Exploratory data analysis to assess the impact of COVID-19 on the Toronto crime statistics

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1. Introduction

According to the report, it reveals that the unemployment rate has rebounded and reached a record low of 4.9% in mid-2022 (Macklem, 2022), which indicates that the Canadian economy has finally recovered from the COVID-19 pandemic. The pandemic has affected many aspects of human society around the world, which means it results in a long-term societal impact and it has reshaped the structure of human society. Alexandre White, a sociologist, and historian from Johns Hopkins, believed that the COVID-19 pandemic has not only affected global health systems but also the global economy and society. In his discussion, he mentions "…have reverberated long after the disease stops spreading" (White, 2020). Hence, even though most countries have already lifted their restrictions in relation to the pandemic, we still need to examine the ongoing and subsequent impacts that result from the COVID-19 pandemic and discover how it shapes our economy and society. In this project, we looked at the dataset about crime in the Toronto, the data set is built by Toronto Police service including data related to arrest and strip searches in 2020 and 2021. Based on the dataset, we were able to analyze what was the trend in police-reported crime in Toronto from 2020 to 2021 under the effects of the COVID-19 pandemic and its subsequent year. We tried to discover the potential relationship between variables in terms of arrest and strip search happening in the Toronto, and to examine how they were interconnected and articulated during the pandemic. The reason why we focused on crime is that we believed the statistics of crime that can be used to measure social stability. On the other hand, according to the data, the US also faced challenges in terms of social security such as the high homicide rate during the pandemic (Rosenfeld et al., 2020). Hence, we wanted to see if the Canadian crime statistics had a similar trend as the US. Our objective is to determine how booked count will be affected by different factors while controlling for strip search count.

Additionally, our analysis will also investigate the potential role of strip searches in determining the likelihood of individuals being booked based on their race, sex, and arrest year. Strip searches are invasive procedures that involve the removal of an individual's clothing in search of weapons, drugs, or other contraband. In recent years, concerns have been raised about the discriminatory use of strip searches, particularly against marginalized communities such as Black and Indigenous people, as well as women. Therefore, our analysis will also explore whether there is any correlation between strip searches and the likelihood of individuals from certain demographics being booked. We will investigate whether there are disparities in strip search rates and booking outcomes for individuals of different races, sexes, and in different arrest years. By doing so, we hope to shed light on the potential impact of systemic bias in the criminal justice system, and the need for reform in policies and practices related to strip searches. In conclusion, we wanted to discover how crime statistics changed during the pandemic for two consecutive years from 2020 to 2021, and we eventually generated three research questions:

Research Questions:

Research Question 1: Is there a significant difference in booked count between different races while controlling for strip search count?

Research Question 2: Is there a significant difference in booked count between different sexes while controlling for strip search count?

Research Question 3: Is there a significant difference in booked count between different years while controlling for strip search count?

Literature Review

As part of our research, we delved into the issue of strip searches during arrest events to gain more insight into our research questions. Our findings show that there is a concerning trend of strip searches being conducted without proper justification and protocol in Ontario, Canada, which violates individuals' rights and may cause emotional distress (Barrison Law, 2021). To address this issue, the report recommends improving police officer training, implementing stricter guidelines for strip searches, and increasing supervision to prevent abuses.

Similarly, a study conducted in British society found that individuals from marginalized communities are more likely to be subjected to strip searches during arrest events (Newburn et al., 2004). Given that Canadian society is diverse with various cultural backgrounds, ethnicities, and economic resources, we sought to investigate if such disparities also exist in Canadian cities, particularly during the COVID-19 pandemic.

Our analysis aims to examine the potential relationship between strip searches and the likelihood of individuals from different demographic groups being booked. We will investigate if there are any disparities in strip search rates and booking outcomes for individuals of different races, sexes, and in different arrest years. By doing so, we hope to shed light on the potential impact of systemic bias in the criminal justice system and advocate for necessary reforms to prevent discrimination and protect individuals' rights.

2. Exploratory Data Analysis

Dataset Description

The dataset we focused on is constructed by the Toronto Police service, and it contains information in terms of arrests and strip searches that took place in the City of Toronto, and the data collection period is from 2020 to 2021. A strip search is when a police officer requires a person to remove some or all clothing to check if someone is carrying concealed or illegal items, usually drugs or weapons. The data also contains related information on booking which refers to the process of a criminal suspect being brought to jail after that suspect's arrest. The location of arrest is formed by different Divisions in Toronto which indicates the division where each arrest took place. Further, the dataset has multiple data elements, which include arrest year and month, perceived race, sex, age group, actions at arrest, arrest location, occurrence category, search reason, items found, and book and strip search counts.

The dataset contains over 65,000 records but also has the problem of missing values, hence, the first step in our data processing and cleaning is going to remove all null data. The problem of missing values is caused by different reasons, and that commonly exists in real-life datasets. For instance, according to the data dictionary, values in 'ArrestLocDiv' are indicated by 'XX' in case the suspect is arrested outside of the Toronto area. As an initial step, we sum up all null or XX values, then we use '996' to replace all null and inconsistent values for the dataset to make our dataset more meaningful. Next, we analyzed the dataset to gather detailed information, in which we utilize the cat-plot to create multiple categorical variable plots to visualize our data. What's more, we observed that some variables like 'EventID', 'ArrestID', and 'PersonID' are meaningless; we would not use them in analysis.

Data Cleaning and Visualization

The first figure we have is a bar chart showing suspects count by perceived race and sex and that provides a basic insight into our dataset. In terms of perceived race, the variable has 9 different types of races including White, Unknown or Legacy, Black, South Asian, Indigenous, Middle Eastern, Latino, East/Southeast Asian, and any invalided values were marked as 996. Based on that, the number of arrests obviously varied among perceived races, we found that male is more likely to be arrested compared to female; meanwhile, white people are more likely to be arrested compared to other races.

We also looked at how arrest counts differed for each perceived race and the contribution of occurrence category for each perceived race. From figure below, we observed that suspects with a perceived race of white accounted for most of the total arrest counts, meanwhile, suspects with a perceived race of black accounted for the second-most of the total arrest counts. Following the observations, we decided to further examine white suspects and black suspects in terms of occurrence category and sex next.

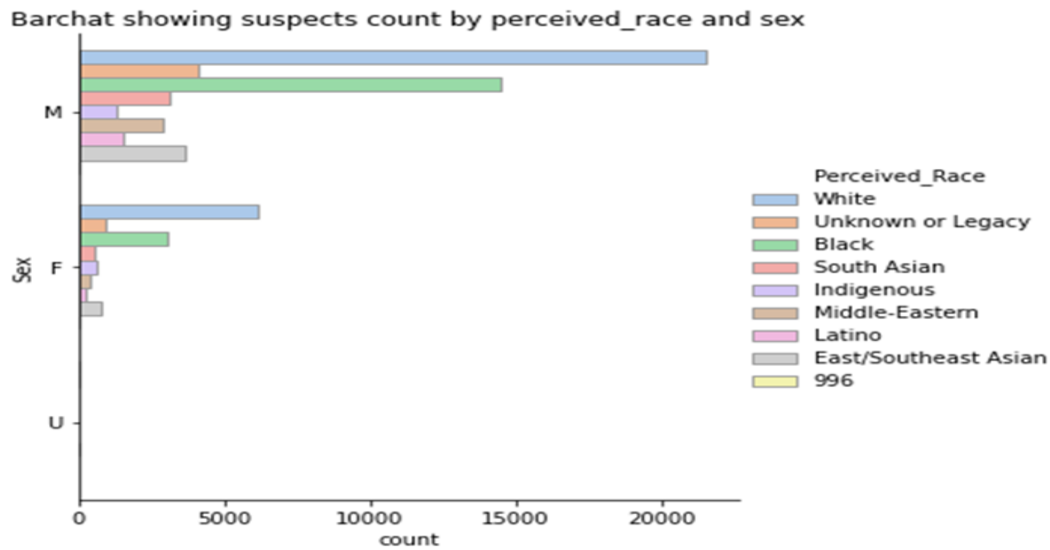

Figure 2.1 Bar chart showing suspects count by perceived_race and sex

Figure below provides a graphical depiction of the contributions from each occurrence category to total arrest counts in relation to white suspects in different sex groups. We compared different occurrence category contributions in terms of suspects with different sex groups, and we found that they are most likely to be arrested when they committed an assault, in terms of male suspects. Similarly, in terms of female suspects, they are most likely to be arrested when they committed an assault too. Therefore, we observed that the occurrence category of assault accounted for most of the total arrest counts regarding white suspects.

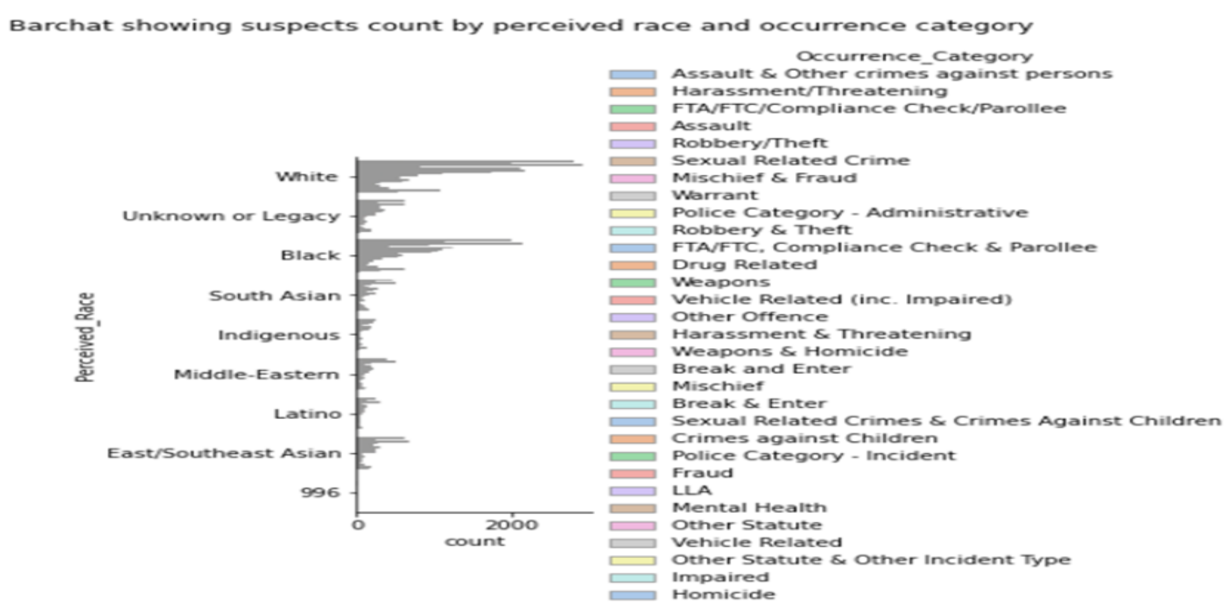

Figure 2.2 Bar chart showing suspects count by perceived_race and occurrence_category

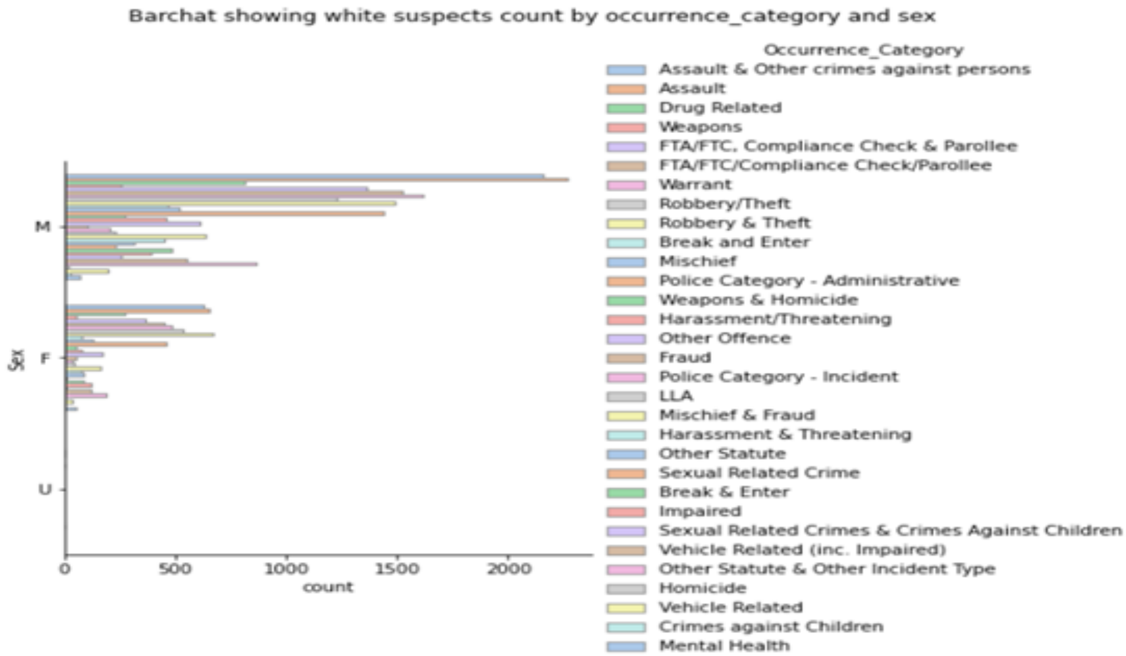

Figure 2.3 Bar chart showing suspects count by occurrence_category and sex for white suspects

Moreover, we also examined the contribution of the occurrence category within black suspects. Based on figure below, we obtain the observation of black suspects, which is like what we had found from white suspects, that they are most likely to be arrested when they committed an assault.

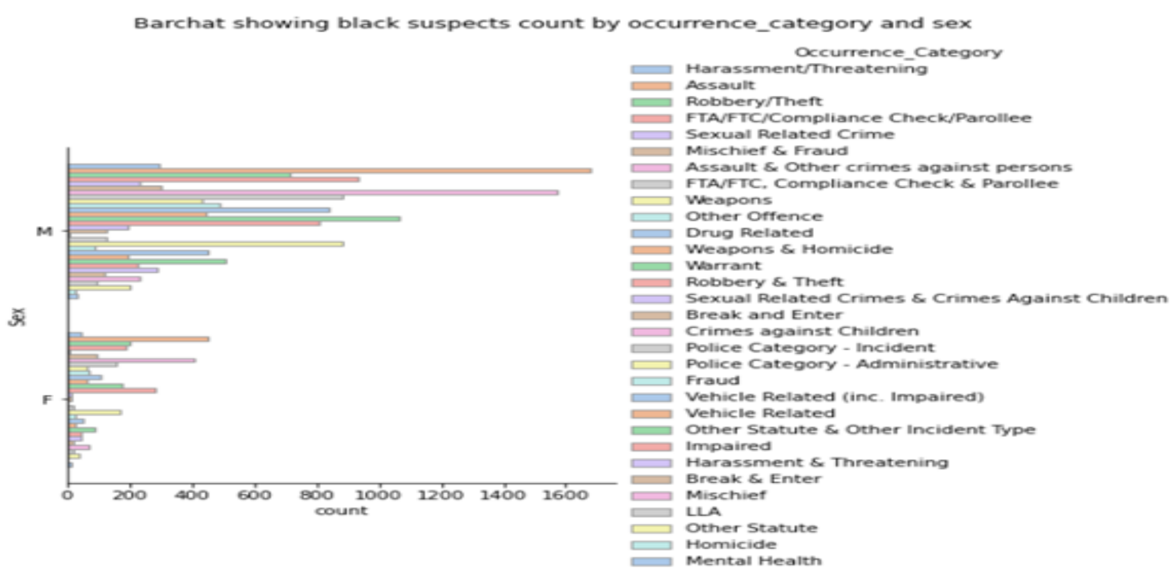

Figure 2.4 Bar chart showing suspects count by occurrence_category and sex for black suspects

Additionally, the distribution of crime type as assault for each perceived race and both sexes are shown in figure below. For each perceived race, we concluded that male suspects are more likely to be arrested due to an assault committed, compared to female suspects.

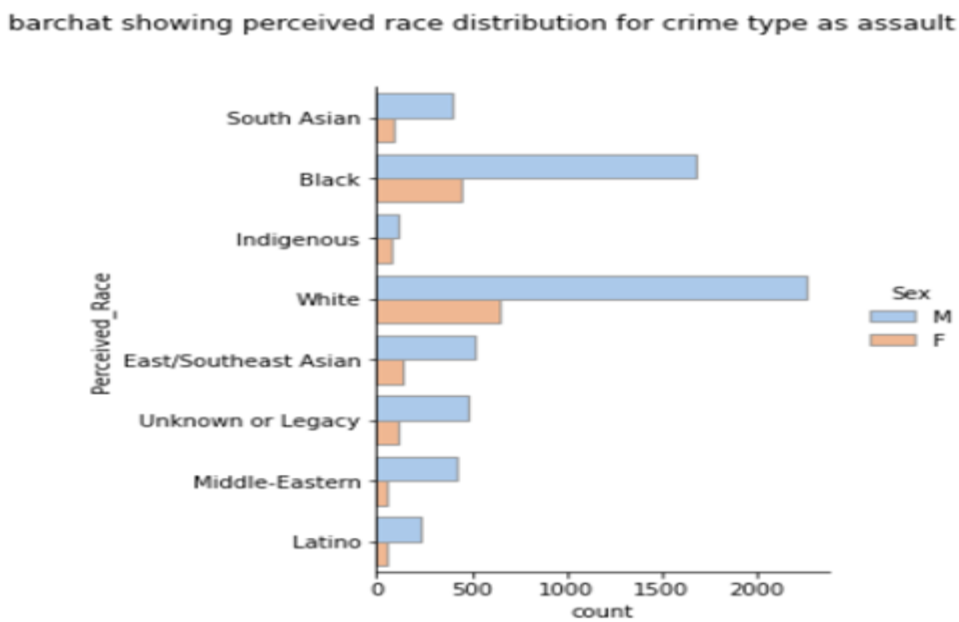

Figure 2.5 Bar chart showing perceived_race distribution for crime type as assault

Since the arrest took place at different police divisions, we wanted to check if there was any location-based correlation with race signifying some sort of race-based bias with the location and the race of the person being arrested. Also, we wanted to check if there was a certain age group that was arrested based on race.

Based on the computations, we get r=0.0035 indicating the relationship between perceived race and location might exist but is very weak. Similarly, we get r=-0.0015 from the correlation computation for age and location which indicates that the relationship between age and location might exist in an inverse way but still is regarded as very weak.

In conclusion, we realized that we still need to seek other potential relationships for other variables. Hence, we expanded the scope of our analysis and tried to explore our dataset referring to different years. By doing so, we produced two subsets after data filtration, they included the data in terms of book count collected in 2020 and 2021, respectively.

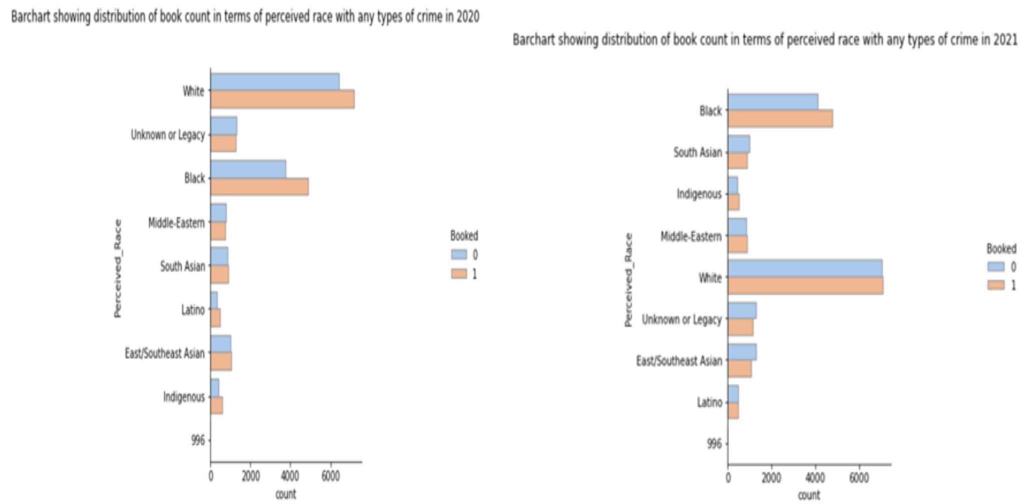

Figure 2.6 Bar chart showing booked count for perceived_race with types of crime in 2020 & 2021

Later, we produced two bar charts for showing the distribution of book count in terms of perceived race for both sexes with any types of crime in 2020 and 2021. As shown in figures above, we marked suspects who were booked as 1 and were not booked as 0. In the case of white and black suspects, as in 2020, the proportion of suspects who were arrested and booked that were higher than those who were arrested but not booked. However, in 2021, a trend that the proportion of white suspects who were arrested and booked and who were arrested but not booked was nearly the same. Further, we took a deeper dive into the subsets we created for each year, and we created frequency tables for each year and both sexes to see the exact number of booked counts in terms of perceived race.

Descriptive Statistics

From all tables, we had the exact number of cases for each race, in which white suspects were the maximum who were booked among perceived races in 2020 and 2021 for both sexes.

Perceived Race	**Booked Count**
Black	4206
East/Southeast Asian	917
Indigenous	419
Latino	421
Middle-Eastern	682
South Asian	803
Unknown or Legacy	1080
White	5772

Perceived Race	Booked Count
Black	679
East/Southeast Asian	120
Indigenous	164
Latino	55
Middle-Eastern	59
South Asian	98
Unknown or Legacy	207
White	1413

From the tables above we can see, the number of arrests made between males and females is significantly different for the year 2020. Generating statistics for the year 2021.

Perceived Race	Booked Count
Black	4120
East/Southeast Asian	947
Indigenous	337
Latino	429
Middle-Eastern	827
South Asian	785
Unknown or Legacy	986
White	5686

Perceived Race	Booked Count
Black	667
East/Southeast Asian	110
Indigenous	154
Latino	60
Middle-Eastern	64
South Asian	91
Unknown or Legacy	163
White	1388

The statistics obtained for both years show that the number of people being booked for different offenses has not really changed and are very close to each other. Generating further statistics to solidify the theory.

Next, we constructed four summary tables for displaying mean, std, and IQR values for both sexes in terms of booked count in 2020 and 2021. As shown in the following tables, the mean booked count of the male suspect from 2020 to 2021 was slightly decreased; meanwhile, the mean booked count of the female suspect from 2020 to 2021 was slightly decreased too.

	Male 2020	**Female 2020**	**Male 2021**	**Female 2021**
count	8	8	8	8
mean	1787.5	349.375	1764.625	337.125
std	2032.422692	475.298684	1995.013565	469.1282
min	419	55	337	60
25%	616.75	88.25	696	84.25
50%	860	142	887	132
75%	1861.5	325	1769.5	289
max	5772	1413	5686	1388

For this reason, we wanted to further examine the relationship between booked number and year, we created a boxplot showing distribution for the number of suspects booked categorized by perceived race and year. Besides, we also created a scatter plot to see if we could have the same relationships among those variables. In conclusion, based on previous data examinations, it was reasonable to believe that a strong relationship might exist between perceived race and booked counts, so we would further identify it based on T-test.

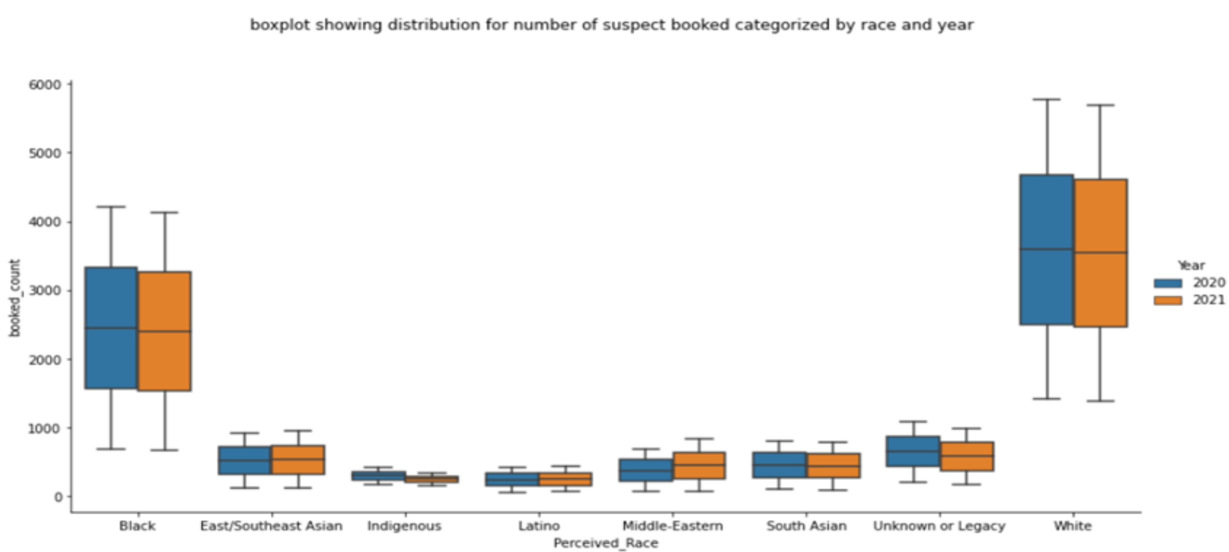

Figure 2.7 Boxplot for people booked, categorized by race & year

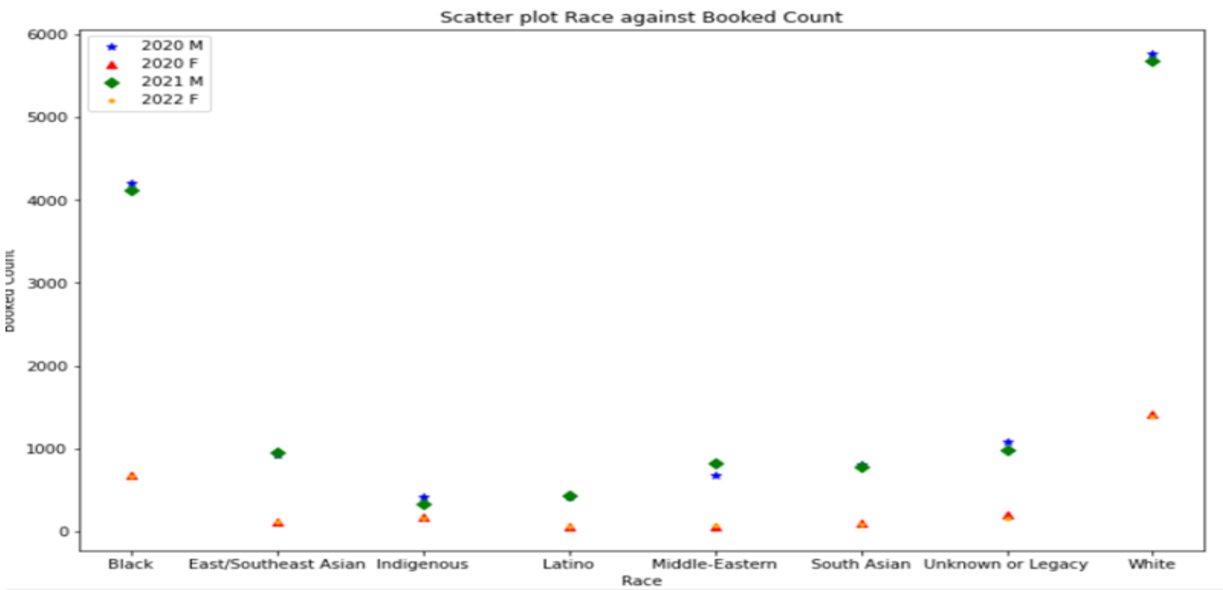

Figure 2.8 Scatterplot for the no. of suspects booked, categorized by race & year

As we are also interested in the relationship between perceived race and cooperation level at arrest, in this case, we believed that only the suspects who were recorded as ‘Actions_at_arrest___Cooperative’ would be considered cooperative. Subsequently, we created a box plot and a scatterplot to gather the distribution for the mean of suspects being cooperative during arrest based on year. As shown in figure below, we observed that East/Southeast Asian suspects were more likely to be cooperative at arrest, compared to other perceived races in both 2020 and 2021. In terms of the comparison between years, we found that suspects were more likely to be cooperative at arrest in 2020, compared to 2021.

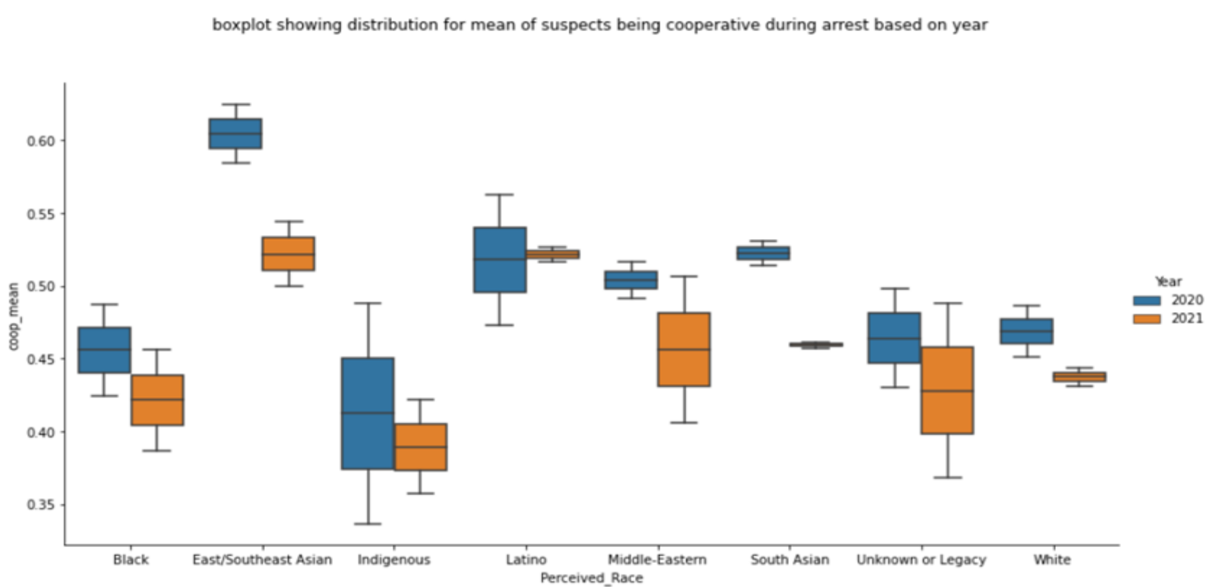

Figure 2.9 Boxplot showing distribution for mean of suspects being cooperative during arrest

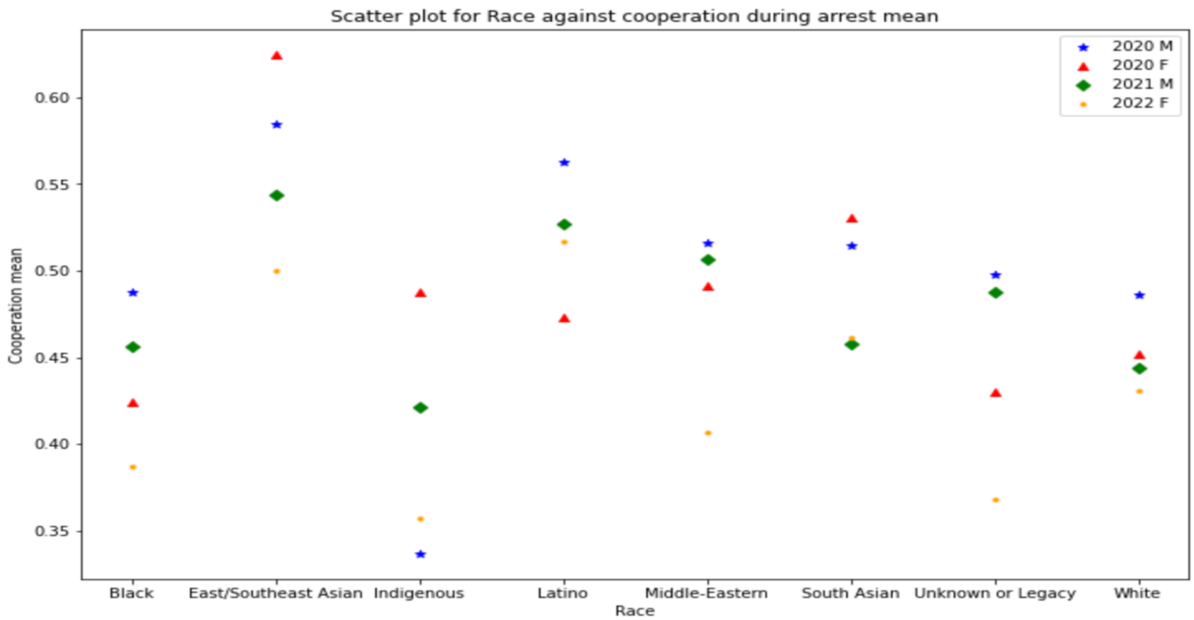

Figure 2.10 Scatterplot for mean for suspects being cooperative during arrest

To add onto for our research questions for ANCOVA, we wanted to see the effects of race, year and sex on the booked count when holding strip search count constant. Therefore, we re-wrangled the dataset to add the strip search count based on booked value of true.

We observed that Black males had the highest number of strip searches in both 2020 and 2021, with 1839 strip searches in 2020 and 189 strip searches in 2021. This is significantly higher than any other group in the dataset. White males had the second-highest number of strip searches in 2020, with 2342 searches, but this number decreased to 235 in 2021. White females had the highest number of strip searches among females, with 640 in 2020 and 74 in 2021.

Indigenous individuals had a relatively low number of strip searches compared to other groups, with only 199 searches for males and 61 searches for females in 2020. Latino individuals had a very low number of strip searches, with only 107 for males and 10 for females in 2020, and almost no strip searches in 2021. Middle Eastern individuals had a moderate number of strip searches, with 175 for males and 15 for females in 2020, and a small number in 2021.

South Asian individuals had a moderate number of strip searches, with 204 for males and 25 for females in 2020, and a small number in 2021. The Unknown or Legacy category had a moderate number of strip searches, with 357 for males and 87 for females in 2020, and a small number in 2021. There were very few strip searches overall in 2021 compared to 2020, which could suggest a change in policy or procedure.

Perceived Race	Arrested at 2020 (M)	Arrested at 2020 (F)	Arrested at 2021 (M)	Arrested at 2021 (F)
Black	1839	228	15	189
East/Southeast Asian	258	22	2	43
Indigenous	199	61	14	6
Latino	107	10	6	0
Middle Eastern	175	15	18	3
South Asian	204	25	15	1
White	2342	640	235	74
Unknown or Legacy	357	87	34	4

Furthermore, we built a boxplot displaying the distribution for the mean of suspects being strip searched during arrests in 2020 and 2021. Referring to the graph, we observed that the boxes of the black and white male suspect are relatively tall; meanwhile, the middle lines of both black and white male suspects are higher than, compared to other race groups, which we considered the mean of both black and white male suspect being strip searched during the arrest were higher than other race groups, in 2020 and 2021. Additionally, we observed that outliers exist in all boxes, and we believe there are several potential reasons causing this to happen.

Firstly, outliers exist in our data due to data entry errors, since the raw data we obtained from the police department has a large number of null and meaningless values that can be considered a sparse dataset with relatively low credibility. Additionally, other technical errors such as sampling errors might be of concern. Secondly, it might be caused due to skewed data issues. As the graph shows, we observed that, except for the black suspect, the distributions for other race groups were positively skewed, because the whiskers and half-box were longer on the top side of the median than on the bottom side. Other information contained in this graph also displayed that, in terms of black and white male suspects, the center of distribution of black is lower than white, at the same time, the white male suspects had the highest dispersion in the dataset, compared to other race groups. In conclusion, compared to the white male suspect, the black male suspects were more likely to get a strip search during the arrest.

Moving on, we also created a scatter plot for race against strip search during arrest, similarly, we discovered the presence of outliers as what we found in the boxplot. Referring to the scatter plot, we also found that the data of the black and white male suspect were more likely to have extreme values and outliers.

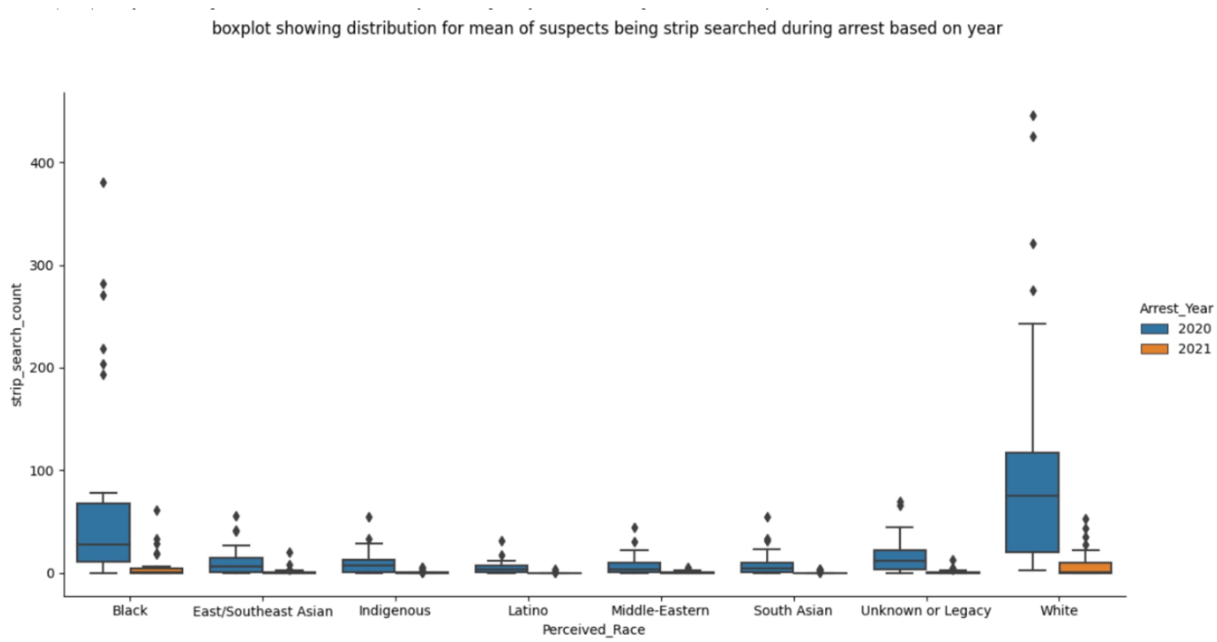

Figure 2.11 Boxplot for the mean of suspects being strip searched during arrest based on year

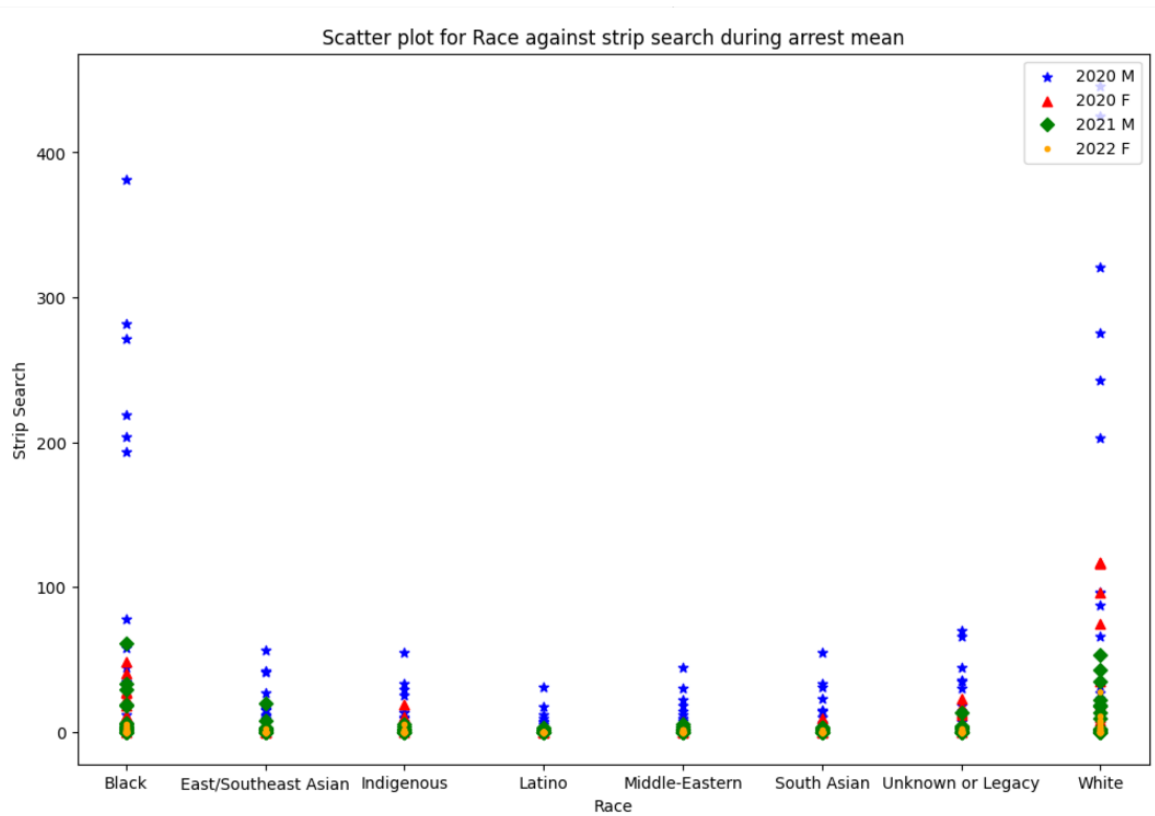

Figure 2.12 Scatterplot for race against strip search during arrest

Shapiro-Wilk test

Firstly, we perform a Shapiro-Wilk test to check if our data in terms of our three research questions are normally distributed, we proposed the following hypothesis for our both variables of interest:

H0 (Null Hypothesis): The sample is normally distributed

H1 (Alternative Hypothesis): The sample is not normally distributed

Setting an alpha level of 0.05, the results suggest that the count of suspects booked is not normally distributed with (p=8.13e-08), we reject the null hypothesis as the p-value is less than 0.05. For our second variable, the results suggest that the strip search count of people while being booked is also not normally distributed with (p=8.03e-39), we reject the null hypothesis as the p-value is less than 0.05.

T-Test

As the above plots show data distribution very similar to each other based on the year, we ran a Welch's T-Test with the continuous variable in the data subsets created for the research questions. Before running the T-Tests, we checked the following assumptions were fulfilled: (1) a nominal two-level explanatory variable; (2) a quantitative outcome variable; (3) normality assumption; (4) independence of errors.

Research Question 1:

H0 (Null Hypothesis): The population mean of the two independent groups, the number of people booked in the year 2020 and the number of people booked in the year 2021, are equal.

H1 (Alternative Hypothesis): The population mean of the two independent groups, the number of people booked in the year 2020 and the number of people booked in the year 2021, are different.

In this trial, setting an alpha level of 0.05, since we fail to reject the null hypothesis as the p-value is greater than 0.05 (p=0.98), the results indicate that the number of people booked in 2020 was similar to the number of people booked in 2021; the mean of booked count in 2020 was 1068.44 that was higher than 1050.88 in 2021; the standard deviation for 2020 was 1607.68 that was higher than 1582.24 for 2021; the confidence interval for 2020 and 2021 was (-1134.13, 1169.25); we also performed a Welch DOF test, for which the results were 29.99.

T-Test concluding remark

As the p-value is greater than the set alpha level of 0.05, we fail to reject the null hypothesis which suggests that the number of people who were booked during the year of the COVID-19 outbreak was the same as the year 2021. This test was conducted with the ***limitation*** that the data was not normally distributed. However, as the sample size is greater than 50, the data distribution would have not a significant effect on the outcome of the test.

Research Question 2:

H0 (Null Hypothesis): The population mean of the two independent groups, the number of people strip searched in the year 2020 and the number of people strip searched in the year 2021, are equal.

H1 (Alternative Hypothesis): The population mean of the two independent groups, the number of people strip searched in the year 2020 and the number of people strip searched in the year 2021, are different.

In this trial, setting an alpha level of 0.05, we can reject the null hypothesis as the obtained p-value is less than 0.05 (p=7.45e-12), the results indicated that the strip searches in 2020 were different than in 2021; the confidence interval for 2020 and 2021 was (20.12, 39.93); we also created a Welch DOF test, the results were 204.97.

T-Test concluding remark

As the p-value is less than the set alpha level of 0.05, we reject the null hypothesis which suggests that the strip search count for people being booked during the year of the COVID-19 outbreak was the different than in the year 2021.

3. Research Design and Methods

Power Analysis

Effect of year on booked count:
The results of the power analysis to calculate the effect size which is performed using Cohen's D indicates the effect size of variable *year* on the dependent variable *booked count* as 0.1569 which is low. This means that year variable has a weak impact on booked count. The sample size required to estimate the mean number of people booked in each year (2020 and 2021) are estimated based on the assumption that the true population standard deviation is equal to the sample standard deviation.

For the year 2021, the required sample size is approximately 763 but the actual sample size is 282. This means that the actual sample size is smaller than the recommended sample size, which results in less accurate estimates of the mean number of people booked in the year 2021 to attain a power of 80%. For the year 2020, the required sample size is approximately 549 but the actual sample size is 203. Again, the actual sample size is smaller than the recommended sample size, which results in less accurate estimates of the mean number of people booked in the year 2020.

Overall, these results indicate that the effect of year on booked count is small but the sample sizes for each year are smaller than the recommended value, which may affect the accuracy of the estimates of the mean number of people booked in each year.

Effect of sex on booked count:
The results of the power analysis to calculate the effect size which is performed using Cohen's D indicates the effect size of variable *sex* on the dependent variable *booked count* as 0.5436 which has a moderate impact on the dependent variable. The sample size required to estimate the mean number of people booked for males and females accurately with the assumption that the true population standard deviation is equal to the sample standard deviation.

For males, the required sample size is approximately 50, but the actual sample size is 264. This means that the actual sample size is larger than the recommended sample size, which results in more accurate estimates of the mean number of people booked for males to attain a power of 80% for the experiment. Similarly, for females, the required sample size is approximately 59 and the actual sample size is 221 meaning, the actual sample size is larger than the recommended sample size, which results in accurate estimates of the mean number of people booked for females.

Overall, these results suggest that the effect of sex on the dependent variable booked count is moderate, and the sample size for both males and females are larger than recommended, which leads to more accurate estimates of the mean number of people booked for each sex.

Effect of race on booked count:
The results of the power analysis to calculate the effect size between perceived races White and Black (as they constitute to the highest numbers of booked and strip search instances) which is performed using Cohen's D indicates the effect size of variable *race* on the dependent variable *booked count* as 0.2562 which has a low impact on the dependent variable. The sample size required to estimate the mean number of people booked for every race accurately with the assumption that the true population standard deviation is equal to the sample standard deviation.

For each race, the required sample size is 241, but the actual sample size for each race is below 70. This means that the actual sample size is smaller than the recommended sample size, which results in less accurate estimates of the mean number of people booked for different races to attain a power of 80% for the experiment.

Overall, these results suggest that the effect size of race on the dependent variable booked count is small, and the sample size for all races are smaller than recommended, which leads to less accurate estimates of the mean number of people booked for each race.

Power Plot

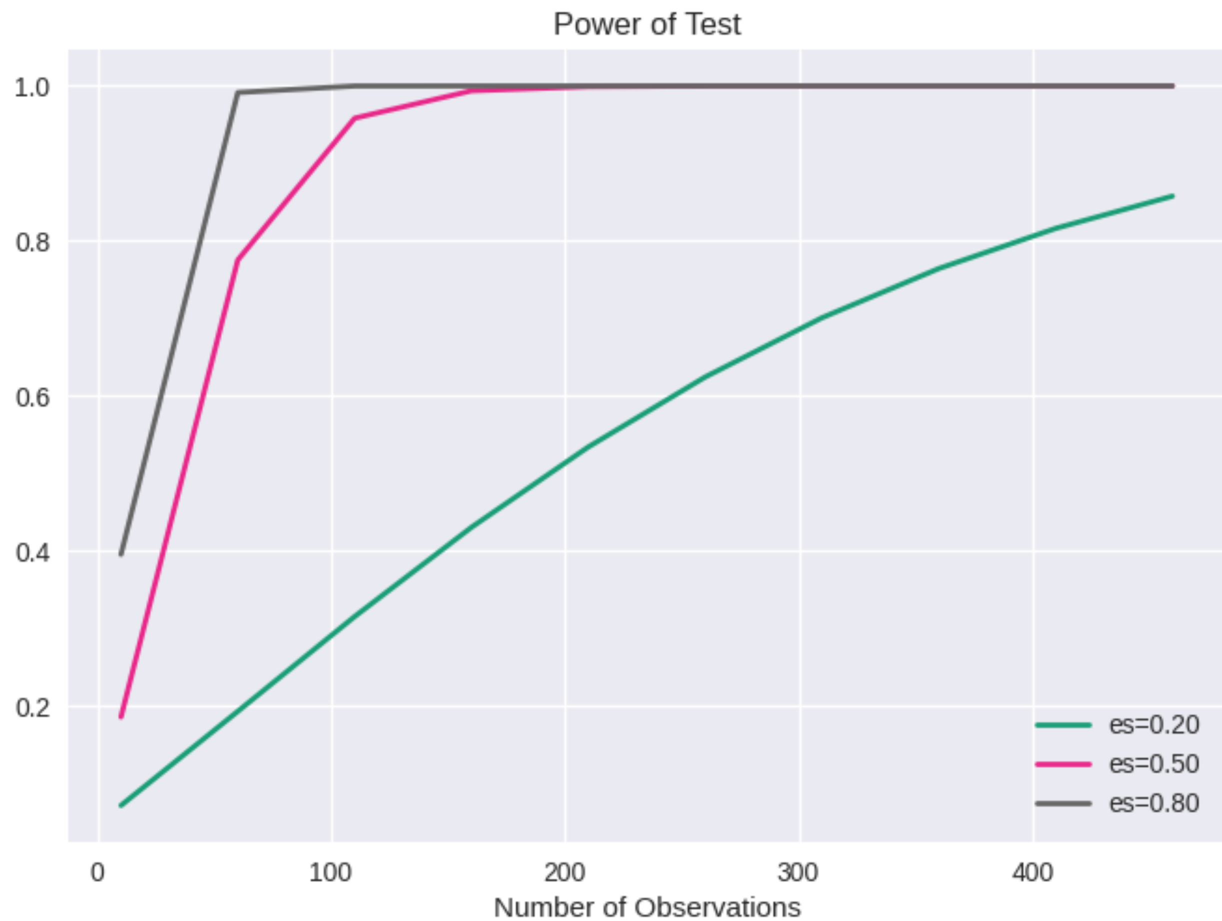

Figure 3.1 Power Plot for variables Sex and Year

The power plot shows the relationship between sample size and statistical power for three different effect sizes, 0.2, 0.5 and 0.8. At a significance level of 0.05, and for variables Sex and Year, the plot indicates that for an effect size of 0.2, a sample size of around 390 samples is required to achieve a power of 80%. For an effect size of 0.5, a sample of around 70 samples is needed to reach the same power level, and for an effect size of 0.8, a sample size of 40 samples is required.

Overall, the plot highlights the required sample size to achieve a power of 80% with designated effect size. A larger effect size is required for a smaller sample size to achieve the same level of power, whereas a smaller effect size requires a larger sample size to achieve a power of 80%.

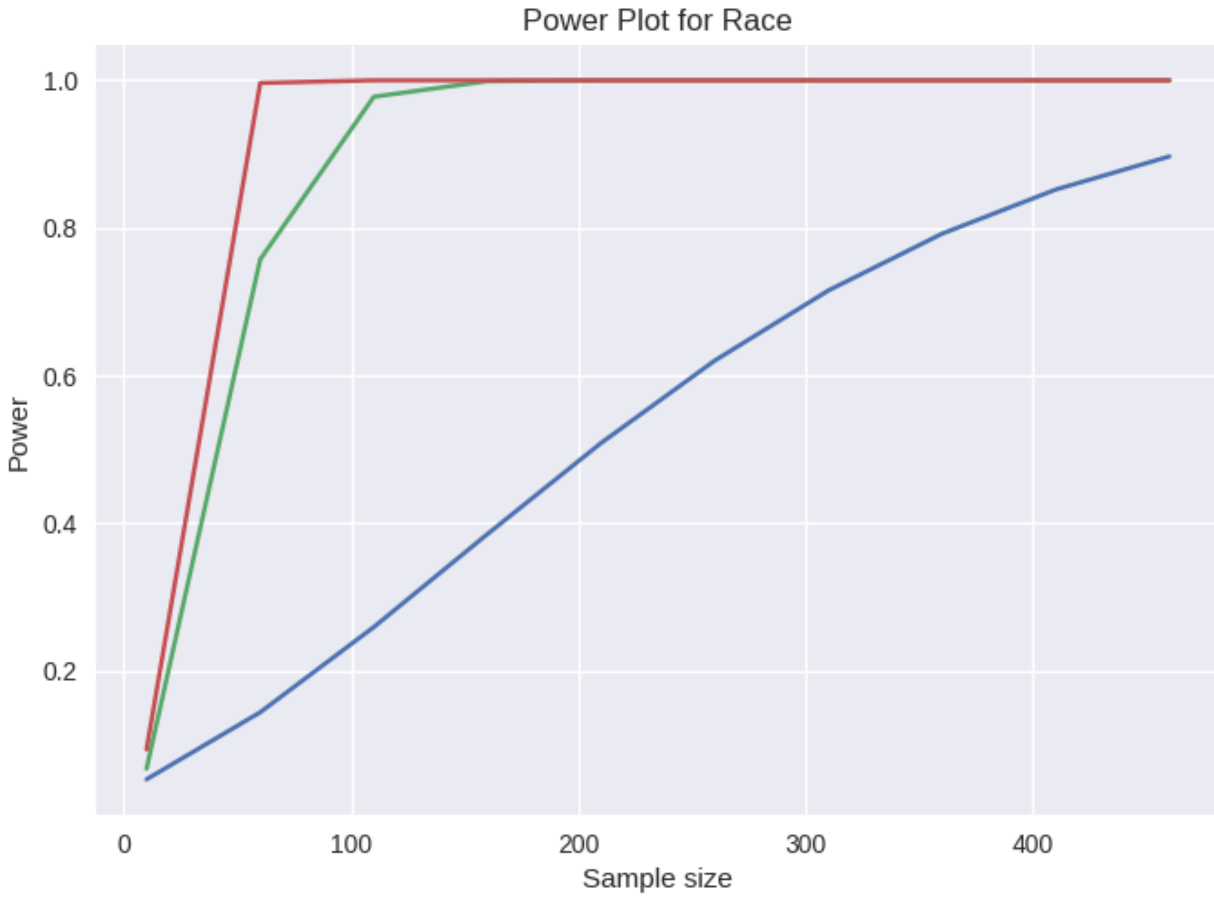

Figure 3.2 Power Plot for variable Perceived Race

The power plot shows the relationship between sample size and statistical power for three different effect sizes, 0.2, 0.5 and 0.8. At a significance level of 0.05, and for variables Perceived Race, the plot indicates that for an effect size of 0.2, a sample size of around 370 samples is required to achieve a power of 80%. For an effect size of 0.5, a sample of around 80 samples is needed to reach the same power level, and for an effect size of 0.8, a sample size of 50 samples is required.

Overall, the plot highlights the required sample size to achieve a power of 80% with designated effect size. A larger effect size is required for a smaller sample size to achieve the same level of power, whereas a smaller effect size requires a larger sample size to achieve a power of 80%

4. Results and Findings

We have made use of ANCOVA and logistic regression to further explore our research questions based on the findings from EDA, t-tests, and power analysis.

Assumption check and limitations of ANCOVA

1. The dependent variable and covariate variables are measured on a continuous scale which satisfies the first assumption.
2. The independent variable consists of two or more categorical, independent groups. Since, variables, year, sex, and perceived race have levels more than or equal to two, this assumption is satisfied.
3. There is independence of observations and there is no relationship between the observations in each group or between the groups themselves therefore satisfying this assumption.
4. The covariate, strip search count has outliers when the data is distributed in a grouped manner for race, year and sex therefore not satisfying this assumption.
5. To check for the normality assumption, a Shapiro-Wilk test was performed for which the obtained p-value was less than 0.05, therefore failing this assumption.
6. To check for the homogeneity of variance, a levene test was performed for which the obtained p-value was less than 0.05, therefore failing this assumption.
7. To check for the linearity assumption, a linregress test was performed and the obtained value for slope was 2.2759 and the correlation coefficient was 0.7038. Since these results are not near zero, this assumption is also not satisfied.
8. To check for the homogeneity of regression slopes, an OLS model was created to check for with interactions and without interactions between the dependent variable, independent variable, and the control factor. The obtained p-value for the ANCOVA f-test was greater than 0.05, therefore satisfying this assumption check.

Limitation: ANCOVA is a statistical test that relies on several key assumptions, including normality of residuals, homogeneity of variance, linearity, independence, and homogeneity of regression slopes. In the case of the below ANCOVA tests, several assumption checks have failed to meet the required criteria, and the results should be interpreted with caution and the potential for bias or other inaccuracies.

ANCOVA

Research Question 1: Is there a significant difference in booked count between different races while controlling for strip search count?

Null Hypothesis (H0): There is no significant difference in booked count between different perceived races while controlling for strip search count.

Alternate Hypothesis (H1): There is a significant difference in booked count between different perceived races while controlling for strip search count.

Source	SS	DF	F	p-unc	np2
Perceived Race	5.651731e+05	7	6.994740243	5.977149e-08	0.09327
Strip Search Count	4.064891e+06	1	352.157605	3.213209e-59	0.42523
Residual	5.494381e+06	476	NaN	NaN	NaN

The result of ANCOVA show that there is significant difference in the booked count between different races. With the alpha level set at 0.05, this is statistically significant results as the obtained p-uncorrected value is 5.977149e-08 which is lower than the p-value of 0.05. Therefore, we can reject the null hypothesis that there is no significant difference in booked count between different perceived races while controlling for strip search count.

ANCOVA for research question 1 concluding remarks:
The ANCOVA analysis examines whether there is significant difference in the booked count between different perceived races while controlling for the effect of strip search count. The results indicate that the main effect of perceived race is statistically significant and there is a difference in booked count between at least two of the eight races.

From the results we can also observe that strip search count is also statistically significant indicating the significant association between strip search and booked count. In summary, the results indicate that there is statistically significant difference in the booked count between the perceived races while controlling for strip search count and that the effect of strip search count on booked count is also very strong.

Research Question 2: Is there a significant difference in booked count between different sexes while controlling for strip search count?

Null Hypothesis (H0): There is no significant difference in booked count between different sex while controlling for strip search count.

Alternate Hypothesis (H1): There is a significant difference in booked count between different sex while controlling for strip search count.

Source	SS	DF	F	p-unc	np2
Sex	2.295774e+05	1	18.98057182	1.614620e-05	0.037886842
Strip Search Count	5.355249e+06	1	442.7513706	3.322519e-70	0.478778821
Residual	5.829977e+06	482	NaN	NaN	NaN

The result of ANCOVA show that there is significant difference in the booked count between different sex. With the alpha level set at 0.05, this is statistically significant results as the obtained p-uncorrected value is 1.614620e-05 which is lower than the p-value of 0.05. Therefore, we can reject the null hypothesis that there is no significant difference in booked count between different sexes while controlling for strip search count.

ANCOVA for research question 2 concluding remarks:
The ANCOVA analysis examines whether there is significant difference in the booked count between different sex while controlling for the effect of strip search count. The results indicate that the main effect of sex is statistically significant and there is a difference in booked count between the two genders.

From the results we can also observe that strip search count is also statistically significant indicating the significant association between strip search and booked count. In summary, the results indicate that there is statistically significant difference in the booked count between the sex while controlling for strip search count and that the effect of strip search count on booked count is also very strong.

Research Question 3: Is there a significant difference in booked count between different years while controlling for strip search count?

Null Hypothesis (H0): There is no significant difference in booked count between different year while controlling for strip search count.

Alternative Hypothesis (H1): There is a significant difference in booked count between different year while controlling for strip search count.

Source	SS	DF	F	p-unc	np2
Arrest Year	2.479882e+05	1	20.56765669	7.272763e-06	0.04092515
Strip Search Count	6.125048e+06	1	507.9995567	2.347097e-77	0.513131095
Residual	5.811566e+06	482	NaN	NaN	NaN

The result of ANCOVA show that there is significant difference in the booked count between different arrest year. With the alpha level set at 0.05, this is statistically significant results as the obtained p-uncorrected value is 7.272763e-06 which is lower than the p-value of 0.05. Therefore, we can reject the null hypothesis that there is no significant difference in booked count between different arrest years while controlling for strip search count.

ANCOVA for research question 3 concluding remarks:
The ANCOVA analysis examines whether there is significant difference in the booked count between different arrest years while controlling for the effect of strip search count. The results indicate that the main effect of arrest year is statistically significant and there is a difference in booked count between the years of arrest.

From the results we can also observe that strip search count is also statistically significant indicating the significant association between strip search and booked count. In summary, the results indicate that there is statistically significant difference in the booked count between the arrest year while controlling for strip search count and that the effect of strip search count on booked count is also very strong.

Logistic Regression

The logistic regression was performed with dependent variable as Booked and the independent variables & control variables are, Arrest Year, Arrest Month, Perceived Race, Sex, Age group at arrest, Youth at arrest under 18 years, Strip Search, Occurrence Category, Actions at arrest Concealed, Actions at arrest Combative, Actions at arrest Resisted, Actions at arrest Mental, Actions at arrest Assaulted, Actions at arrest Cooperative, and Items Found.

The values of occurrence category were re-formatted to suit the logistic regression and techniques of one-hot encoding were implemented on variables Arrest Month, Perceived Race, Sex, Age group at arrest, Youth at arrest under 18 years and Occurrence Category.

	coef	Standard Error	z	P>lzl	Lower CI	Upper CI
Intercept	-222.6913	46.031	-4.838	0.000	-312.911	-132.472
Arrest Year	0.1096	0.023	4.813	0.000	0.065	0. 154
Strip Search	2.6521	0.063	41.945	0.000	2.528	2.776
Actions at arrest concealed	0.5846	0. 199	2.941	0.003	0.195	0.974
Actions at arrest combative	1.061	0.06	17.537	0.000	0.942	1.18
Actions at arrest Resisted	0.506	0.058	8.76	0.000	0.393	0.619
Actions at arrest Mental	0.9971	0.068	14.582	0.000	0.863	1.131
Actions at arrest assaulted	0.5982	0. 162	3.692	0.000	0.281	0.916
Actions at arrest cooperative	0.3885	0.02	19. 199	0.000	0.349	0.428
Items Found	0.1699	0. 104	1.633	0.103	-0.034	0.374
Jan - Mar	0.201	0.028	7. 105	0.000	0.146	0.256
July - Sept	0.1341	0.028	4.75	0.000	0.079	0. 189
Oct - Dec	0.2526	0.028	8.947	0.000	0.197	0.308
East or Southeast Asian	-0.1769	0.042	-4.205	0.000	-0.259	-0.094
Indigenous	0.0036	0.062	0.058	0.954	-0.117	0. 124
Latino	-0.0065	0.061	-0.105	0.916	-0.127	0. 114
Middle Eastern	-0.126	0.047	-2.673	0.008	-0.218	-0.034
South Asian	-0.1394	0.046	-3.045	0.002	-0.229	-0.05
Unknown or Legacy	-0.2078	0.04	-5.159	0.000	-0.287	-0.129
White	-0.1094	0.025	-4.378	0.000	-0.158	-0.06
Male	0.3941	0.026	15.429	0.000	0.344	0.444
Aged 17 years and younger	0.2451	5.09e+13	4.82e-15	1.000	-9.97e+13	9.97e+13
Aged 18 to 24 years	0.7346	0.024	30.224	0.000	0.687	0.782
Aged 25 to 34 years	0.7624	0.017	44.09	0.000	0.728	0.796
Aged 35 to 44 years	0.7312	0.019	39.208	0.000	0.695	0.768
Aged 45 to 54 years	0.7089	0.021	33.422	0.000	0.667	0.75
Aged 55 to 64 years	0.5074	0.038	13.336	0.000	0.433	0.582
Aged 65 and older	0.3716	0.101	3.695	0.000	0.174	0.569
Aged 65yearsand01der	0.2823	0.095	2.982	0.003	0.097	0.468
Youth aged 17 and younger	0.2451	5.09e+13	4.82e-15	1.000	-9.97e+13	9.97e+13
Youth aged 17 years and under	0.5801	0.068	8.548	0.000	0.447	0.713

Assault	-0.1066	0.042	-2.53	0.011	-0.189	-0.024
Break & enter	-0.2756	0.07	-3.926	0.000	-0.413	-0.138
Crimes against children	1.9795	0.434	4.564	0.000	1.129	2.83
Drugs	0.2182	0.065	3.354	0.001	0.091	0.346
Fraud	-1.2565	0.069	-18.108	0.000	-1.392	-1.12
Harassment	-0.0276	0.06	-0.463	0.643	-0.144	0.089
Homicide	1.347	0.369	3.654	0.000	0.624	2.07
Impaired	1.1701	0.084	13.936	0.000	1.006	1.335
Incident	-2.8212	0. 189	-14.918	0.000	-3.192	-2.451
LLA	0.7878	0. 119	6.623	0.000	0.555	1.021
Mental Health	-3.7884	0.375	-10.095	0.000	-4.524	-3.053
Mischief	-0.9903	0.077	-12.945	0.000	-1.14	-0.84
Other	-1.0372	0.052	-19.955	0.000	-1.139	-0.935
Parolee	0.4258	0.047	9. 137	0.000	0.334	0.517
Robbery	-1.3227	0.048	-27.425	0.000	-1.417	-1.228
Sexual related crime	0.0991	0.069	1.426	0. 154	-0.037	0.235
Vehicle	-0.6176	0.06	-10.243	0.000	-0.736	-0.499
Warrant	-0.2031	0.055	-3.717	0.000	-0.31	-0.096
Weapons	-0.2835	0.066	-4.328	0.000	-0.412	-0.155

The one-hot encoding increases the number of independent variables to 48 for the logistic regression model.

Interpretation

- The intercept value is -222.6913, which means that if all other independent variables are zero, the log odds of being booked is -222.6913. This is statistically significant as the p-value is less than 0.05.
- For one unit increase in the variable Arrest Year, the log odds of being booked increases by 0.1096. This suggests that there is a positive relationship between the year and the likelihood of being booked. This is statistically significant as the p-value is less than 0.05.
- For those who underwent strip search, the log odds of being booked increases by 2.6521. This suggest that undergoing strip search is strongly associated with being booked. This is statistically significant as the p-value is less than 0.05.
- For those whose actions at the time of arrest were concealed item, the log odds of being booked increase by 0.5846. This suggests that concealed item during the arrest is associated with a positive likelihood of being booked. This is statistically significant as the p-value is less than 0.05.
- For those whose actions at the time of arrest were combative, the log odds of being booked increase by 1.0610. This suggests that being combative during the arrest is

associated with a higher likelihood of being booked. This is statistically significant as the p-value is less than 0.05.

- For those whose actions at the time of arrest were resistive, the log odds of being booked increase by 0.5060. This suggests that being resistive during the arrest is associated with a positive likelihood of being booked. This is statistically significant as the p-value is less than 0.05.
- For those whose actions at the time of arrest were mental inst, the log odds of being booked increase by 0.9971. This suggests that having mental inst during the arrest is associated with a higher likelihood of being booked. This is statistically significant as the p-value is less than 0.05.
- For those whose actions at the time of arrest were assault, the log odds of being booked increase by 0.5982. This suggests that assaulting an officer during the arrest is associated with a positive likelihood of being booked. This is statistically significant as the p-value is less than 0.05.
- For those whose actions at the time of arrest were cooperative, the log odds of being booked increase by 0.3885. This suggests that even being cooperative during the arrest is associated with a positive likelihood of being booked. This is statistically significant as the p-value is less than 0.05.
- For a unit change in items found, the log odds of being booked increase by 0.1699. However, this result is not statistically significant at the 0.05 level, as indicated by the p-value of 0.103.
- The coefficient Jan – Mar, when compared to Apr – Jun (intercept), the predicted log odds of being booked is 0.2010 higher than other variable when other variables are constant. This coefficient is statistically significant as the associated p-value is less than 0.05.
- The coefficient July – Sep, when compared to Apr – Jun (intercept), the predicted log odds of being booked is 0.1341 higher than other variable when other variables are constant. This coefficient is statistically significant as the associated p-value is less than 0.05.
- The coefficient Oct – Dec, when compared to Apr – Jun (intercept), the predicted log odds of being booked is 0.2526 higher than other variable when other variables are constant. This coefficient is statistically significant as the associated p-value is less than 0.05.
- The coefficient East or South-east Asian, when compared to Black (intercept), the predicted log odds of being booked is -0.1769 lower than other variable when other variables are constant. This coefficient is statistically significant as the associated p-value is less than 0.05.
- The coefficient Indigenous, when compared to Black (intercept), the predicted log odds of being booked is 0.0036 higher than other variable when other variables are constant. This coefficient is not statistically significant as the associated p-value is greater than 0.05.
- The coefficient Latino, when compared to Black (intercept), the predicted log odds of being booked is -0.0065 lower than other variable when other variables are constant. This coefficient is not statistically significant as the associated p-value is greater than 0.05.
- The coefficient Middle-Easter, when compared to Black (intercept), the predicted log odds of being booked is -0.1260 lower than other variable when other variables are constant. This coefficient is statistically significant as the associated p-value is less than 0.05.
- The coefficient South Asian, when compared to Black (intercept), the predicted log odds of being booked is -0.1394 lower than other variable when other variables are constant. This coefficient is statistically significant as the associated p-value is less than 0.05.
- The coefficient Unknown or Legacy, when compared to Black (intercept), the predicted log odds of being booked is -0.2078 lower than other variable when other variables are constant. This coefficient is statistically significant as the associated p-value is less than 0.05.

- The coefficient White, when compared to Black (intercept), the predicted log odds of being booked is -0.1094 lower than other variable when other variables are constant. This coefficient is statistically significant as the associated p-value is less than 0.05.
- The coefficient Male, when compared to Female (intercept), the predicted log odds of being booked is 0.3941 higher than other variable when other variables are constant. This coefficient is statistically significant as the associated p-value is less than 0.05.
- The coefficient aged 17 years and younger, when compared to Aged 17 years and under (intercept), the predicted log odds of being booked is 0.2451 higher than other variables when other variables are constant. This coefficient is not statistically significant as the associated p-value is greater than 0.05.
- The coefficient aged 18 to 24 years, when compared to Aged 17 years and under (intercept), the predicted log odds of being booked is 0.7346 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient aged 25 to 34 years, when compared to Aged 17 years and under (intercept), the predicted log odds of being booked is 0.7624 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient aged 35 to 44 years, when compared to Aged 17 years and under (intercept), the predicted log odds of being booked is 0.7312 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient aged 45 to 54 years, when compared to Aged 17 years and under (intercept), the predicted log odds of being booked is 0.7089 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient aged 55 to 64 years, when compared to Aged 17 years and under (intercept), the predicted log odds of being booked is 0.5074 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient aged 65 and older, when compared to Aged 17 years and under (intercept), the predicted log odds of being booked is 0.3716 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient aged 65 years and older, when compared to Aged 17 years and under (intercept), the predicted log odds of being booked is 0.2823 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient youth aged 17 and younger, when compared to not a youth (intercept), the predicted log odds of being booked is 0.2451 higher than other variables when other variables are constant. This coefficient is not statistically significant as the associated p-value is greater than 0.05.
- The coefficient youth aged 17 and under, when compared to not a youth (intercept), the predicted log odds of being booked is 0.5801 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient assault, when compared to administrative (intercept), the predicted log odds of being booked is -0.1066 lower than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.

- The coefficient break and enter, when compared to administrative (intercept), the predicted log odds of being booked is -0.2756 lower than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient crime against children, when compared to administrative (intercept), the predicted log odds of being booked is 1.9795 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient drugs, when compared to administrative (intercept), the predicted log odds of being booked is 0.2182 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient fraud, when compared to administrative (intercept), the predicted log odds of being booked is -1.2565 lower than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient harassment, when compared to administrative (intercept), the predicted log odds of being booked is -0.0276 lower than other variables when other variables are constant. This coefficient is not statistically significant as the associated p-value is greater than 0.05.
- The coefficient homicide, when compared to administrative (intercept), the predicted log odds of being booked is 1.3470 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient impaired, when compared to administrative (intercept), the predicted log odds of being booked is 1.1701 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient incident, when compared to administrative (intercept), the predicted log odds of being booked is -2.8212 lower than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient LLA, when compared to administrative (intercept), the predicted log odds of being booked is 0.7878 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient mental health, when compared to administrative (intercept), the predicted log odds of being booked is -3.7884 lower than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient mischief, when compared to administrative (intercept), the predicted log odds of being booked is -0.9903 lower than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient other, when compared to administrative (intercept), the predicted log odds of being booked is -1.0372 lower than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient parolee, when compared to administrative (intercept), the predicted log odds of being booked is 0.4258 higher than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient robbery, when compared to administrative (intercept), the predicted log odds of being booked is -1.3227 lower than other variables when other variables are

constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.

- The coefficient sexual related crime, when compared to administrative (intercept), the predicted log odds of being booked is 0.0991 higher than other variables when other variables are constant. This coefficient is not statistically significant as the associated p-value is greater than 0.05.
- The coefficient vehicle, when compared to administrative (intercept), the predicted log odds of being booked is -0.6176 lower than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient warrant, when compared to administrative (intercept), the predicted log odds of being booked is -0.2031 lower than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.
- The coefficient weapons, when compared to administrative (intercept), the predicted log odds of being booked is -0.2835 lower than other variables when other variables are constant. This coefficient is statistically significant as the associated p-value is greater than 0.05.

Odds Ratio

	Odds Ratio	**Lower CI**	**Upper CI**
Intercept	1.93E-97	1.27E-136	2.94E-58
Arrest Year	1.12E+00	1.067147E+00	1.17E+00
Strip Search	1.42E+01	1.25E+01	1.61E+01
Actions at arrest concealed	1.79E+00	1.22E+00	2.65E+00
Actions at arrest combative	2.89E+00	2.57E+00	3.25E+00
Actions at arrest Resisted	1.66E+00	1.48E+00	1.86E+00
Actions at arrest Mental	2.71E+00	2.37E+00	3.10E+00
Actions at arrest assaulted	1.82E+00	1.32E+00	2.50E+00
Actions at arrest cooperative	1.47E+00	1.42E+00	1.53E+00
Items Found	1.19E+00	9.67E-01	1.45E+00
Jan - Mar	1.22E+00	1.16E+00	1.29E+00
July - Sept	1.14E+00	1.08E+00	1.21E+00
Oct - Dec	1.29E+00	1.22E+00	1.36E+00
East or Southeast Asian	8.38E-01	7.72E-01	9.10E-01
Indigenous	1.00E+00	8.89E-01	1.13E+00
Latino	9.935617e-01	8.81E-01	1.12E+00
Middle Eastern	8.82E-01	8.04E-01	9.67E-01
South Asian	8.70E-01	7.95E-01	9.52E-01
Unknown or Legacy	8.12E-01	7.51E-01	8.79E-01
White	8.963295e-01	8.53E-01	9.41E-01
Male	1.48E+00	1.41E+00	1.559212E+00

Aged 17 years and younger	1.28E+00	0.00E+00	inf
Aged 18 to 24 years	2.08E+00	1.99E+00	2.19E+00
Aged 25 to 34 years	2.143364e+00	2.07E+00	2.22E+00
Aged 35 to 44 years	2.08E+00	2.00E+00	2.15E+00
Aged 45 to 54 years	2.03E+00	1.95E+00	2.12E+00
Aged 55 to 64 years	1.66E+00	1.54E+00	1.79E+00
Aged 65 and older	1.45E+00	1.190642e+00	1.77E+00
Aged 65 years and under	1.33E+00	1.101591e+00	1.60E+00
Youth aged 17 and younger	1.28E+00	0.00E+00	inf
Youth aged 17 years and under	1.79E+00	1.56E+00	2.04E+00
Assault	8.988512e-01	8.28E-01	9.76E-01
Break & enter	7.591414e-01	6.62E-01	8.71E-01
Crimes against children	7.239276e+00	3.09E+00	1.69E+01
Drugs	1.24E+00	1.09E+00	1.41E+00
Fraud	2.846581e-01	2.48E-01	3.26E-01
Harassment	9.727655e-01	8.65E-01	1.093352e+00
Homicide	3.846050e+00	1.87E+00	7.922068e+00
Impaired	3.22E+00	2.73E+00	3.80E+00
Incident	5.95E-02	4.11E-02	8.62E-02
LLA	2.198611e+00	1.74E+00	2.78E+00
Mental heath	2.263288e-02	1.08E-02	4.72E-02
Mischief	3.71E-01	3. 197259e-01	4.32E-01
Other	3.54E-01	3.20E-01	3.92E-01
Parolee	1.53E+00	1.40E+00	1.68E+00
Robbery	2.66E-01	2.42E-01	2.93E-01
Sexual related crime	1.10E+00	9.64E-01	1.27E+00
Vehicle	5.392288e-01	4.79E-01	6.07E-01
Warrant	8.16E-01	7.33E-01	9.08E-01
Weapons	7.531126e-01	6.62E-01	8.56E-01

Interpretation

- The odds ratio for the Intercept is 1.93e-97, which suggests that the Intercept is not a meaningful predictor of the outcome variable.
- The odds ratio for Arrest Year is 1.115871, which indicates that a one-unit increase in Arrest Year is associated with 1.11 times increase in the odds of the outcome variable.
- The odds ratio for Strip Search is 14.18315, which indicates that individuals who were subjected to a strip search were 14 times more likely to have the outcome variable than those who were not strip searched, holding all other variables constant.
- The odds ratio for Actions at arrest as concealed is 1.794267, which indicates that individuals who concealed their actions during arrest were 1.79 times more likely to have the outcome variable than those who did not conceal their actions, holding all other variables constant.

- The odds ratio for Actions at arrest as combative is 2.889137, which indicates that individuals who were combative during arrest were 2.89 times more likely to have the outcome variable than those who were not combative, holding all other variables constant.
- The odds ratio for Actions at arrest as resisted is 1.658652, which indicates that individuals who resisted arrest were 1.66 times more likely to have the outcome variable than those who did not resist, holding all other variables constant.
- The odds ratio for Actions at arrest as mental is 2.710521, which indicates that individuals who displayed mental instability during arrest were 2.71 times more likely to have the outcome variable than those who did not display mental instability, holding all other variables constant.
- The odds ratio for Actions at arrest as assaulted is 1.818812, which indicates that individuals who assaulted an officer during arrest were 1.82 times more likely to have the outcome variable than those who did not assault an officer, holding all other variables constant.
- The odds ratio for Actions at arrest Cooperative is 1.474760, which indicates that individuals who were cooperative during arrest were 1.47 times more likely to have the outcome variable than those who were not cooperative, holding all other variables constant.
- The odds ratio for items found is 1.185153, which suggests that there is a weak positive association between the number of items found during arrest and the outcome variable. Specifically, a one-unit increase in the number of items found is associated with 1.18 times increase in the odds of the outcome variable, holding all other variables constant. However, this is not statistically significant as the p-value is greater than 0.05.
- The odds ratio for Jan-Mar is 1.222601, which suggests that individuals who were arrested during Jan-Mar were 1.22 times more likely to have the outcome variable than those who were arrested during April-June, holding all other variables constant.
- The odds ratio for July-Sept is 1.143534, which suggests that individuals who were arrested during July-Sept were 1.14 times more likely to have the outcome variable than those who were arrested during April-June, holding all other variables constant.
- The odds ratio for Oct-Dec is 1.28739, which suggests that individuals who were arrested during October-December were 1.28 times more likely to have the outcome variable than those who were arrested during April-June, holding all other variables constant.
- The odds ratio for East or Southeast Asian is 0.8378307, which suggests that individuals in this group were 0.17 times less likely to have the outcome variable than Black individuals, holding all other variables constant.
- The odds ratio for Indigenous is 1.003582, which suggests that Indigenous individuals had almost similar odds of the outcome variable as Black individuals, holding all other variables constant. However, this is not statistically significant as the p-value is greater than 0.05.
- The odds ratio for Latino is 0.9935617, which suggests that individuals in this group were almost equally likely as Black individuals to have the outcome variable, holding all other variables constant. However, this is not statistically significant as the p-value is greater than 0.05.
- The odds ratio for Middle Eastern is 0.8815882, which suggests that individuals in this group were 0.12 times less likely to have the outcome variable than Black individuals, holding all other variables constant.
- The odds ratio for South Asian is 0.8698857, which suggests that individuals in this group were 0.14 times less likely to have the outcome variable than Black individuals, holding all other variables constant.

- The odds ratio for Unknown or Legacy is 0.8123678, which suggests that individuals in this group were 0.19 times less likely to have the outcome variable than Black individuals, holding all other variables constant.
- The odds ratio for White is 0.8963295, which suggests that individuals in this group were 0.11 times less likely to have the outcome variable than Black individuals, holding all other variables constant.
- The odds ratio for Male is 1.483073, with the reference level set at females. This suggests that male individuals were 1.48 times more likely to have the outcome variable than female individuals, holding all other variables constant.
- Aged 17 years and younger has an odds ratio of 1.277798, which suggests that individuals in this age group had 1.27 times higher odds of the outcome variable compared to individuals aged 17 years and under, holding all other variables constant.
- Aged 18 to 24 years has an odds ratio of 2.08459, which suggests that individuals in this age group had more than twice the odds of the outcome variable compared to individuals aged 17 years and under, holding all other variables constant.
- Aged 25 to 34 years has an odds ratio of 2.143364, which suggests that individuals in this age group had more than twice the odds of the outcome variable compared to individuals aged 17 years and under, holding all other variables constant.
- Aged 35 to 44 years has an odds ratio of 2.077616, which suggests that individuals in this age group had more than twice the odds of the outcome variable compared to individuals aged 17 years and under, holding all other variables constant.
- Aged 45 to 54 years has an odds ratio of 2.031748, which suggests that individuals in this age group had more than twice the odds of the outcome variable compared to individuals aged 17 years and under, holding all other variables constant.
- Aged 55 to 64 years has an odds ratio of 1.660898, which suggests that individuals in this age group had 1.66 times higher odds of the outcome variable compared to individuals aged 17 years and under, holding all other variables constant.
- Aged 65 and older has an odds ratio of 1.45005, which suggests that individuals in this age group had 1.45 times higher odds of the outcome variable compared to individuals aged 17 years and under, holding all other variables constant.
- Aged 65 years and under has an odds ratio of 1.326222, which suggests that individuals in this age group had 1.32 times higher odds of the outcome variable compared to individuals aged 17 years and under, holding all other variables constant.
- Youth aged 17 and younger has an odds ratio of 1.277798, which suggests that individuals in this age group had 1.27 times higher odds of the outcome variable compared to individuals who were not youth, holding all other variables constant. However, this is not statistically significant as the p-value is greater than 0.05.
- Youth aged 18 years and older has an odds ratio of 1.786217, which suggests that individuals in this age group had 1.78 times higher odds of the outcome variable compared to individuals who were not youth, holding all other variables constant.
- Assault has an odds ratio of 0.8988512, which suggests that individuals arrested for assault had 0.11 times lower odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Break & enter has an odds ratio of 0.7591414, which suggests that individuals arrested for break & enter had 0.24 times lower odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Crimes against children has an odds ratio of 7.239276, which suggests that individuals arrested for crimes against children had 7.23 times higher odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.

- Drugs has an odds ratio of 1.243871, which suggests that individuals arrested for drugs had 1.24 times higher odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Fraud has an odds ratio of 0.2846581, which suggests that individuals arrested for fraud had 0.72 times lower odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Harassment has an odds ratio of 0.9727655, which suggests that individuals arrested for harassment had 0.03 times lower odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant. However, this is not statistically significant as the p-value is greater than 0.05.
- Homicide has an odds ratio of 3.84605, which suggests that individuals arrested for homicide had 3.84 times higher odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Impaired has an odds ratio of 3.222451, which suggests that individuals arrested for impaired driving had 3.22 times higher odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Incident has an odds ratio of 0.05953718, which suggests that individuals arrested for incidents had 0.94 times lower odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- LLA has an odds ratio of 2.198611, which suggests that individuals arrested for LLA had 2.19 times higher odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Mental Health has an odds ratio of 0.02263288, which suggests that individuals arrested for mental health reasons had 0.98 times lower odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Mischief has an odds ratio of 0.371449, which suggests that individuals arrested for mischief had 0.63 times lower odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Other has an odds ratio of 0.3544472, which suggests that individuals arrested for other reasons had 0.64 times lower odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Parolee has an odds ratio of 1.530754, which suggests that individuals arrested for parole violations had 1.53 times higher odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Robbery has an odds ratio of 0.2664065, which suggests that individuals arrested for robbery had 0.73 times lower odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Sexual related crimes have an odds ratio of 1.104134, which suggests that individuals arrested for sexual related crimes had 1.1 higher odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant. However, this is not statistically significant as the p-value is greater than 0.05.
- Vehicle has an odds ratio of 0.5392288, which suggests that individuals arrested for vehicle had 0.46 times lower odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Warrant has an odds ratio of 0.8161659, which suggests that individuals arrested for warrant had 0.19 times lower odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.
- Weapons has an odds ratio of 0.7531126, which suggests that individuals arrested for weapons had 0.25 times lower odds of the outcome variable compared to individuals arrested for administrative reasons, holding all other variables constant.

Accuracy and Confusion Matrix
The dataset is split in a ratio of 80-20 and the samples are stratified resulting in better distribution of sample points in both train and test dataset. Approximately 48% records have the value 1 in the column booked.

Using the function call confusion_matrix from sklearn.metrics, we were able to get true positive, true negative, false positive and false positive values which were predicted by the trained model.

The below image represents all the four classes which were predicted by the logistic regression model on the train dataset. As we can see from the image below, 18,872 instances were predicted as positive and were actually positive (true positives). 8,505 instances were predicted as positive but were actually negative (false positives). 8,255 instances were predicted as negative but were actually positive (false negatives). 16,578 instances were predicted as negative and were actually negative (true negatives).

In summary, the model correctly predicted the positive class for 18,872 instances, but it incorrectly predicted the positive class for 8,505 instances which are the type I errors. Similarly, it correctly predicted the negative class for 16,578 instances but incorrectly predicted the negative class for 8,255 instances which are type II errors.

With these metrics, the achieved accuracy for the model on train dataset is 67.9%. This means that for every 100 values, the model accurately predicts 68 datapoints and their correct classes.

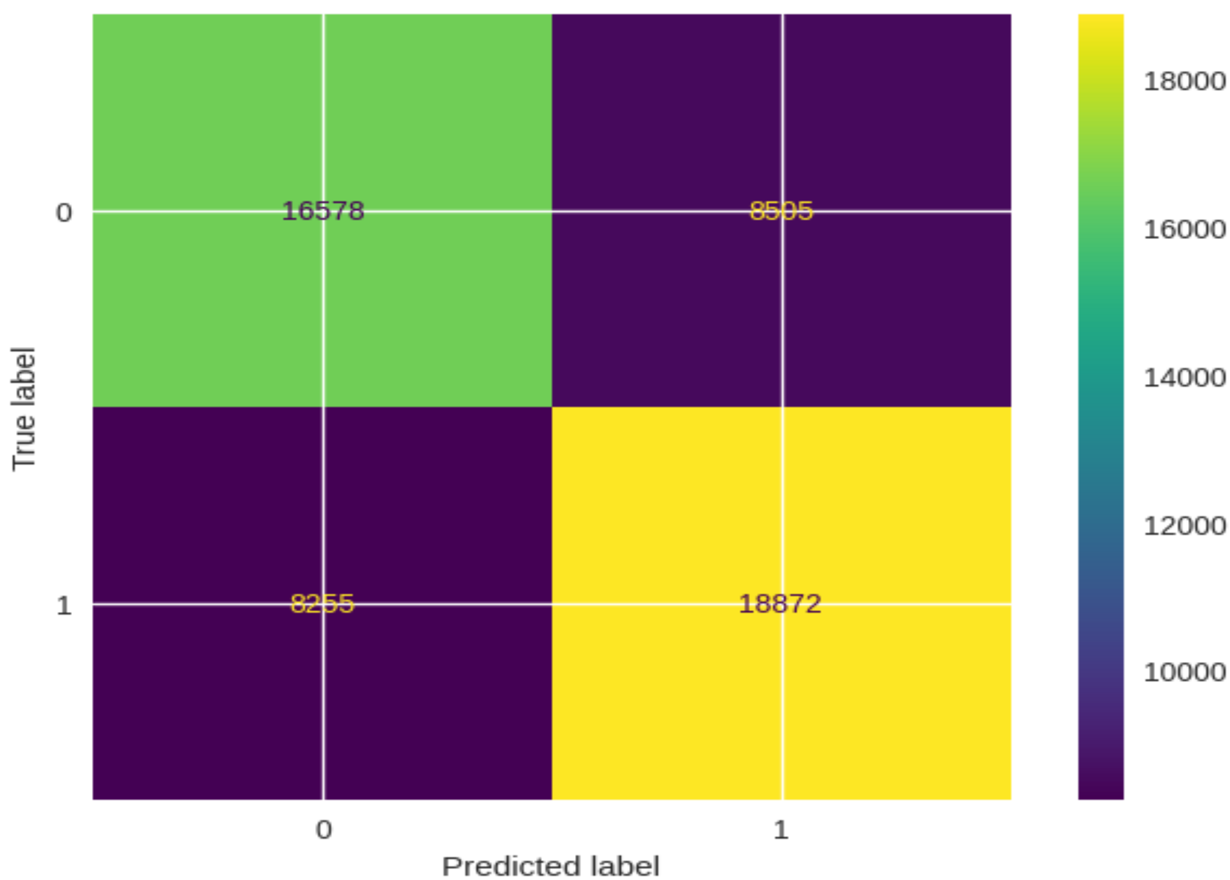

Figure 4.1 Confusion Matrix on Train data-subset

The below image represents all the four classes which were predicted by the logistic regression model on test dataset. As we can see from the image below, 4,735 instances were predicted as positive and were actually positive (true positives). 2,131 instances were predicted as positive but were actually negative (false positives). 2,047 instances were predicted as negative but were actually positive (false negatives). 4,140 instances were predicted as negative and were actually negative (true negatives).

In summary, the model correctly predicted the positive class for 4,735 instances, but it incorrectly predicted the positive class for 2,131 instances which are the type I errors. Similarly, it correctly predicted the negative class for 4,140 instances but incorrectly predicted the negative class for 2,047 instances which are type II errors.

With these metrics, the achieved accuracy for the model on test dataset is 67.99% which is very similar to that of train dataset. This means that for every 100 values, the model accurately predicts 68 datapoints and their correct classes.

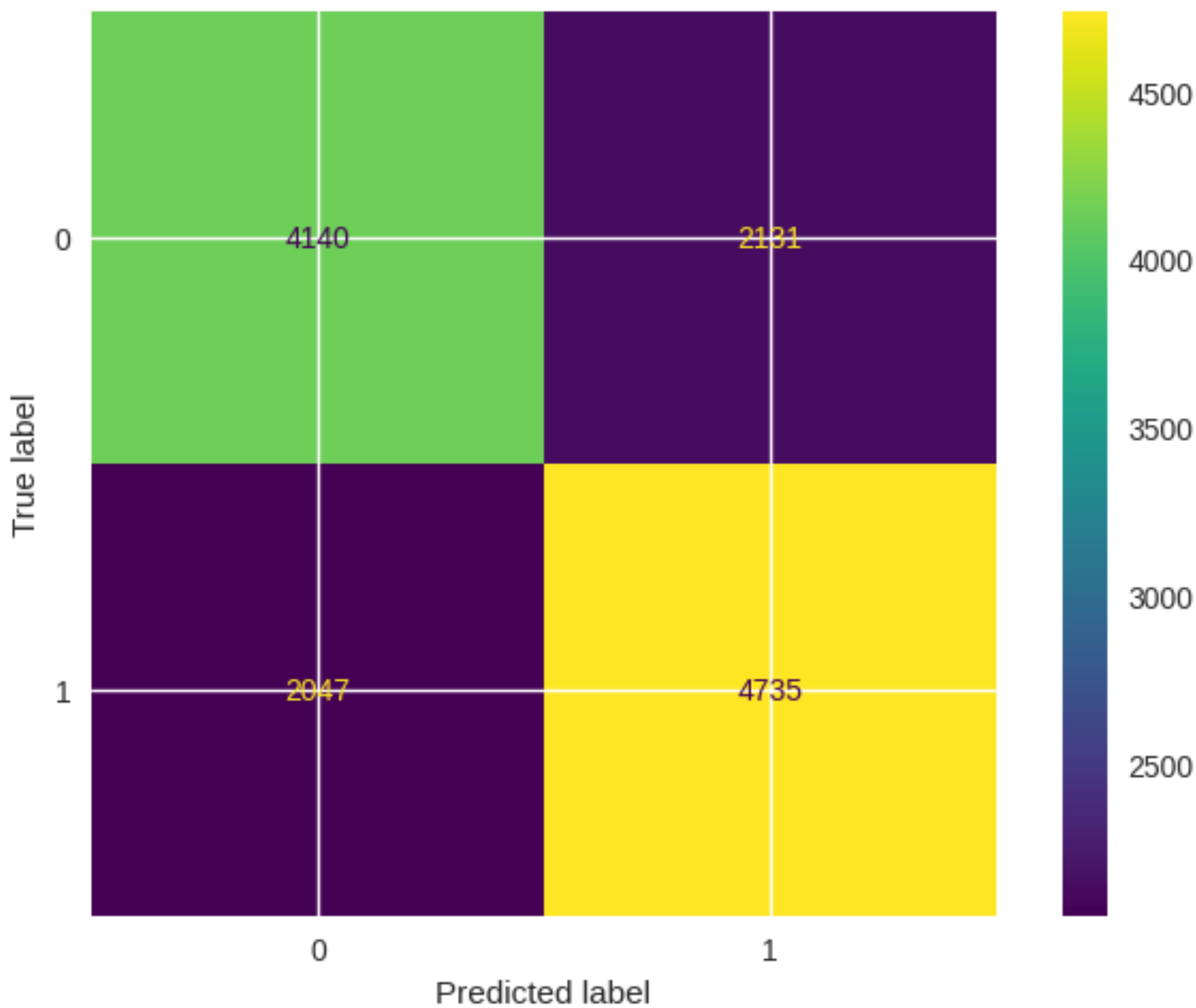

Figure 4.2 Confusion Matrix on Test data-subset

Prediction Interval
The plot is created for dependent variable booked and independent variable perceived race. The blue line represents the predicted probabilities of being booked based on perceived race from the logistic regression model and the shaded green area around the line is the 95% confidence interval.

From the plot, we can clearly see that the model predicts higher probability of being booked for races Black and East/Southeast Asians when compared to other categories. The model also predicts a lower probability for races Unknown or Legacy and White. The probabilities for Indigenous, Latino, Middle Eastern and South Asian are in between these two extremes. However, we can also see that the predictions intervals are larger for races Black, East/Southeast Asian, and White when compared to others which means that the predictions are less reliable.

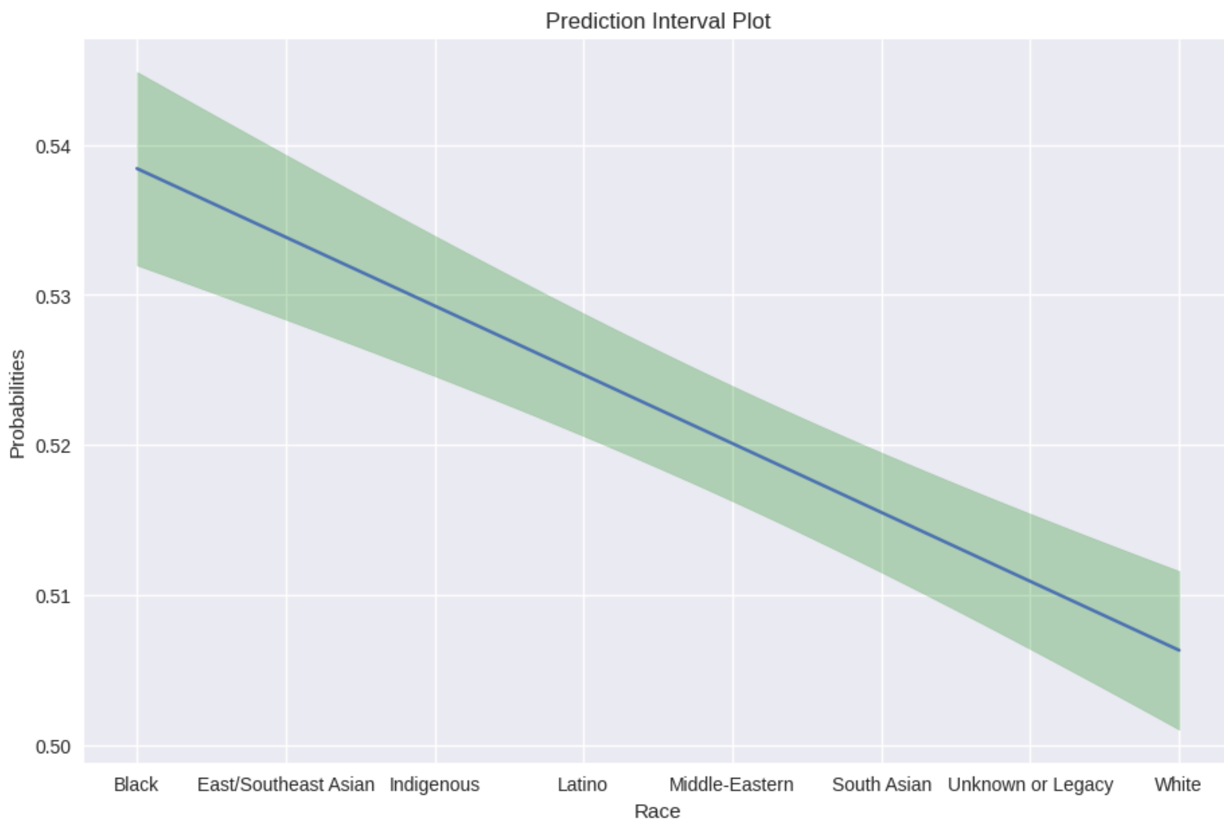

Figure 4.3 Prediction interval for logistic regression

5. Discussions

Building upon our literature review, we aimed to investigate the potential relationship between booked count and different variables, such as year, perceived race, and sex, while controlling for the presence of strip searches during arrest events. Our research aimed to address the concern that strip searches are being conducted without proper justification and protocol in Ontario, which could lead to violations of individuals' rights and emotional distress.

To further understand the potential impact of strip searches on booked count, we also examined existing research related to the issue. Studies have suggested that strip searches may disproportionately affect marginalized groups, including people of color and low-income individuals. For example, research conducted in the UK found that black and Asian individuals were more likely to be subjected to strip searches than white individuals, despite no significant differences in the likelihood of carrying contraband (Newburn et al., 2004). Additionally, reports have shown that strip searches can cause significant emotional distress, with individuals reporting feelings of humiliation, powerlessness, and trauma. For example, a report by the Ontario Human Rights Commission found that strip searches can lead to negative mental health impacts and can be particularly traumatizing for individuals who have experienced sexual violence or abuse (Ontario Human Rights Commission, 2017).

By analyzing the effects of COVID-19 on booked count, we sought to understand how the pandemic may have influenced crime statistics in Toronto. Our research aimed to shed light on how different factors, including race, sex, and year, may impact booked count, while also taking into account the presence of strip searches. Through our statistical analysis, which included power analysis, ANCOVA, and logistical regression, we aimed to provide a comprehensive understanding of the potential relationships between these variables.

Given these concerns, it is important to examine the potential impact of strip searches on booked count, while also considering how demographic factors, such as race and sex, may influence the likelihood of being subjected to a strip search. By analyzing these factors and controlling for the presence of strip searches, our research aims to contribute to the ongoing dialogue around criminal justice reform and promote greater equity and fairness in the system. Our research aims to contribute to the larger discussion around systemic bias and provide insights into potential disparities in how different demographic groups are treated during arrest events. By identifying any potential trends or disparities, we hope to inform policy changes and advocate for the protection of individuals' rights and a more just criminal justice system.

6. Conclusion

The COVID-19 pandemic has had a significant impact on various aspects of life, including law enforcement procedures. It is crucial to understand how these procedures have been altered by the pandemic and how race and sex may influence them. Our investigation focused on examining the role of race and sex in police procedures and analyzing the effect of COVID-19 on arrest and strip search statistics in Toronto. We employed various quantitative techniques to analyze data from 2020 and 2021 on individuals booked for offenses in Toronto, including their race and sex. Additionally, we collected data on the number of strip searches conducted during arrests.

Based on the results from ANCOVA and logistic regression analysis, it was found that there was a significant positive relationship between the number of strip searches conducted during an arrest and the likelihood of police use of force. Specifically, the strip search count was a significant predictor of police use of force in all three models (i.e., ANCOVA and logistic regression models examining the effects of perceived race, sex, and arrest year). The effect size was also relatively large, with strip search count accounting for 42-51% of the variance in police use of force across the three models. The logistic regression analysis examining the effects of sex and arrest year found that there were significant relationships between these variables and police use of force, but the effect sizes were relatively small (less than 5% of the variance in police use of force). This suggests that strip search count may be a stronger predictor of police use of force than sex or arrest year.

Finally, the logistic regression analysis also examined the effects of various actions taken by the arrestee at the time of arrest and demographic variables (e.g., age, gender, race/ethnicity) and several of these variables were found to be significant predictors, including the arrestee's level of cooperation, age, and gender. However, the effect sizes of these variables were generally smaller than the effect size of strip search count, suggesting that strip search count may be the most important predictor of police use of force in this dataset.

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