# A Quantitative Analysis of Fatal Police Shootings: Demographic Disparities and Situational Factors

## ISSUES:

1. How prevalent are signs of mental illness among individuals involved in fatal police shootings?
2. Does the presence of mental illness influence the outcome of police encounters?
3. How does the type of weapon carried by the individual (if any) affect the likelihood of a fatal shooting?
4. Does the use of body cameras by police officers correlate with a reduction in fatal shooting incidents?
5. What patterns emerge when comparing incidents with and without body camera footage?
6. What are the patterns in fleeing behaviour among victims of fatal police shootings?
7. Are there any noticeable trends in the frequency or nature of fatal police shootings over time?
8. Are there any specific states or cities that exhibit significantly higher rates of fatal police shootings?
9. How do gender and race interplay in the context of fatal police shootings?
10. Are there disparities in outcomes based on these demographic factors.

## FINDINGS:

**1. Mental Illness Prevalence:**

The analysis of the dataset revealed that approximately 20.9% of individuals involved in fatal police shootings showed signs of mental illness. This significant proportion suggests that mental health considerations are a critical factor in many of these incidents.

**2. Threat Level and Weapon Involvement:**

Most fatal police shootings were categorized under 'attack' threat level, indicating a perceived immediate threat by the police. Interestingly, a substantial number of these incidents involved individuals armed with guns, followed by knives, highlighting the prevalence of lethal weapons in these encounters.

**3. Impact of Body Cameras:**

In the dataset, only 14.2% of the incidents involved the use of body cameras by police officers. This relatively low percentage limits the potential for accountability and transparency that body cameras are meant to provide in law enforcement encounters.

**4. Patterns in Fleeing Behaviour**

A notable finding was that a significant number of victims (over 55%) were not fleeing at the time of the shooting. This raises questions about the circumstances and decisions leading to the use of lethal force in situations where the victim was not actively attempting to evade the police.

**5. Temporal Trends:**

A temporal analysis of the data suggested an increasing trend in the number of fatal police shootings over the years covered by the dataset. This trend underscores the growing urgency of addressing the factors contributing to these incidents.

**6. Geographical Analysis:**

An examination of the geographical distribution of these incidents revealed notable differences across states and cities, with higher incidence rates observed in certain urban areas. This variation suggests that local factors, such as law enforcement practices and community-police relations, may significantly influence the occurrence of these events.

**7. Gender and Race Dynamics**:

The data indicates disparities in the race and gender of victims in fatal police shootings, with a higher prevalence among minority groups and males. This finding aligns with broader societal concerns regarding racial and gender biases in law enforcement practices.

## DISCUSSIONS:

Mental Health Considerations: Our analysis highlighted the significant presence of mental illness among victims of fatal police shootings. This finding emphasizes the importance of mental health considerations in law enforcement training and protocols. The high prevalence of mental illness suggests a need for more effective crisis intervention strategies and mental health support services.

Threat Perception and Weapon Involvement: The predominance of 'attack' as the threat level in these incidents raises critical questions about the assessment and response protocols in high-pressure situations. The frequent involvement of firearms and other lethal weapons underscores the complexity of these encounters and the challenges faced by law enforcement in making split-second decisions.

Role of Body Cameras in Accountability: The low usage rate of body cameras in the recorded incidents points to a gap in policy implementation and its potential impact on transparency and accountability. This observation leads to discussions about the need for widespread adoption of body cameras and policies to ensure their effective use.

Implications of Fleeing Behaviour: The finding that most victims were not fleeing at the time of the shooting raises critical questions about the use of force and the decision-making processes in these scenarios. It invites a deeper investigation into law enforcement training, engagement rules, and the escalation of force.

Temporal Trends and Evolving Dynamics: The increasing trend in fatal police shootings over the years indicates escalating tensions and challenges in police-civilian interactions. This pattern calls for a closer examination of changes in law enforcement practices, societal dynamics, and potential contributory factors.

Geographical Variations and Local Factors: The geographical analysis of the incidents revealed significant variations across different regions, suggesting the influence of local factors such as law enforcement policies, community relations, and socio-economic conditions. This finding points to the necessity for localized approaches in addressing the issues related to police shootings.

Disparities in Gender and Race: The disparities observed in the race and gender of victims align with broader societal concerns about systemic biases. This aspect of the findings invites further discussions on racial and gender biases in law enforcement, as well as the need for more inclusive and equitable policing practices.

## Appendix A: Method

We acquired the "fatal-police-shootings-data" dataset in Excel format, which includes a comprehensive range of data columns such as age, gender, race, armed status, signs of mental illness, threat level, and body camera usage, among others. Our analysis was structured to explore various dimensions of these incidents.

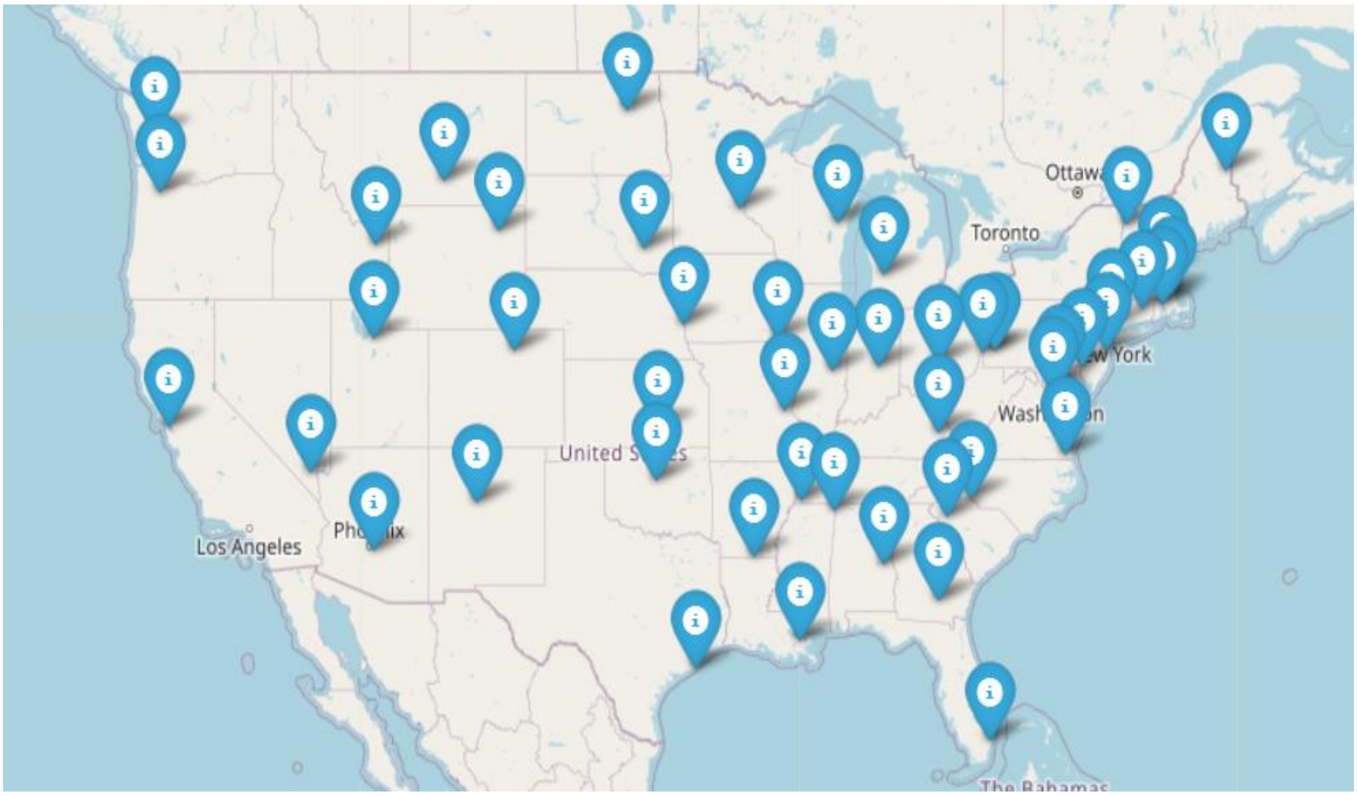
We first focused on the prevalence of mental illness among the victims. This involved categorizing the data based on the presence or absence of signs of mental illness and analysing the proportion and characteristics of these incidents. Then examined the relationship between the perceived threat level and the armed status of the individuals. This required categorizing incidents by threat levels and types of weapons used, followed by a comparative analysis to understand the dynamics of these encounters. The analysis of body camera usage involved segregating the data based on whether body cameras were used. We then conducted a comparative analysis to assess the impact of body camera usage on the outcomes of these incidents.

We analysed the fleeing behaviour of the victims, categorizing the incidents based on whether the victims were fleeing and, if so, the mode of fleeing (e.g., on foot, by car). This analysis helped in understanding the circumstances surrounding the use of lethal force. A longitudinal analysis was conducted to identify trends over time in the occurrence of fatal police shootings. This involved plotting the incidents over the years covered by the dataset and analysing changes in the frequency and nature of these incidents.

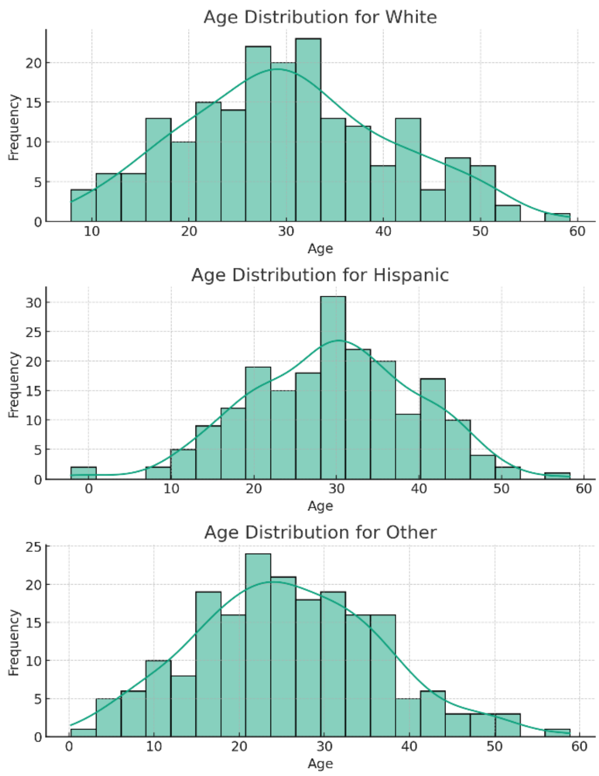
We explored the geographical distribution of the incidents using the available latitude and longitude data. This involved mapping the incidents to identify patterns and hotspots, despite some limitations due to missing geographic coordinates. Finally, we examined the gender and race of the victims. This included a comparative analysis of the distribution of these demographic factors across the incidents to identify any disparities or notable trends.

## Appendix B: Results

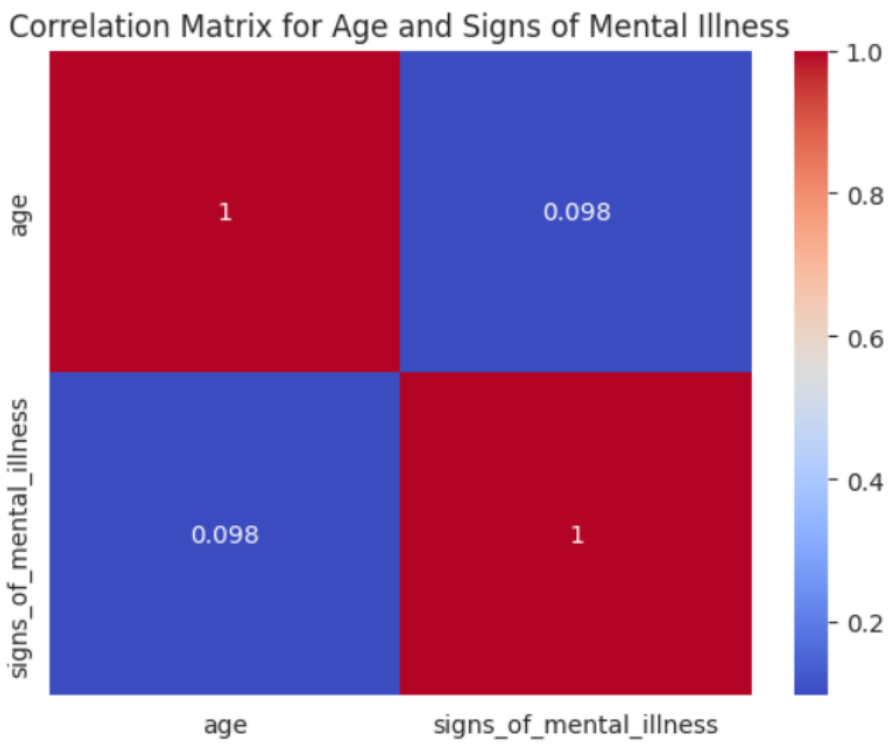
### Analysis of Fatalities: Folium Map Visualization in Python:




### Comparative Age Distribution Histograms by Race: White, Black, Hispanic, Asian, and Other Demographics:




These histograms show the age distributions for different racial groups. They give a visual representation of the age structure within each racial category, with the potential to identify specific age groups that are more prominent within each race.



The matrix displays the correlation coefficients between age and signs of mental illness. The coefficient of 0.098 indicates a very weak positive correlation between the variables, suggesting that age is not a strong predictor of signs of mental illness in this dataset.

## Demographic and Geospatial Analysis Report: Statistical Overview of Age, Gender, and Race Distributions:

```
                id          age    longitude     latitude
count  8002.000000  8002.000000  7162.000000  7162.000000
mean   4415.429643    37.070357   -97.040644    36.675719
std    2497.153259    12.576313    16.524975     5.379965
min       3.000000     2.000000  -160.007000    19.498000
25%    2240.250000    28.000000  -112.028250    33.480000
50%    4445.500000    35.000000   -94.315000    36.105000
75%    6579.750000    45.000000   -83.151500    40.026750
max    8696.000000    92.000000   -67.867000    71.301000
M    7613
F     358
Name: gender, dtype: int64
W    3300
B    1766
H    1166
A     129
N     105
O      19
Name: race, dtype: int64
```

### Age and Geolocation Statistics:

Count: The dataset consists of 8,002 recorded ages and corresponding geographical locations.

Mean Age: The average age within the dataset is approximately 37 years.

Age Range: The ages span from as young as 2 years old to as senior as 92 years old.

Standard Deviation: There is a standard deviation of 12.58 years in age, indicating variability in the age distribution.

Geographical Spread: The longitudinal data suggest a spread across the Western Hemisphere, with a mean longitude of approximately -97.04 and a mean latitude of 36.68.

### Quartile Distribution:

The 25th percentile indicates that a quarter of the individuals are 28 years old or younger.

The median age (50th percentile) is 35 years, suggesting that half of the population is below this age.

The 75th percentile shows that three-quarters of the individuals are 45 years old or younger.

### Geographical Coordinates Range:

Longitude: The data spans from -160.007 to -67.867, indicating a wide range across different longitudes.

Latitude: The latitude range from 19.498 to 71.301, highlighting a considerable latitudinal spread.

**Gender Distribution:**

The dataset predominantly consists of male individuals (M) with a count of 7,613, while females (F) are significantly less with a total of 358.

Race Distribution

White (W): 3,300 individuals

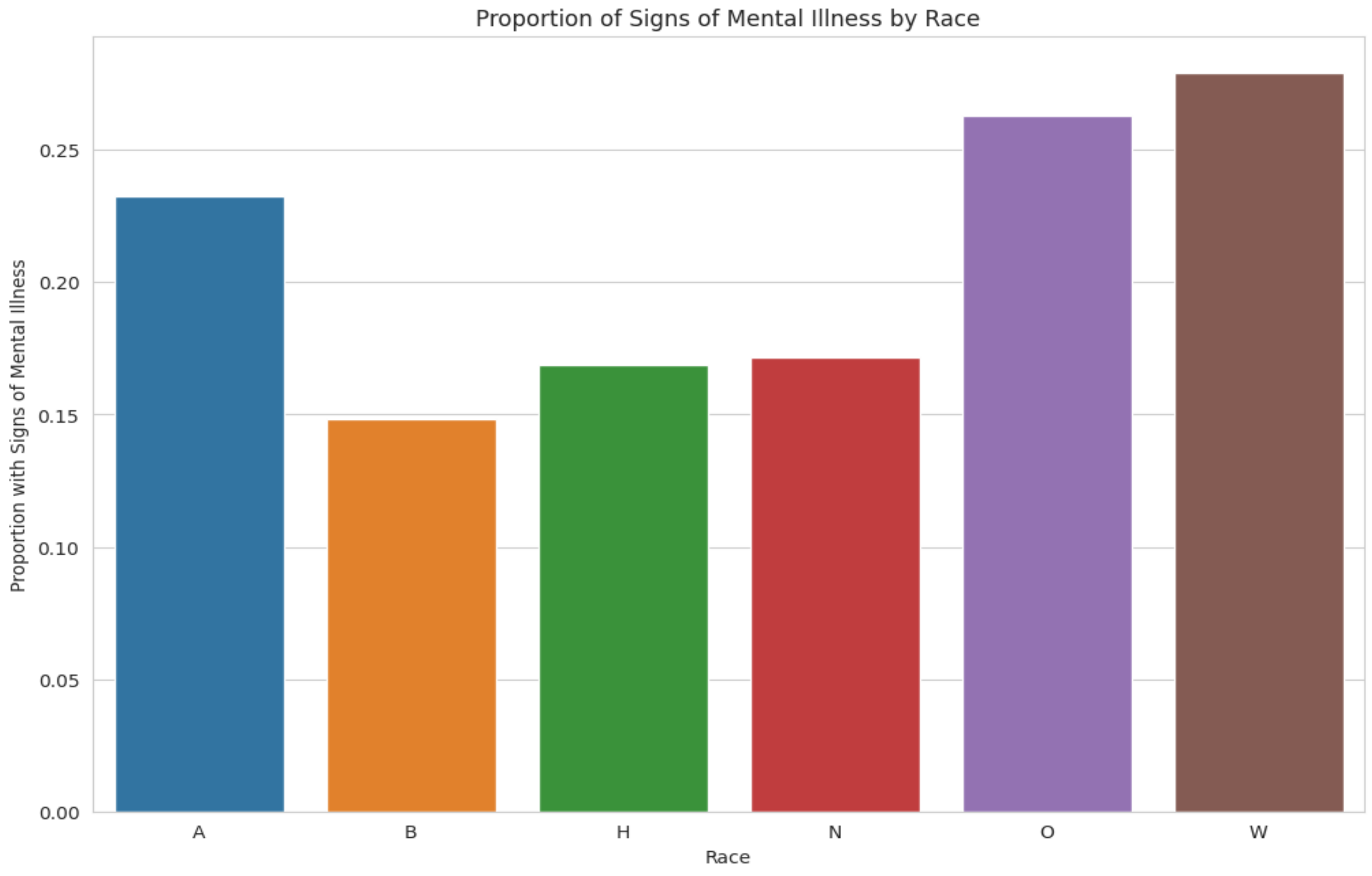
Black (B): 1,766 individuals

Hispanic (H): 1,166 individuals

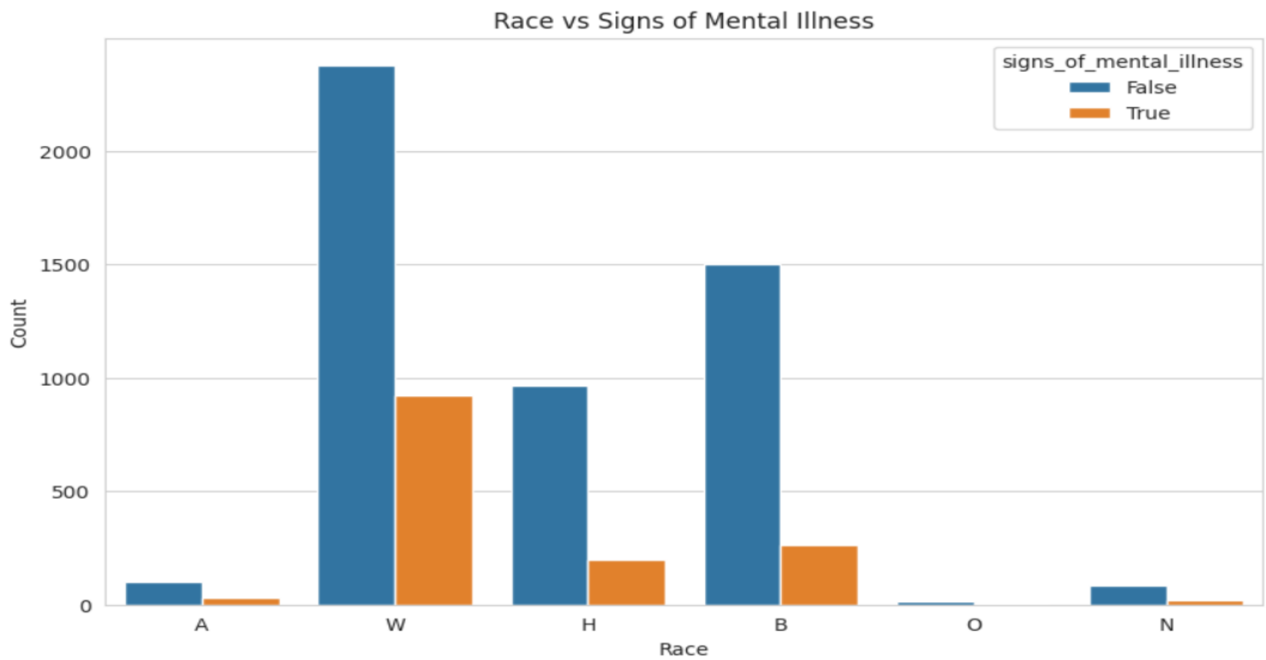
Asian (A): 129 individuals

Native (N): 105 individuals

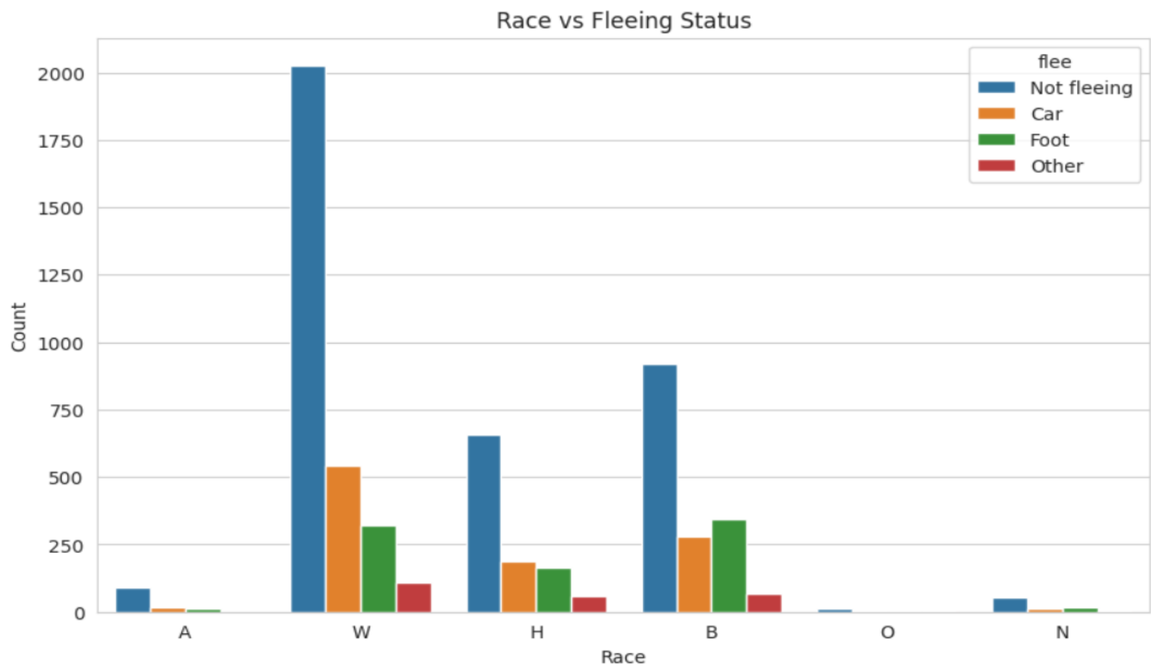
Other (O): 19 individuals



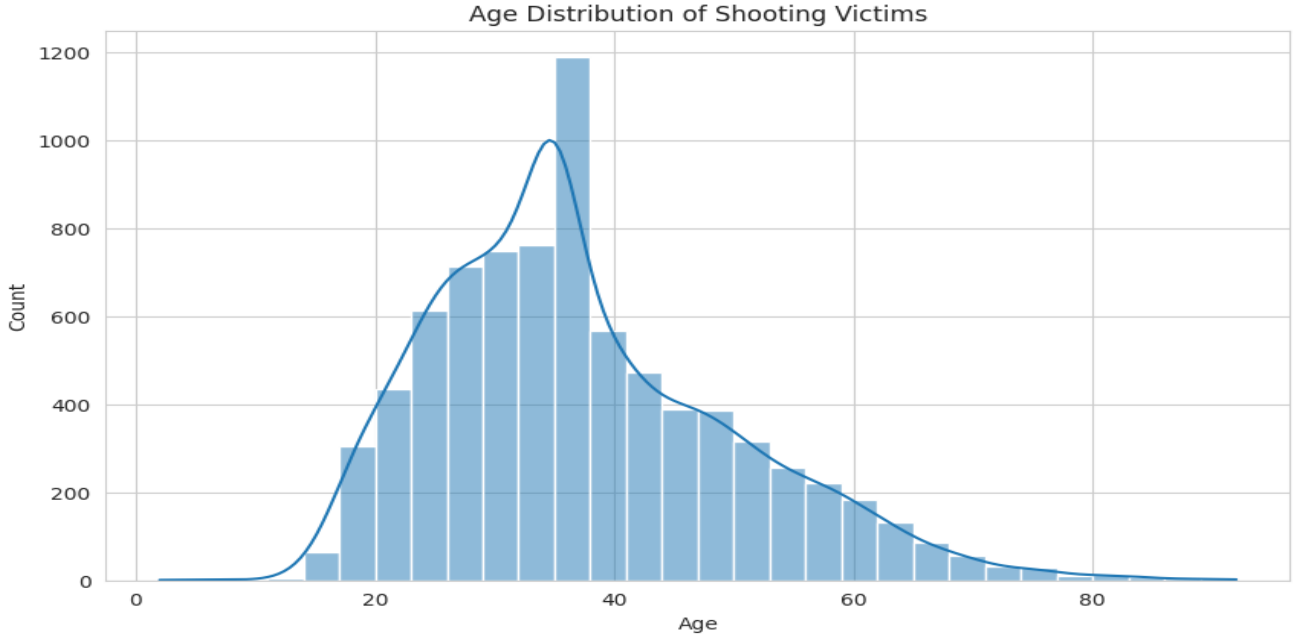

This bar chart presents the proportion of individuals showing signs of mental illness by race. It's a different representation from the absolute count, focusing instead on the proportion relative to each racial group's size. This can provide a more nuanced view of mental illness prevalence across races, considering the population size of each group.



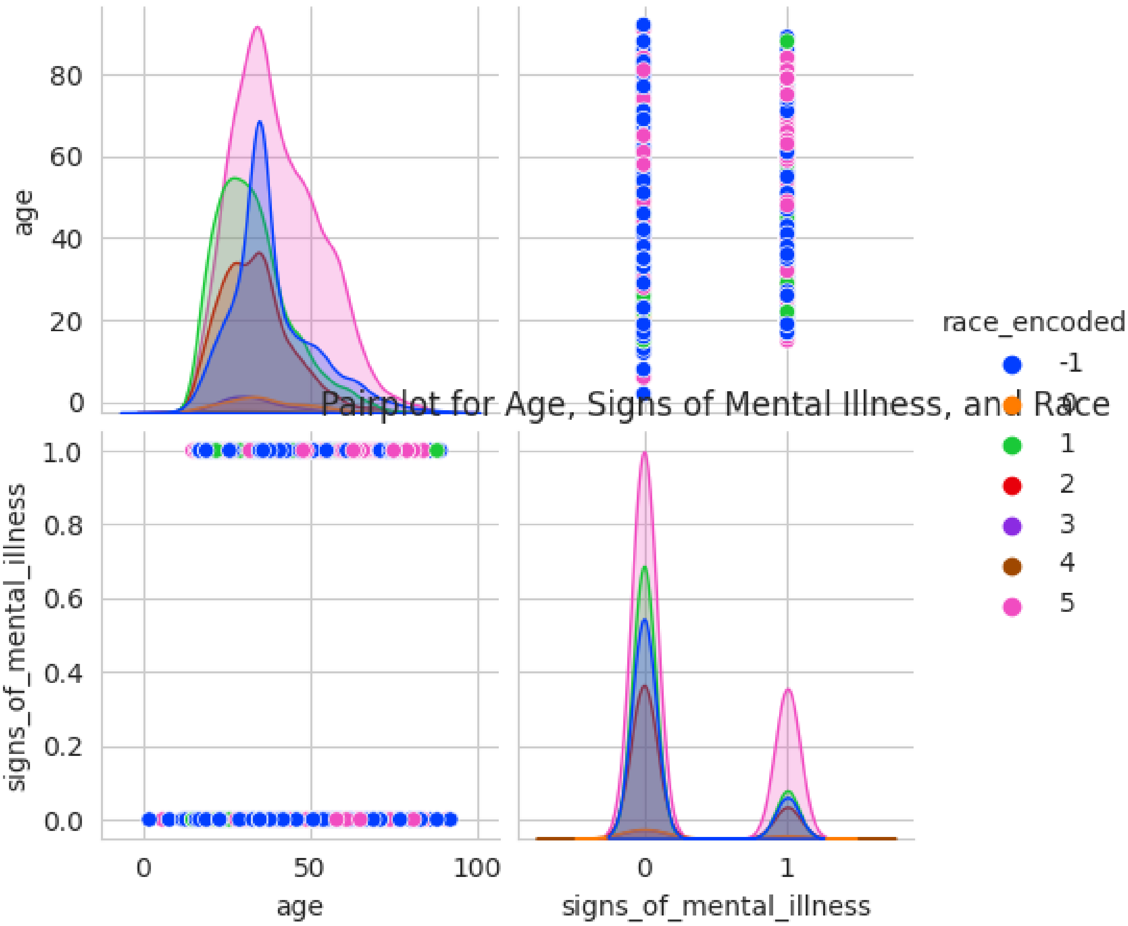

The bar chart compares the count of individuals within different racial groups who show signs of mental illness. The chart distinguishes between those who exhibit signs and those who do not. This visualization could be used to analyse the prevalence of mental health indications among different racial demographics.



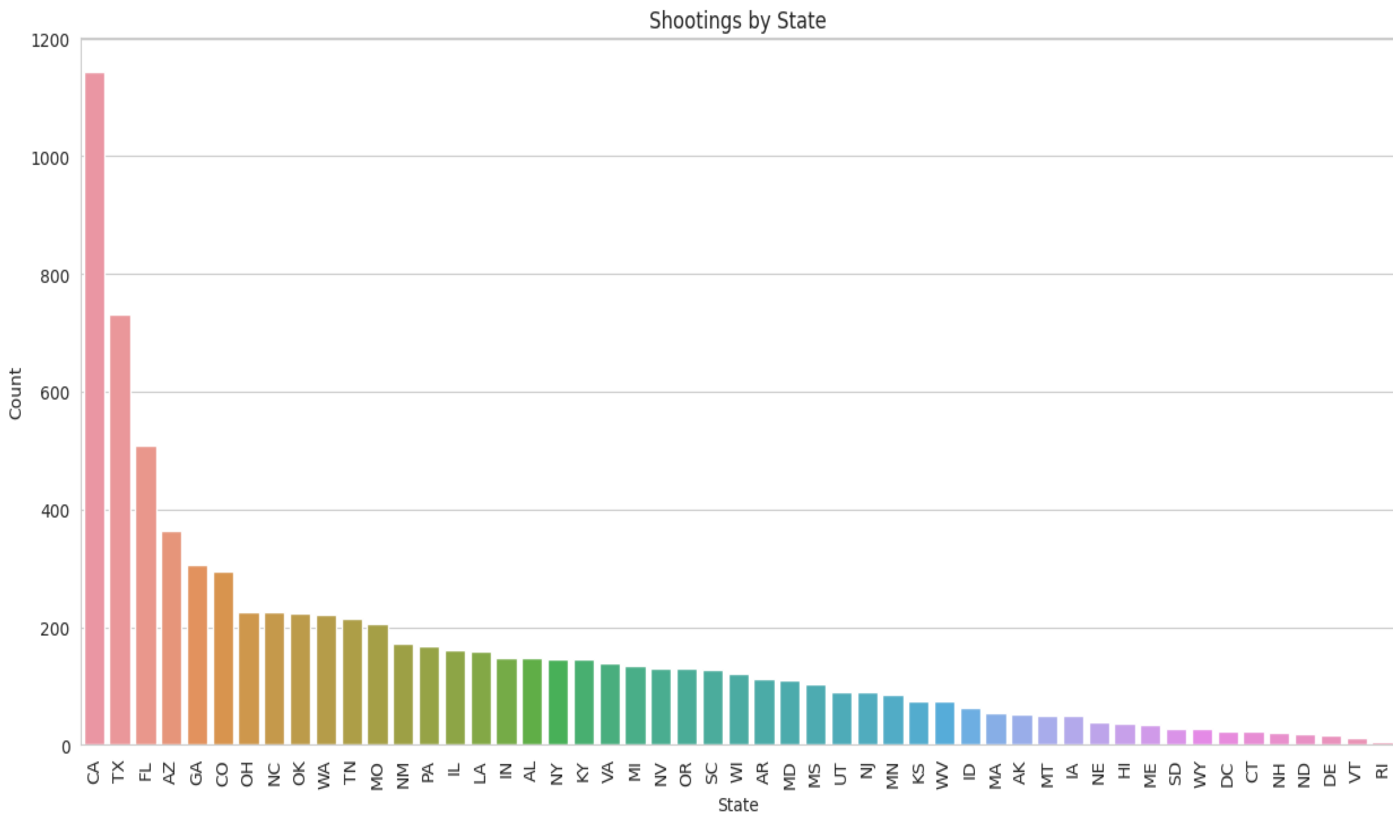

This bar chart illustrates the fleeing status of individuals involved in shooting incidents, categorized by race. The chart differentiates between not fleeing, fleeing by car, on foot, or by other means. It shows that within certain racial groups, there are noticeable differences in fleeing behaviour, which could lead to discussions about underlying social or cultural dynamics.




This histogram overlaid with a kernel density estimate shows the age distribution of shooting victims. There's a clear peak around the late 20s, indicating that this age group is disproportionately affected by shootings. The distribution tails off as age increases, which could imply that younger populations are at a higher risk.




The pair plot depicts the relationships between age, signs of mental illness, and race. The diagonal plots are kernel density plots for the distribution of each variable, while the off-diagonal plots show scatter plots for the variable pairings. The color-coded points indicate race, suggesting a possible exploration into how these variables correlate across different racial groups.




This bar chart displays the count of shootings across different states, with states on the x-axis and the count of shootings on the y-axis. It appears that California (CA) has the highest number of shootings, followed by Texas (TX) and Florida (FL). The data suggests a significant variance in shooting incidents across states, which could warrant a deeper analysis of regional factors that might contribute to this distribution.

**APPENDIX C: CODE**

**Code For Geospatial Plot using Folium:**

```
import folium
from IPython.display import display

# Create a list to store the maps
maps = []


m= folium.Map(zoom_start=5)

for state , ak in nrdf.groupby("state"):
#     ak=nrdf[nrdf["state"]=="AK"]
    total_count = len(ak)
    most_killed_AgeGroup=list(ak['age'].mode())
    top_3Cities =list(ak["city"].value_counts().index[:3])

    ageP=pd.DataFrame(ak["gender"].value_counts())
```

```
    raceP=pd.DataFrame(ak["race"].value_counts())
    ageP['percentage'] = (round(ageP['count'] / total_count,1) * 100)
    raceP['percentage'] = (round(raceP['count'] / total_count,1) * 100)
    ageP.reset_index(inplace=True)
    raceP.reset_index(inplace=True)
    ak["flee"].value_counts().index[0]

    gender=ageP.set_index('gender')['percentage'].to_dict()
    race=raceP.set_index('race')['percentage'].to_dict()
    longitude=ak["longitude"].values[0]
    latitude=ak["latitude"].values[0]

#     log,lati=ak

    dis={}
    dis["state"]=state
    dis["MostKilledAgeGrp"]=most_killed_AgeGroup
    dis["GenderRatio"]=gender
    dis["Top3Cities"]=top_3Cities
    dis["Race Distribution"] =race

#     print([state,most_killed_AgeGroup,gender,top_3Cities,race])


    s=folium.Map( [latitude, longitude])
    folium.Marker(
        location=[latitude, longitude],
        popup=dis,
        icon=folium.Icon(icon='info-sign')
    ).add_to(m)


    # Add the map to the list
    maps.append(s)
```

**Contributions**:

**Manoj Sankuru:** Contributed to the Issues, Discoveries, Methods, Coding, and Outcome sections. Worked on graphs, the findings and utilized different regression analysis techniques and evaluations to interpret the data.

**Suram Karthik Reddy:** Delved into the preliminary investigations, refined the data, and explored various modelling options. Tested the efficiency of different fits and evaluated non-linear models to interpret the relationships within predictors.

**Rama Satya Sai Prasad Appari:** Focused on the issues and crafting the code for analytical models. He was also responsible for generating the graphics based on these models.

**Medipalli Anji Reddy**: Engaged with the Issues, Conversations, Methods, and Outcomes sections. Independently graphed data interpretations using the techniques described in the document.