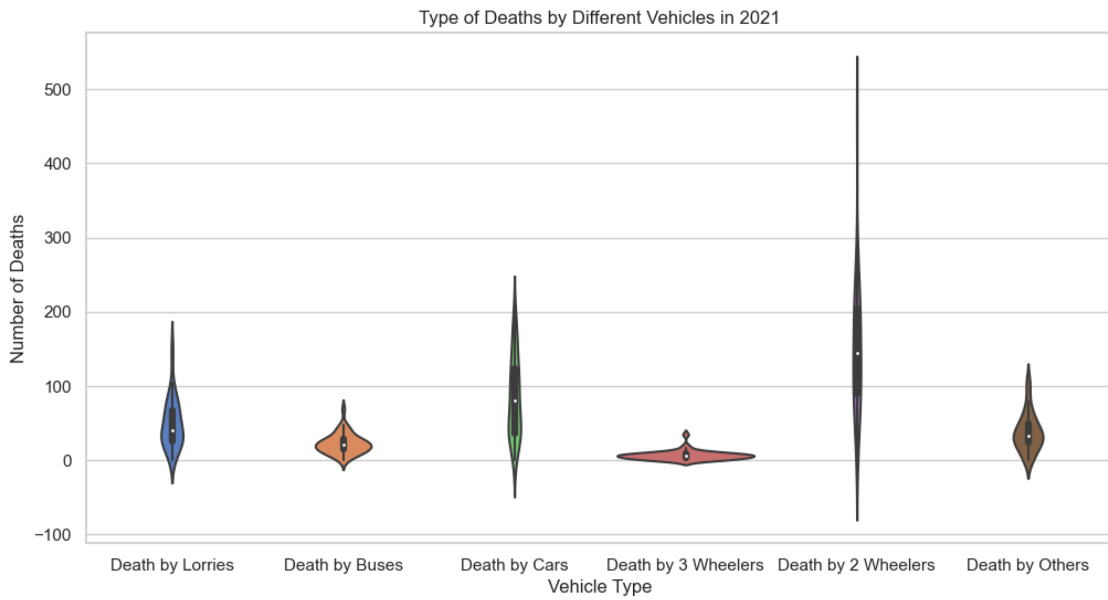


Analysis of the heatmap reveals that overspeeding is the primary cause of accidents in Tamil Nadu, contributing approximately 70% to the total incidents. Careless driving follows as the second significant factor leading to road accidents.

Death by Type of Vehicles in Tamil Nadu (2021) Let's examaine the fatalities categorized by the type of vehicles involved in Tamil Nadu.

[41]:
```
df3 = df3.rename(columns={
    'Death by Lorries - 2021': 'Death by Lorries',
    'Death by Buses-2021': 'Death by Buses',
    'Death by Cars/Jeeps 2021': 'Death by Cars',
    'Death by Three-wheelers - 2021': 'Death by 3 Wheelers',
    'Death by Two-wheelers 2021': 'Death by 2 Wheelers',
    'Death by Others 2021': 'Death by Others'
})

subset_df = df3[['Death by Lorries', 'Death by Buses', 'Death by Cars',
                 'Death by 3 Wheelers', 'Death by 2 Wheelers', 'Death by␣
 ↪Others']]
subset_df_melted = subset_df.melt()

sns.set(style="whitegrid")

# a violin plot
plt.figure(figsize=(12, 6))
sns.violinplot(x='variable', y='value', data=subset_df_melted, palette='muted')
```

```
plt.title('Type of Deaths by Different Vehicles in 2021')
plt.xlabel('Vehicle Type')
plt.ylabel('Number of Deaths')
plt.show()
```



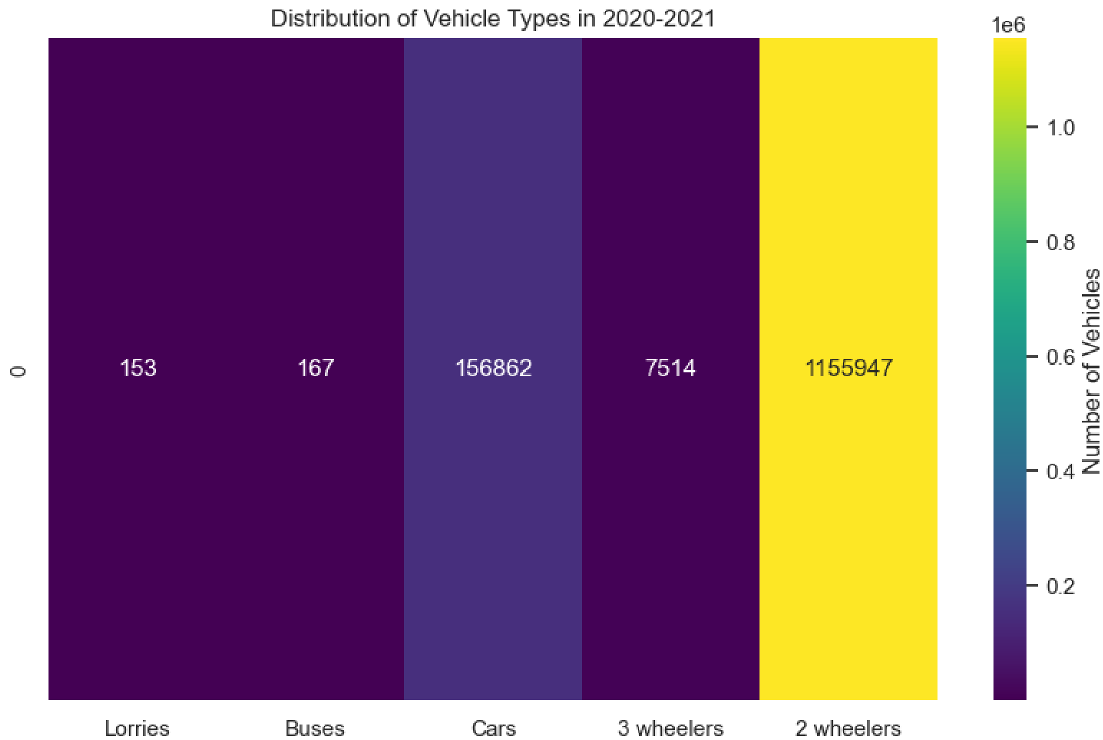
As evident from the violin plot, death caused by two-wheelers made a significant contribution to road accidents in Tamil Nadu in 2021. This was followed by car accidents and accidents involving lorries, indicating the varying degrees of impact each vehicle type had on the overall death count during that year.

Type of Vehicles Registered in Tamil Nadu (2021) Overview of the types of vehicles registered in Tamil Nadu in 2021. Insights into the vehicular composition.

[42]:
```
selected_columns = ["Category of Vehicle", "2020-2021"]

#filtering data
two_wheeler_rows = df5.loc[df5["Category of Vehicle"].isin(["MOTOR CYCLE",␣
 ↪"SCOOTER"]), selected_columns]
buses_rows = df5.loc[df5["Category of Vehicle"].isin(["OMNIBUS", "LMV OMNI␣
 ↪BUS", "SCHOOL BUS", "MINI BUS"]), selected_columns]
three_wheeler_rows = df5.loc[df5["Category of Vehicle"].isin(["AUTO", "3␣
 ↪WHEELER"]), selected_columns]
trailors_row = df5.loc[df5["Category of Vehicle"].isin(["TRAILORS"]),␣
 ↪selected_columns]
motor_car_row = df5.loc[df5["Category of Vehicle"].isin(["MOTOR CAR"]),␣
 ↪selected_columns]
```

```
two_wheeler_rows["2020-2021"] = pd.to_numeric(two_wheeler_rows["2020-2021"],␣
 ↪errors="coerce")
buses_rows["2020-2021"] = pd.to_numeric(buses_rows["2020-2021"],␣
 ↪errors="coerce")
three_wheeler_rows["2020-2021"] = pd.
 ↪to_numeric(three_wheeler_rows["2020-2021"], errors="coerce")
trailors_row["2020-2021"] = pd.to_numeric(trailors_row["2020-2021"],␣
 ↪errors="coerce")
motor_car_row["2020-2021"] = pd.to_numeric(motor_car_row["2020-2021"],␣
 ↪errors="coerce")

#summarizing data
two_wheeler_sum = two_wheeler_rows["2020-2021"].sum()
buses_sum = buses_rows["2020-2021"].sum()
three_wheeler_sum = three_wheeler_rows["2020-2021"].sum()
trailors_sum = trailors_row["2020-2021"].sum()
motor_car_sum = motor_car_row["2020-2021"].sum()

categories = ["Lorries", "Buses", "Cars", "3 wheelers", "2 wheelers"]
values = [trailors_sum, buses_sum, motor_car_sum, three_wheeler_sum,␣
 ↪two_wheeler_sum]
```

[43]:
```
data = {
    "Lorries": [trailors_sum],
    "Buses": [buses_sum],
    "Cars": [motor_car_sum],
    "3 wheelers": [three_wheeler_sum],
    "2 wheelers": [two_wheeler_sum]
}
df_heatmap = pd.DataFrame(data)
plt.figure(figsize=(10, 6))
sns.set(style="whitegrid")
sns.heatmap(df_heatmap, annot=True, fmt=".0f", cmap="viridis",␣
 ↪cbar_kws={'label': 'Number of Vehicles'})
plt.title('Distribution of Vehicle Types in 2020-2021')
plt.show()
```



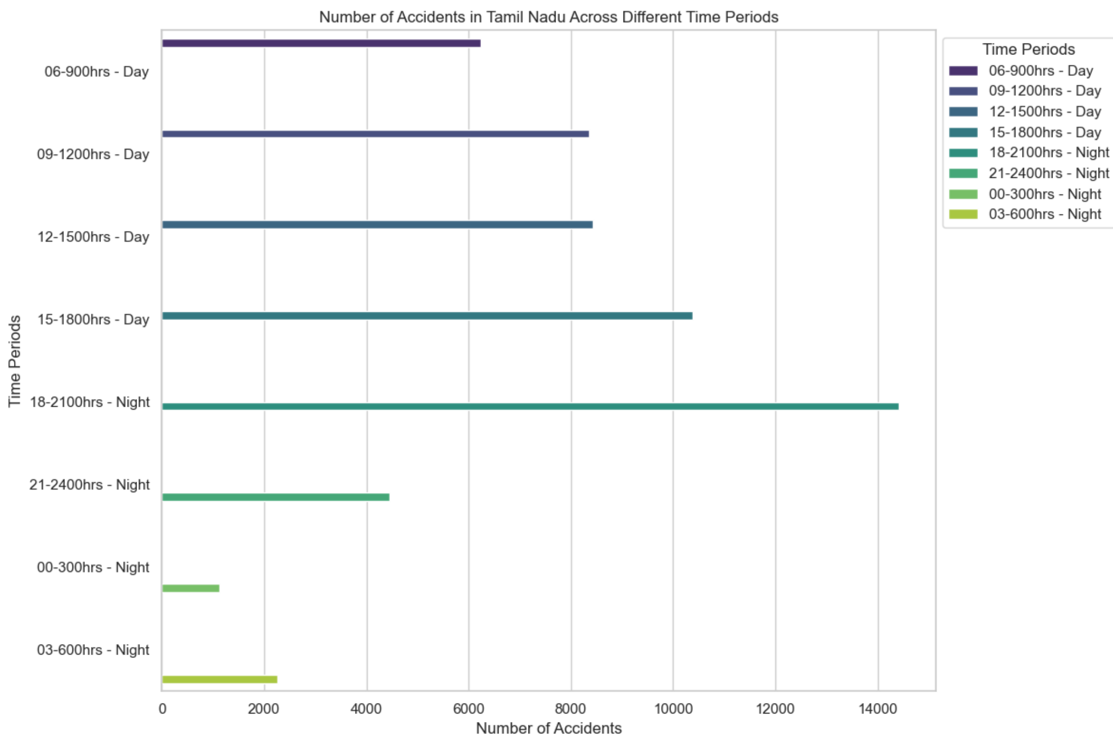
The heatmap illustrates that a substantial 86.9% of vehicles registered in 2020-2021 were two-wheelers. This high percentage underscores the dominance of two-wheelers on the roads.

The correlation between the high registration of two-wheelers and the significant contribution to road accident deaths suggests a potential link between the prevalence of a vehicle type and its involvement in fatal accidents.

Time of Occurrence in a Day in Tamil Nadu (2021) Analysis of road accidents based on the time of day in Tamil Nadu and identification of peak hours and trends.

[44]:
```
tn_data = df4[df4['States/UTs'] == 'Tamil Nadu']
tn_data = tn_data.drop(columns=['Total Accidents', 'Unknown Time'])
tn_data_melted = tn_data.melt(id_vars=['States/UTs'], var_name='Time Period',␣
 ↪value_name='Number of Accidents')

sns.set(style="whitegrid")

plt.figure(figsize=(12, 8))
sns.barplot(x='Number of Accidents', y='Time Period', hue='Time Period',␣
 ↪data=tn_data_melted, palette='viridis')
plt.title('Number of Accidents in Tamil Nadu Across Different Time Periods')
plt.xlabel('Number of Accidents')
plt.ylabel('Time Periods')
```

```
plt.legend(title='Time Periods', bbox_to_anchor=(1, 1), loc='upper left')
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()
```



Most accidents in Tamil Nadu are occurring during the time frame of 18:00 to 21:00 (6:00 PM to 9:00 PM), particularly at night. This peak hour coincides with the time when citizens are typically commuting back home from their offices. This insight is derived from the data on the number of accidents in Tamil Nadu across different time periods.

1.8.3 WordCloud

Webscarping

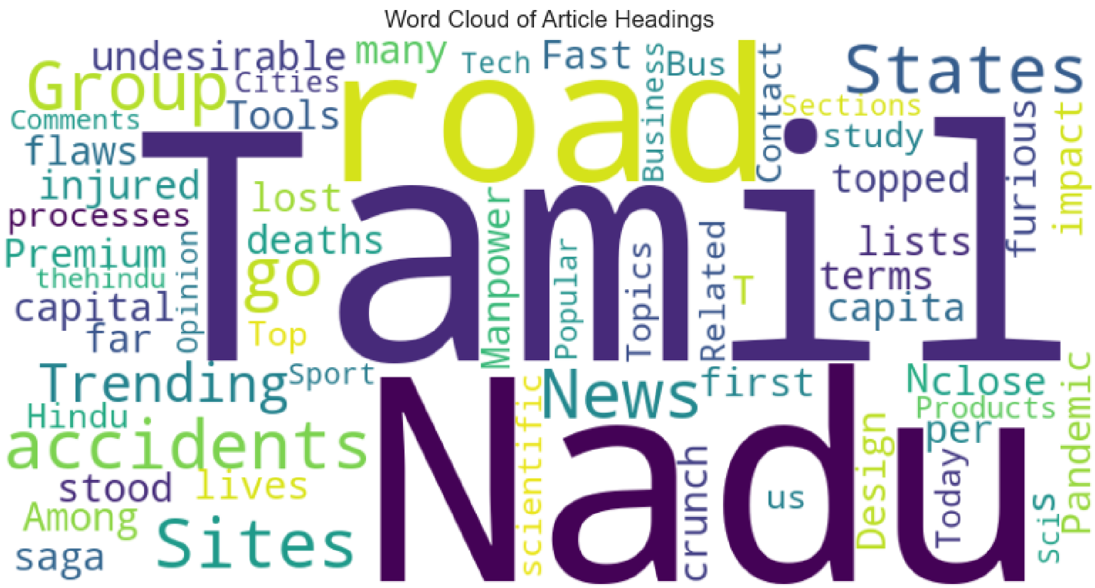
[46]:
```
import requests
import bs4

# URL of the article
url = "https://www.thehindu.com/news/national/tamil-nadu/
 ↪fast-and-furious-tn-road-saga/article65876800.ece"

# Send an HTTP request to the URL
response = requests.get(url)

# Check if the request was successful (status code 200)
```

```
if response.status_code == 200:
    soup = BeautifulSoup(response.text, 'html.parser')

    # Find all the headings
    headings = soup.find_all(['h1', 'h2', 'h3', 'h4', 'h5', 'h6'])

    # Extract and print the text content of the headings
    for heading in headings:
        print(heading.text.strip())

    # Save the headings to a text file
    with open("article_headings.txt", "w", encoding="utf-8") as file:
        for heading in headings:
            file.write(heading.text.strip() + "\n")
else:
    print(f"Failed to fetch the page. Status code: {response.status_code}")
```

```
Fast and furious: Tamil Nadu road saga
Premium
With close to 1,000 lives lost and over 5,000 injured in 2021, Tamil Nadu’s
capital topped many undesirable lists as far as road accidents go. Among States,
T.N. stood first in terms of per capita deaths.
Pandemic impact
Design flaws
Manpower crunch
Tools and processes
A scientific study
Bus accidents go up
Related Topics
Top News Today
The Hindu
Contact us
Group News Sites
Other Products
Popular Sections
Opinion
Business
Sport
Sci-Tech
States
Cities
Trending on thehindu.com
Trending on our Group sites
Comments
```

[47]:
```
from wordcloud import WordCloud
import matplotlib.pyplot as plt
```

```
with open("article_headings.txt", "r", encoding="utf-8") as file:
    text_data = file.read()

wordcloud = WordCloud(width=800, height=400, background_color="white").
 ↪generate(text_data)

plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation="bilinear")
plt.axis("off")
plt.title("Word Cloud of Article Headings")
plt.show()
```



[48]:
```
# Read the content of the text file
with open("article_headings.txt", "r", encoding="utf-8") as file:
    text_data = file.read()

# Load image
mask_image = np.array(Image.open('road.jpg'))

stopwords = set(STOPWORDS)

wordcloud = WordCloud(width=800, height=400, background_color='#DD571C',␣
 ↪stopwords=stopwords,
                       mask=mask_image, contour_width=10,␣
 ↪contour_color='orange').generate(text_data)
```

```
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis('off')
plt.show()
```

Results of the Wordcloud This snapshot of insights derived from the word cloud serves as a compelling call to action. It emphasizes the urgent need for targeted interventions, policy reforms, and community engagement to mitigate the impact of road accidents in Tamil Nadu.

1.9 Conclusion

In conclusion, the 2021 road accident data for Tamil Nadu underscores the urgency for comprehensive and targeted interventions in areas such as overspeeding, two-wheeler safety, and evening commute hours. This research contributes significantly to the broader conversation on road safety in India and provides valuable insights that can guide future policies and initiatives aimed at reducing accidents and fatalities.

1.10 References:

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3. Vaidyanathan R. (2023). Tamil Nadu - Crime Data - Tamil Nadu District and Citywise Road Accident Deaths in 2019 to 2021. OpenCity - Urban Data Portal. [https://data.opencity.in/dataset/tamil-nadu-crime-data/resource/tamil-nadu-district-and-citywise-road-accident-deaths-in-2019-to-2021]
4. Tamil Nadu - Vehicle Registration Data - Collections - OpenCity - Urban Data Portal. [https://data.opencity.in/dataset/tamil-nadu-vehicles-registration-data]
5. Government of India. (2021). State/UT/City-wise Time Occurrence Number of Traffic Accidents During 2021. Open Government Data (OGD) Platform India. [https://data.gov.in/resource/stateutscity-wise-time-occurrence-number-traffic-accidents-during-2021]
6. Government of India. (2023). State-UT Wise Total Number of Road Accidents in India Classified According to Cause of Accidents. Open Government Data (OGD) Platform India. [https://data.gov.in/catalog/state-ut-wise-total-number-road-accidents-india-classified-according-cause-accidents]
7. Government of India. (2017-2021). Year-wise Total Number of Road Accident Fatalities and Injuries in the Country from 2017 to 2021. Open Government Data (OGD) Platform India. [https://data.gov.in/dataset-group-name/road-accidents]