Factors Contributing to Disproportionate Strip Searches in Racialized Groups: An Examination of Possible Causes Based on the Dataset from Toronto Police Service

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Introduction

Strip searches are a controversial and often invasive law enforcement practice used to detect hidden contraband or weapons. While strip searches are intended to be carried out only under certain circumstances and with proper oversight, concerns have been raised about their potential misuse or abuse, particularly among vulnerable populations such as minors or people of color. In recent years, reports have suggested that black and Latino individuals are at higher risk of being subjected to strip searches than other racial groups. This study aims to examine the relationship between the likelihood of strip searches and specific demographic characteristics such as age, race, and gender. By analyzing data and patterns, this report aims to provide insight into any potential concerns or areas for improvement related to the use of strip searches in law enforcement, particularly among vulnerable populations.

Literature Review

Strip checking, the practice of requiring individuals to remove some or all of their clothing for the purpose of security screening, has been a controversial and often debated topic for many years.

> *"I can't say no. No is not an option here. There is no choice, no consent, no opt out. My body is not mine.*
>
> *But of course, I can't express panic. I can't show the nausea and fear that has overtaken my body. Instead I just nod and obey her commands."*
> (McMurphy, 2018)

The excerpt written by McMurphy in the article describes the distressing emotional experience that a young college student endured during her first strip search. Strip checking can cause physical and psychological harm, particularly in minors, who may not fully understand the reasons for the screening and may be embarrassed or traumatized by the process. Furthermore, some studies have suggested that strip checking practices may be influenced by the race and gender of the individuals being screened.

> *"...concerned by ethnic disproportionality after the data showed that of children aged 10 to 17 who were strip-searched between 2018 and 2020, almost three out of five (58%) were black, as described by the officer."* (Weale & Dodd, 2022)

The data reveals that nearly three out of five children who were subjected to strip searches during this time period were black, according to an officer's description. This is a particularly sensitive issue, as it may have lasting emotional and psychological impacts on people. Another source of concern is that certain ethnic or racial groups may be more likely than others to be subjected to strip searches, even when no reasonable suspicion of wrongdoing exists.The evidence suggests that people of color, particularly Black and Latin American individuals, may be disproportionately targeted for strip searches.

The issue of police violence and racism in Toronto has been a concern for many communities of color. In a study conducted by La Prairie and Murphy (2016), community members shared their experiences and recommendations for addressing this problem. The study found that members of marginalized communities, particularly Black and Indigenous peoples, were more likely to be subjected to police violence and racism. Community members recommended increased training for police officers on issues related to diversity and cultural competency, as well as greater accountability and transparency in cases of police misconduct. These recommendations point towards the need for systemic changes in policing practices to address the issue of police violence and racism in Toronto.

In this report, we will be looking at various factors affecting the likelihood of strip checking in people of color.

Research Objective and Questions

Building on the findings from our literature review, our objective is to investigate whether there is a disparity in the likelihood of strip searches between Black or Latino individuals and other racial groups. We will also examine whether there is a correlation between age and the probability of being subjected to a strip search. Additionally, this study aims to identify which gender has the highest likelihood of being strip searched in law enforcement encounters.

- **RQ1:** Can demographic attributes such as age, race, and sex influence the probability of strip searches in law enforcement encounters? Furthermore, is it possible to determine which attribute has the strongest impact on the likelihood of such searches?

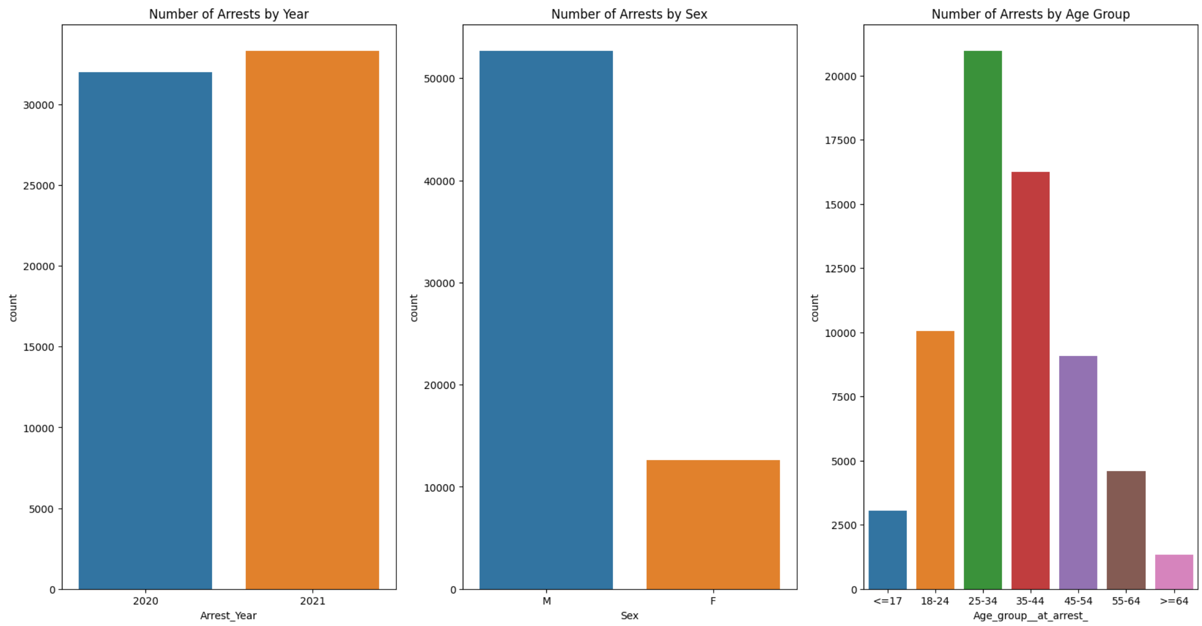
- **RQ2:** How do the number of arrests, number of items found during a strip search, sex, and perceived race predict the likelihood of a strip search being conducted (yes/no) in Toronto?

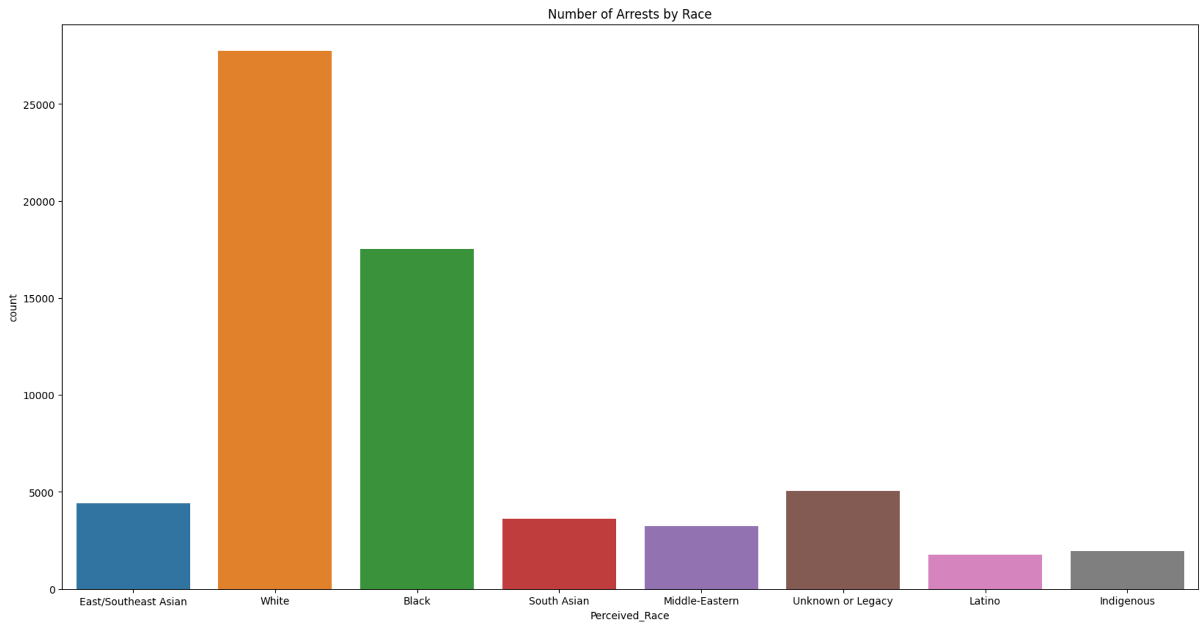
Exploratory Data Analysis

We want to focus on finding the factors that would affect the number of arrests and strip searches. We picked a few variables out of 25 that fit our research topic. Prior to the deeper investigation, we did exploratory data analysis to better understand the connection and relationship between variables.

Because not all arrests need strip searches, we first study the number of arrests and then analyze the counts of arrests using several categories. We choose the year, gender, age group and race to make a simple comparison of the number of arrests. The bar charts in Figure 1 show a small increase in the number of arrests in 2021 compared with the number of arrests in 2020. The number of females is only ¼ of the number of males and the number of arrests is mainly concentrated in the middle age group. For different races, Whites and Blacks make up the majority, while Latinos and Indigenous had the lowest number of arrests.

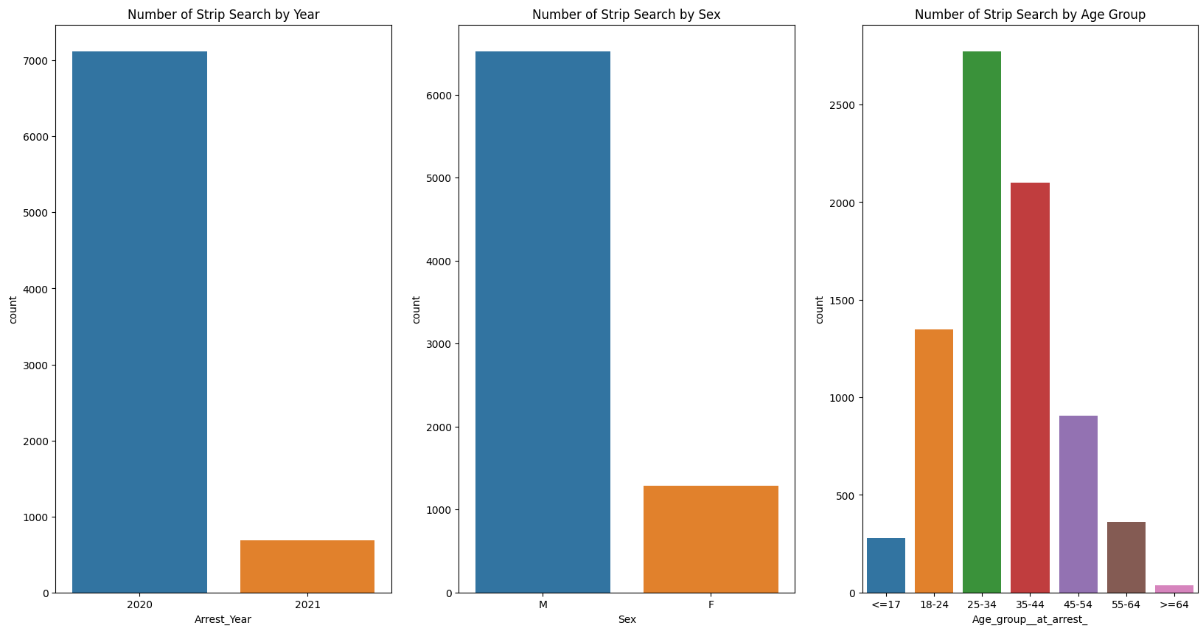
Figure 1. Number of Arrests by Year, Sex, Age Groups, and Race





After a basic understanding of the number of arrests, we used and analyzed the same categories as the number of arrests to show the counts of the strip searches. Figure 2 shows that the number of strip searches has clearly dropped a lot. The number of strip searches is conducted against males far more than females. The most number of strip searches are concentrated in the ages of 18-54. Blacks have the largest percentage of strip searches among minorities.

Figure 2. Number of Strip Search by Year, Sex, Age Groups, and Race



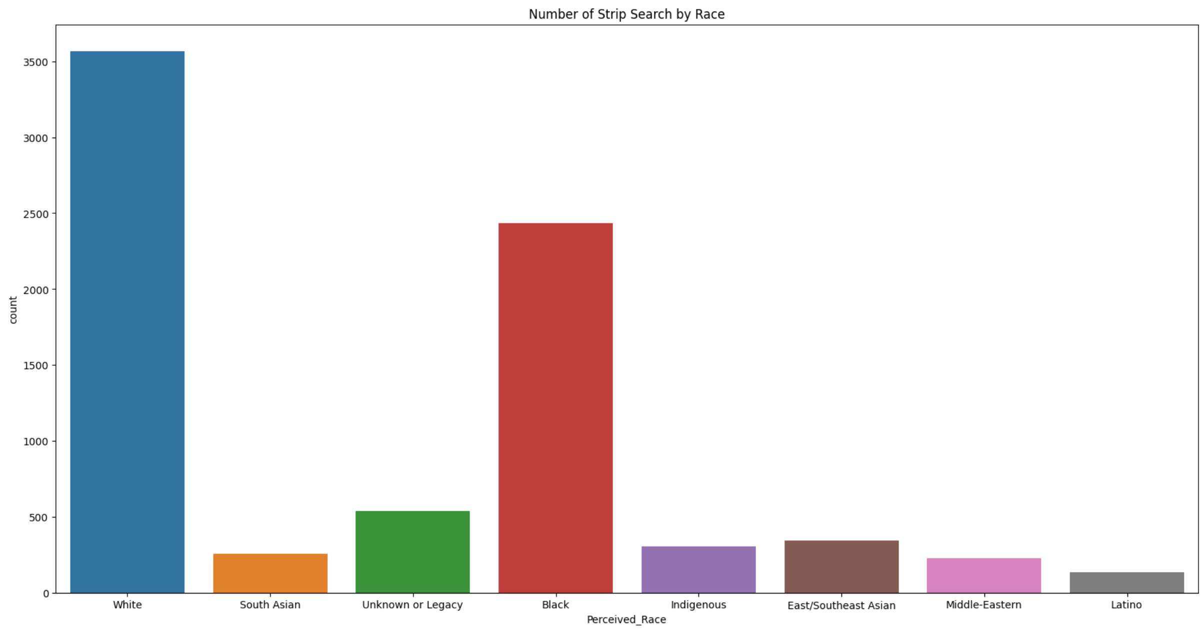
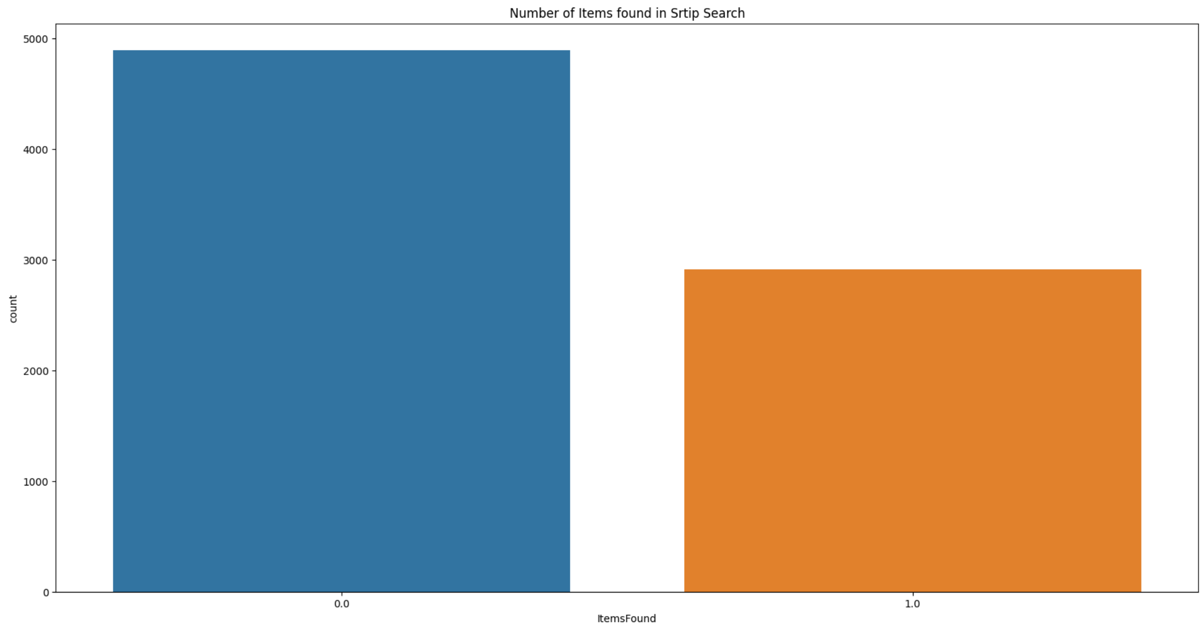


Figure 3 shows that the number of items not found in the strip search is greater than the number of items found. So we reasonably guess that the police will have unreasonable reasons or biases to perform strip checks.

Figure 3. Number of Items Found in Strip Search



We attempted to analyze the pattern of arrests over time, but our findings were inconclusive. We observed a uniform distribution of arrests across all months, which did not reveal any clear trends or patterns.

Figure 4. Shows number of arrests across different months

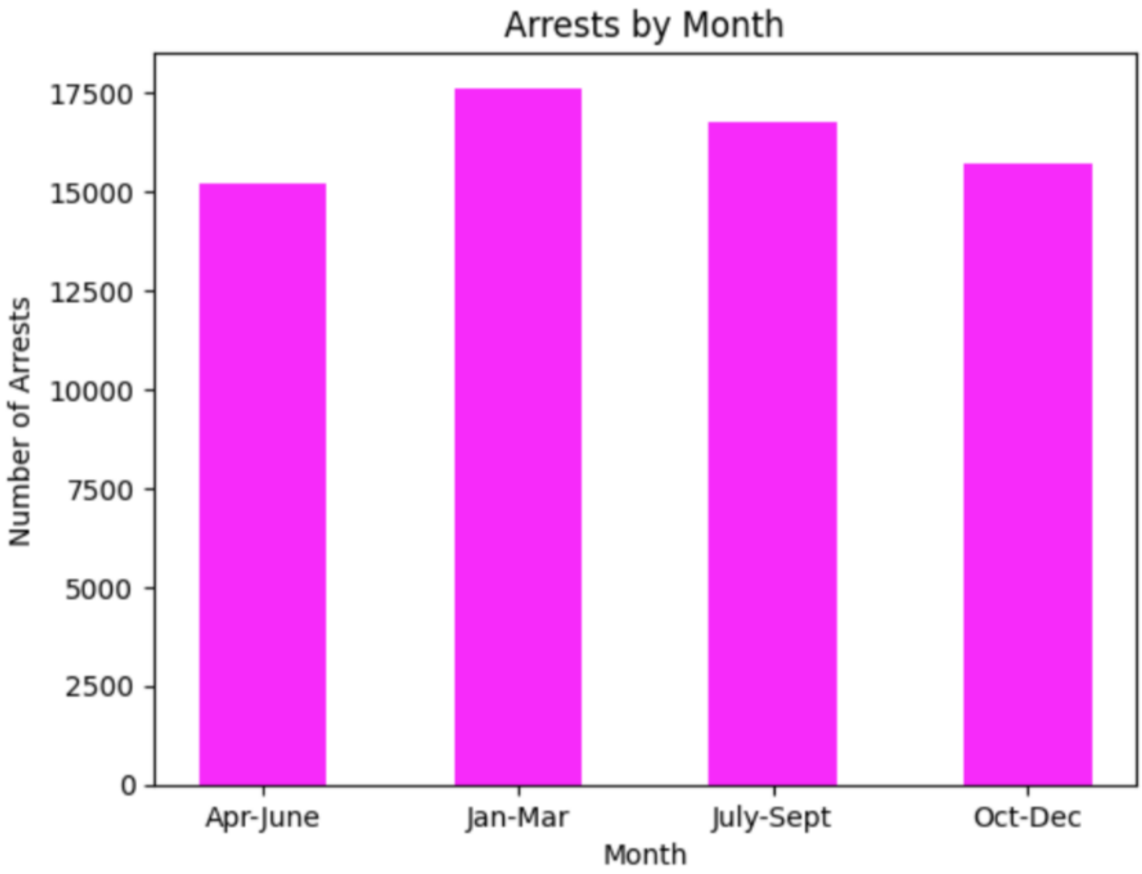
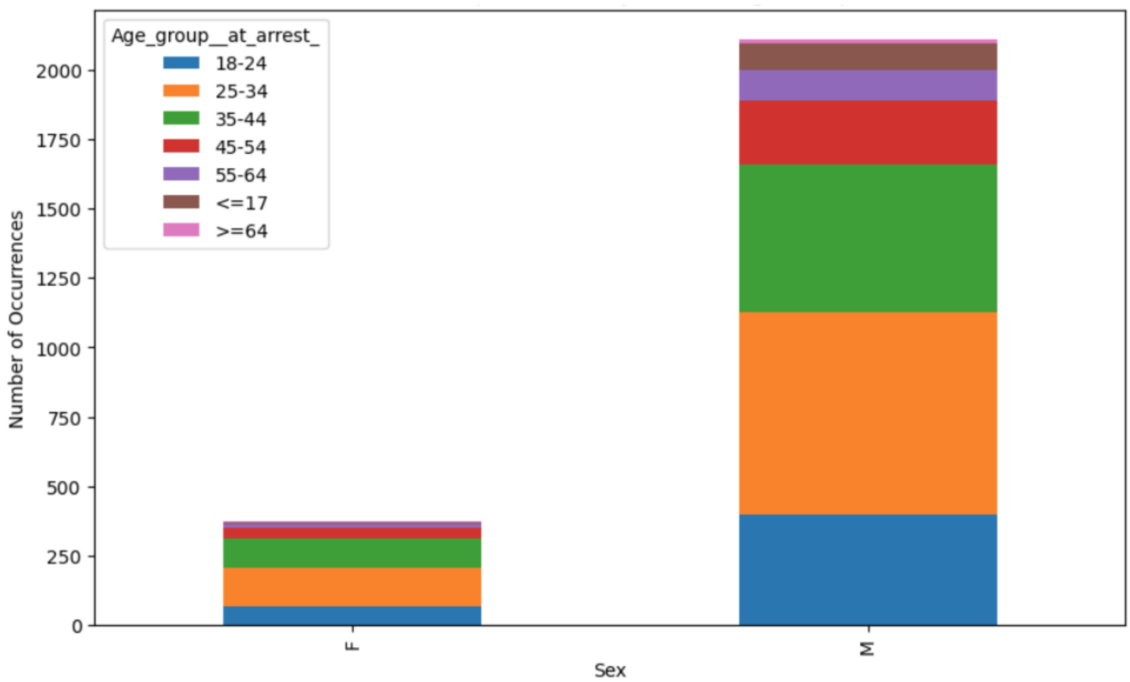


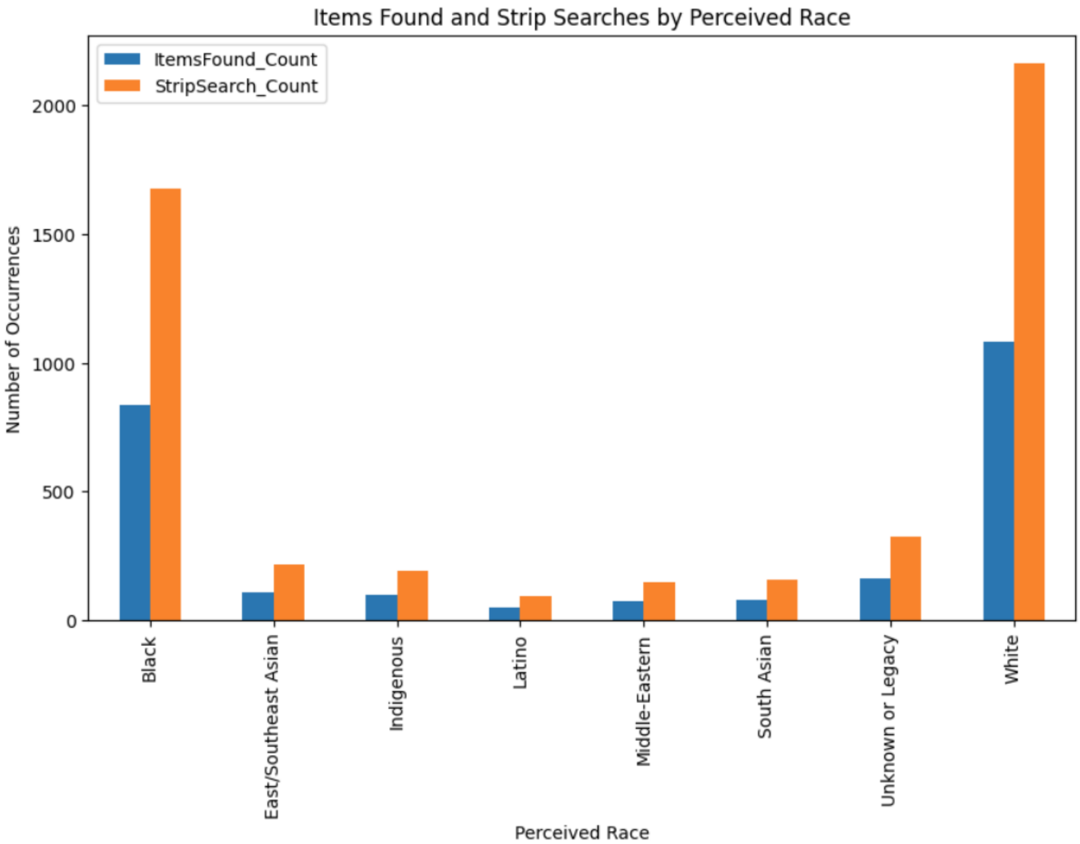
Figure 5. Shows Strip Search by Sex and Age Group at Arrest.



We further analyzed the occurrence of strip searches in males and females by creating a bar chart. The results showed a significant disparity, with males being subjected to strip searches four times more often than females. Additionally, we examined the age ranges of suspects who were subjected to strip searches and found that males between the ages of 25-44 had the highest occurrence rate. This data highlights potential gender bias in the use of strip searches by law enforcement officials. Further analysis and investigation may be necessary to determine the underlying reasons for this disparity, and whether it is warranted or indicative of systemic issues.

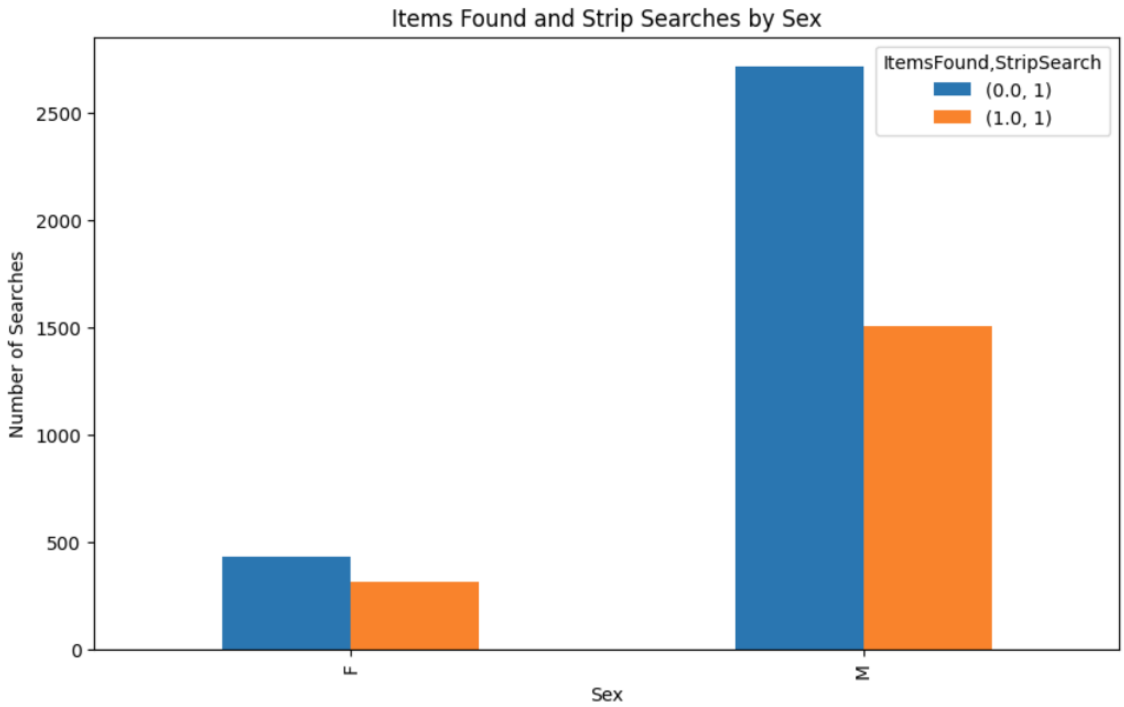
We sought to explore the relationship between the number of items found during strip searches and the racial groups of the individuals being searched. To visualize this relationship, we created a bar chart. Our findings revealed that the racial groups with the highest number of items found during strip searches were White and Black individuals. However, we acknowledge that this observation may be influenced by the fact that White and Black individuals make up the majority of the population and arrests.

Figure 6. Shows items found during strip searches by perceived race.



Next, we conducted a comparison of the items found during strip searches between males and females. Our analysis revealed a concerning gender disparity in the strip search outcomes. Almost all females who were subjected to strip searches had something in their possession that warranted the search. In contrast, for 40% of the males who were strip searched, no items were found, indicating that they were potentially subjected to strip searches unnecessarily. This disparity in strip search outcomes between males and females is alarming and may reflect underlying issues of gender bias and discrimination. It is important for law enforcement officials to conduct strip searches only when necessary and to ensure that they are carried out fairly and without any implicit biases.

Figure 7. Shows items found during strip search by Sex.



Methods

Dataset

We will conduct our analysis using Arrest and Strip Searches data downloaded from the Toronto Police Service - Public Safety Data Portal (Toronto Police Service, 2022). This dataset contains information on 65,276 instances of arrest and strip searches and includes 25 different features.

Three variables are numeric values that uniquely identify an occurrence: *EventID, ArrestID***,** and *PersonID*. *PersonID* is a unique identifier for each individual, while *ArrestID* may occur multiple times for an individual. Additionally, multiple suspects may or may not be involved in a single event, which is uniquely identified by *EventID*.

Arrest_Year and *Arrest_Month* are categorical variables that specify the year and month in which the event occurred. *Occurrence_Category* is another categorical variable that specifies the type of offense the individual is suspected for.

There are 5 demographic variables that are all categorical in nature: *Perceived_Race, Sex, Age_group__at_arrest_, and Youth_at_arrest__under_18_years*. Additionally, there are 10 dichotomous variables, including *StripSearch* (whether the individual was strip checked or not), *Booked* (whether the person was booked within 24hrs of arrest or not), and *ItemsFound* (whether an item was found during strip checking or not).

Furthermore, there is a list of variables that record actions at arrest and reasons for strip checking, which are recorded as boolean values (0 for no and 1 for yes). These variables include *Actions_at_arrest___Concealed_i, Actions_at_arrest___Combative__, Actions_at_arrest___Resisted__d, Actions_at_arrest___Mental_inst, Actions_at_arrest___Assaulted_o,* and *Actions_at_arrest___Cooperative* for actions, and *SearchReason_CauseInjury, SearchReason_AssistEscape, SearchReason_PossessWeapons,* and *SearchReason_PossessEvidence* for search reasons.

Lastly, *ArrestLocDiv* is a categorical variable that stores a numeric value for the division where the arrest took place.

Descriptive Statistics

The dataset records the data of arrests and strip searches in the Toronto area from 2020 to 2021. As a result of many empty data in 2021, we don't have enough datasets to compare the trend across the year. We have a total of 65,276 datasets and dropped the empty data before analysis. We created a new numerical variable that describes the number of times an arrestee with the same person ID has been strip checked between 2020 and 2021. The number of times ranges from 1 to 17. To further investigate the effect on the number of strip searches, we started our analysis with demographic attributes and 4 reasons for search as independent variables. In addition to the analysis of all persons, we focused on the age group of minors.

Table 1. Descriptive Statistics for Variables in Analysis (N = 65,276)

Variables	Frequency	%
Independent Variables		
Categorical		

Age (in years)			
under 17	3042	4.7	
18 - 24	10041	15.3	
25 - 34	20949	32.0	
35 - 44	16242	24.9	
45 - 54	9066	13.9	
55 - 64	4590	7.0	
above 65	1322	2.0	
Sex			
Female	12617	19.4	
Male	52650	80.6	
Unisex	9	0.01	
Perceived Race			
Black	17526	26.8	
East/Southeast Asian	4415	6.76	
Indigenous	1934	2.96	
Latino	1768	2.70	
Middle-Eastern	3237	4.96	
South Asian	3613	5.53	
Unknown or Legacy	5056	7.75	
White	27723	42.5	

	Mean	**SD**	**Range**
Numerical			
No. of Arrests	4.13	5.40	1 - 54
No. of Items Found	0.27	0.87	0 - 13
Dependent Variable			
Numerical			
No. of Strip Searches	0.73	1.63	0 - 17

	Frequency	**%age**
Categorical		
Strip Search		
Yes	7801	12
No	57475	88

In the beginning, we looked at the overall distribution of the number of strip searches through histograms (Figure 1), with most people concentrating on having one strip search. Only one outlier people with 17 times of strip searches. From table 1, we can see that the average number of times strip searches is at least twice per person. For variance, we can calculate from the standard deviation that $2.24^2 = 5.02$.

We created three new continuous variables to work on our research. A detailed description of them is shown in Table 1 above. No. of Arrests give us the total number of times each person was arrested. Similarly, no. of strip searches is the total number of times a person was strip searched and no. of items found is total number of items found during those searches.

Methods

For this study, we used EDA and descriptive analysis to acquire basic information about each variable and to investigate the connection and distribution of each variable. We performed a power analysis to determine the minimum sample size required to detect an appropriate effect size in desired alpha. After that, we did the ANCOVA to increase the accuracy of our analysis and reduce the risk of confounding variables to support us to run the logistic regression.

RQ1 asks whether demographic attributes such as age, race, and sex have an impact on the likelihood of strip searches in law enforcement encounters, and if so, which attribute has the strongest impact. ANCOVA (Analysis of Covariance) is a statistical technique that can be used to examine the relationship between a categorical predictor variable (such as race, sex, or age group) and a continuous outcome variable (such as the likelihood of a strip search). In this study, the dependent variable would be the likelihood of a strip search, and the independent variables would include demographic attributes such as age, race, and sex. ANCOVA allows us to examine the effect of each demographic attribute on the likelihood of a strip search while controlling for other variables that may also impact the outcome (such as the nature of the encounter).

For RQ2, the dependent variable (Y) is whether or not a strip search was conducted (yes/no), and the independent variables (X) include the number of arrests, number of items found during the strip search, sex, and perceived race of the individual. We will be using logistic regression analysis to examine the relationship between these variables and the likelihood of a strip search being conducted. The goal of the study would be to identify factors that contribute to the use of strip searches by law enforcement in Toronto and to inform policy and practice to reduce the use of potentially invasive and discriminatory practices in policing.

Results

Power Analysis

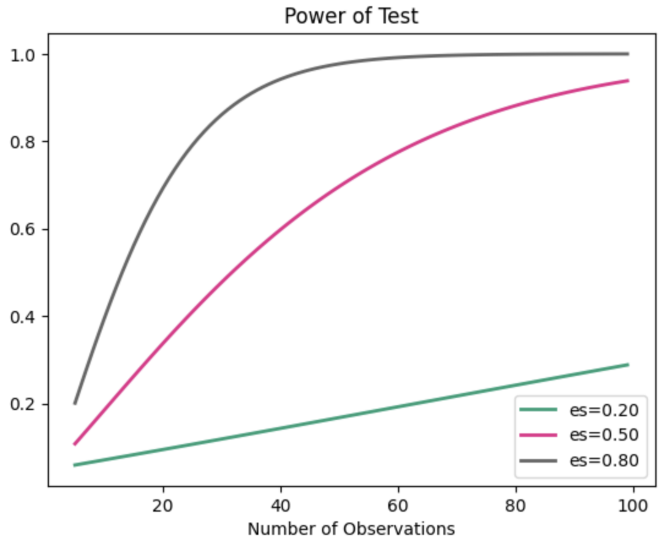
Sex vs Times of Strip Searches

To analyze the times of strip searches(outcome variable) difference between Male and Female (two-level explanatory variable), we calculated the effect size (Cohen's D) which was 0.0005. After getting the effect size, the required minimum sample size was computed using the calculated effect size we had with 0.05 alpha level and establishing the desired statistical power at 0.8. The result indicated that a minimum sample size of 42,777,198 was required for males, while a minimum sample size of 178,506,738 was required for females. Power analysis is a significant part to check the reliability of the results. The sample size provided by this dataset is not enough, we need to increase the sample size to achieve greater power.

Table 2. Summary of Results of Power Analysis

	Sample Size	Actual Size
Male	42,777,198	52,650
Female	178,506,738	12,617
Effect Size (Cohen's D)		0.0005
Ratio		4.17

Power Curve



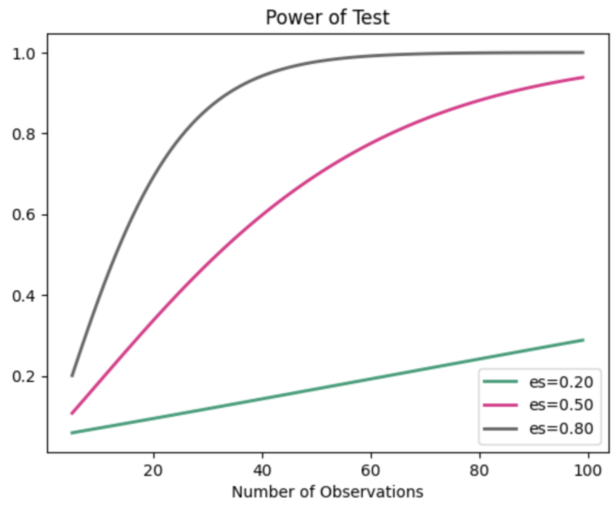
Age vs Times of Strip Searches

To analyze the times of strip searches(outcome variable) difference between Adult (>17) and Youth (<=17) (two-level explanatory variable), we calculated the effect size (Cohen's D) which was 0.0004. After getting the effect size, the required minimum sample size was computed using the calculated effect size we had with 0.05 alpha level and establishing the desired statistical power at 0.8. The result indicated that we need a minimum sample size of 42,777,198 was required for adults, while a minimum sample size of 1,312,254,150 was required for youths. Power analysis is a significant part to check the reliability of the results. The sample size provided by this dataset is not enough, we need to increase the sample size to achieve greater power.

Table 3. Summary of Results of Power Analysis

	Sample Size	**Actual Size**
Adult (>17)	42,777,198	62,234
Youth (<=17)	1,312,254,150	3,042
Effect Size (Cohen's D)		0.0004
Ratio		20.46

Power Curve



ANCOVA

Sex, Times of Strip Search, Times of Arrests

Null Hypothesis: The average times of strip searches are same among people from all genders after accounting the times of arrests

Alternative Hypothesis: The average times of strip searches are different among people from all genders after accounting the times of arrests

From the ANCOVA output in Table 4, the p-value for sex is 0.00 which is less than 0.05. We can reject the null hypothesis. As a result, there is a significant difference in the average times of strip searches among each gender, even after controlling for the times of arrests.

Table 4. Summary of Results of ANCOVA

Source	SS	DF	F	p-unc	Reject null?
Sex	29.49	2	11.86	0.00	Yes
#Arrests	92330.81	1	74244.82	0.00	Yes
Residual	81172.23	65,272	NaN	NaN	NaN

Age, Times of Strip Search, Times of Arrests

Null Hypothesis: The average times of strip searches are the same among people from all age groups after accounting for the times of arrests

Alternative Hypothesis: The average times of strip searches are different among people from all age groups after accounting for the times of arrests

From the ANCOVA output in Table 5, the p-value for age groups is 0.00 which is less than 0.05. We can reject the null hypothesis. As a result, there is a significant difference in the average times of strip searches among each age group, even after controlling for the times of arrests.

Table 5. Summary of Results of ANCOVA

Source	SS	DF	F	p-unc	Reject null?
Age_group__at_arrest_	29.37	1	23.61	0.00	Yes
#Arrests	91841.72	1	73826.18	0.00	Yes
Residual	81171.48	65249	NaN	Nan	Nan

Race, Times of Strip Search, Times of Arrests

Null Hypothesis: The average times of strip searches are the same among people from all races after accounting for the times of arrests

Alternative Hypothesis: The average times of strip searches are different among people from all races after accounting for the times of arrests

From the ANCOVA output in Table 6, the p-value for age groups is 5.59e-49 which is less than 0.05. We can reject the null hypothesis. As a result, there is a significant difference in the average times of strip searches among each race, even after controlling for the times of arrests.

Table 6. Summary of Results of ANCOVA

Source	SS	DF	F	p-unc	Reject null?
Perceived_Race	302.83	7	34.90	5.59e-49	Yes
#Arrests	88861.67	1	71689.79	0.00	Yes
Residual	80895.47	65263	Nan	Nan	Nan

Logistic Regression

A logistic regression was applied on the dependent variable, strip search incidence. The results of the regression are included in the table below.

We conducted a logistic regression analysis to examine the effects of sex, perceived race, police activity, arrests, the number of items found during police activity, and strip searches on the likelihood of individuals being subjected to strip searches.

Table 7. Summary of Results of Logistic Regression.

Variable	Estimate	Pr(>|z|)
Demographic Factors		
Gender		
Male	0.1512	0.000***
Other	-19.5071	0.998
Perceived Race		
Southeast Asian	-0.4424	0.000***
Indigenous	-0.0568	0.560
Latino	-0.3713	0.001**
Middle Eastern	-0.4650	0.000***
South Asian	-0.4283	0.000***
Unknown/Legacy	-0.1728	0.007*
White	-0.0369	0.323
Police Activity		
No. of times Arrested	-0.3291	0.000***
No. of Items Found	-0.0772	0.001**
Itercept (Constant)	-2.1358	0.000***

Significance Level: 0 '' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1***

Statistically Significant Variables

Table 7 presents the results of the logistic regression model used to predict the impact of demographic attributes on the incidence of strip checking. At a significance level of alpha = 0.05, it was found that of the 5 attributes being measured, Gender ($p < 0.001$), Perceived Race ($p < 0.01$), No. of time arrested ($p < 0.001$) and No. of items found ($p < 0.001$), were all statistically significant predictors of strip checking events.

Results show that increasing chances of arrest by one unit is associated with a decrease in the predicted log odds of getting strip checked by 0.3291, holding all other variables constant. And increasing items found by one unit is associated with a decrease in the predicted log odds of getting strip checked by 0.0772, holding all other variables constant.

Compared to suspects who are Black, the predicted log of odds of getting strip checked in suspects who are Southeast Asian is 0.4424 times lower, holding all other variables constant. Similarly, the predicted log of odds of getting strip checked in suspects who are Latino is 0.3713 times lower, holding all other variables constant. The predicted log of odds of getting strip checked in suspects who are Middle Eastern is 0.4650 times lower, holding all other variables constant.The predicted log of odds of getting strip checked in suspects who are South Asian is 0.4283 times lower, holding all other variables constant.There was also a significant number of people whose racial background was unclear. The predicted log of odds of getting strip checked in suspects who had Legacy background is 0.1728 times lower, holding all other variables constant.

Compared to suspects who are females, the predicted log odds of a male suspect getting strip checked is 0.1512 times higher, holding all other variables constant.

Intercept

The value for the intercept in the model is -2.1358 which represents the predicted log odds of getting strip checked when all the predictor variables are equal to zero. In this case, it means that when all other variables are held constant, the predicted log odds of getting strip checked is -2.1358. However, since there are no variables that can have a value of zero (e.g., gender and perceived race are categorical variables), the interpretation of the intercept is not as meaningful as the interpretation of the coefficients of the predictor variables.

Confusion Matrix

Table 8. Summary results of Confusion Matrix.

Confusion Matrix		**Actual Value**	
		Negative (1)	**Positive (0)**
Predicted Value	**Negative (1)**	True Negative 11232	False Negative 273
	Positive (0)	False Positive 1181	True Positive 370

Next, we calculate the confusion matrix for our model. The results show that there are 11232 instances that are truly negative and were correctly classified as negative (true negatives), and

370 instances that are truly positive and were correctly classified as positive (true positives). These are the correct classifications.

On the other hand, there are 273 instances that are truly negative but were incorrectly classified as positive (false positives), and 1181 instances that are truly positive but were incorrectly classified as negative (false negatives). These are the incorrect classifications.

To report the performance of the model based on this confusion matrix, several metrics can be calculated. The most commonly used metrics are accuracy, precision, recall (sensitivity), and F1-score.

Table 9. Model Diagnostics.

Accuracy	(11232 + 370) / (11232 + 273 + 1181 + 370)	**89%**
Precision	370 / (273 + 370)	**57.5%**
Recall (Sensitivity)	370 / (1181 + 370)	**23.8%**
F1-score	2 * precision * recall / (precision + recall)	**36.2%**

The model has an accuracy of 89.0% which indicates that the model is able to correctly predict the outcome in 89.0% of cases. The proportion of true positive predictions among all positive predictions. In this case, the precision indicates that when the model predicts a positive outcome, it is correct 57.5% of the time. The proportion of true positive predictions among all truly positive instances. In this case, the recall indicates that when there is a positive outcome, the model is able to correctly identify it only 23.8% of the time. The F1-score is 36.2%. This indicates that the model has a moderate performance in terms of both precision and recall. While the precision is relatively high at 57.5%, indicating that when the model predicts a positive outcome, it is correct in more than half of the cases, the recall is relatively low at 23.8%, indicating that the model is missing a significant proportion of the positive cases.

Overall, while the accuracy of the model is high at 89.0%, the F1-score indicates that there is room for improvement in terms of the model's ability to correctly identify positive cases while minimizing false positives.

Discussion

Through EDA, power analysis, ANCOVAs and logistic regression, we obtained much information to support the research questions we created.

The logistic regression model analyzed the impact of five demographic attributes on the incidence of strip checking, and found that four of them (Gender, Perceived Race, No. of times arrested, and No. of items found) were statistically significant predictors of strip checking events.

The results show that the No. of times arrested and No. of items found were negatively associated with the predicted log odds of getting strip checked, meaning that an increase in these variables led to a decrease in the likelihood of getting strip checked. This suggests that the police may be less likely to perform strip searches on individuals who have been previously arrested or have fewer items on them.

The analysis also found that suspects who are Black are more likely to be strip searched compared to those who are Southeast Asian, Latino, Middle Eastern, or South Asian. This means that race plays a significant role in the likelihood of being strip searched. It is important to note that there was also a significant number of people whose racial background was unclear, and this may have influenced the results.

In terms of gender, the analysis found that male suspects are more likely to be strip searched compared to female suspects. This result indicates that gender also plays a significant role in the likelihood of being strip searched.

Overall, these findings suggest that demographic attributes are significant predictors of strip checking events and highlight the potential for bias and discrimination in police practices.

Conclusion

In conclusion, through a series of analyses and comparisons in this project. Initially, we started by looking at the effect of demographic characteristics on the probability of strip searches. It was determined that different age groups and different races have significant statistical significance in strip searches. The biggest limitation of this research is the data recorded by police officers, where the same personal ID corresponds to different races. In order to ensure the reliability of our research results, we need to increase our sample size to meet required the minimum amount of sample size.

There is the Colab link:
https://colab.research.google.com/drive/1HkljYJqaT78T4aHdehem7dBYlFaD9SjP#scrollTo=XE5Qi-Tq_7K7

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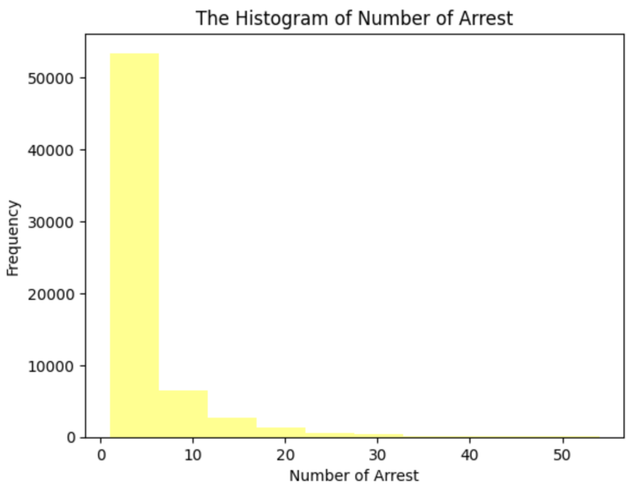
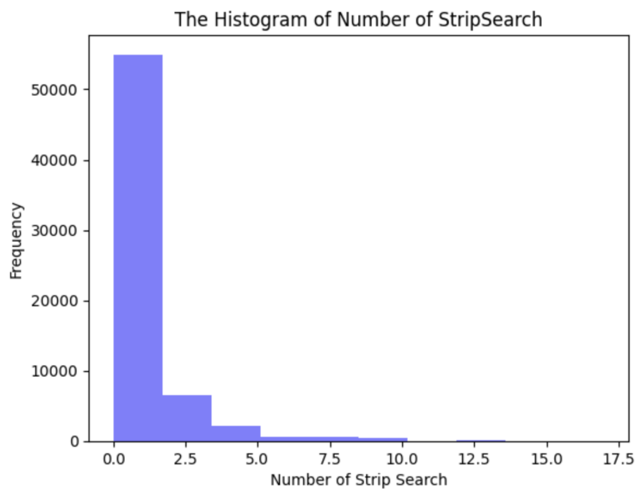
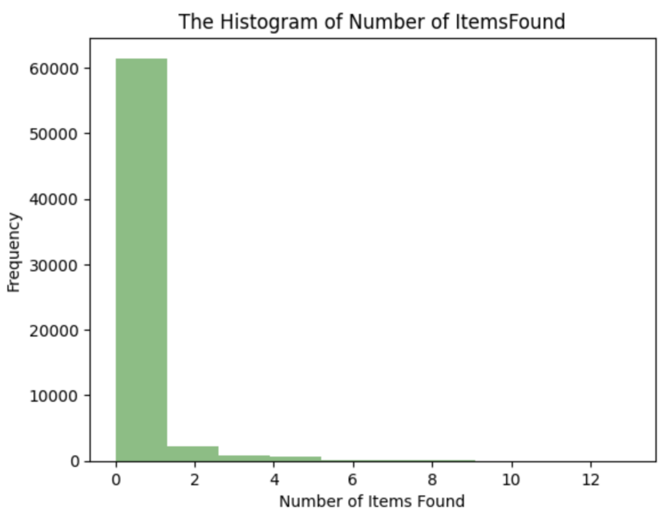
Appendix



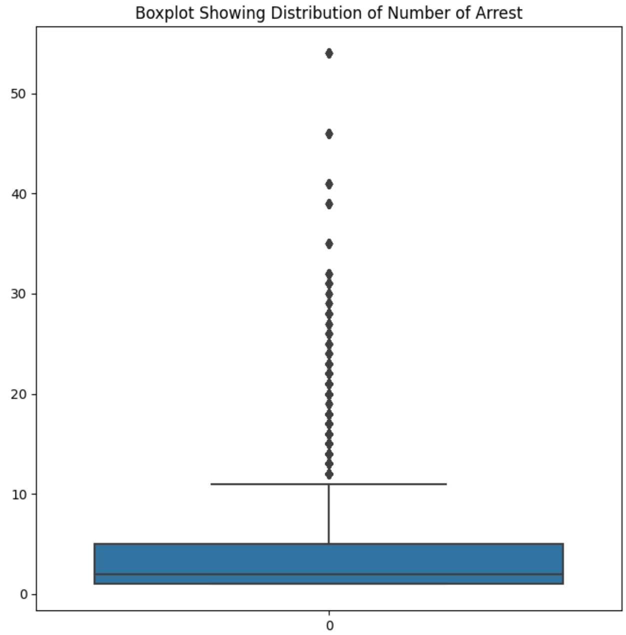
The Histogram of Number of Arrest
Frequency
0
10000
20000
30000
40000
50000
0
10
20
30
40
50
Number of Arrest

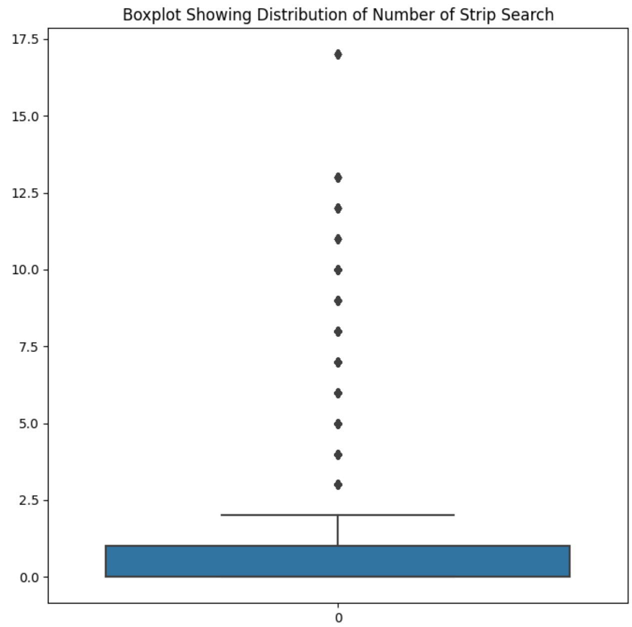


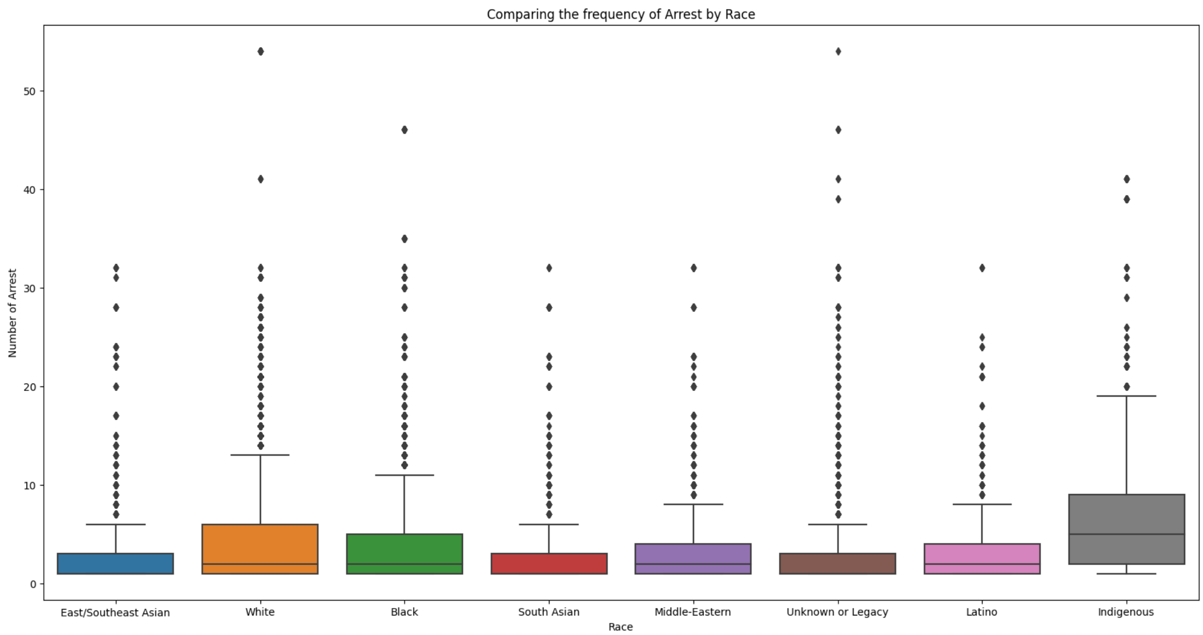
The Histogram of Number of StripSearch
Frequency
0
10000
20000
30000
40000
50000
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Number of Strip Search

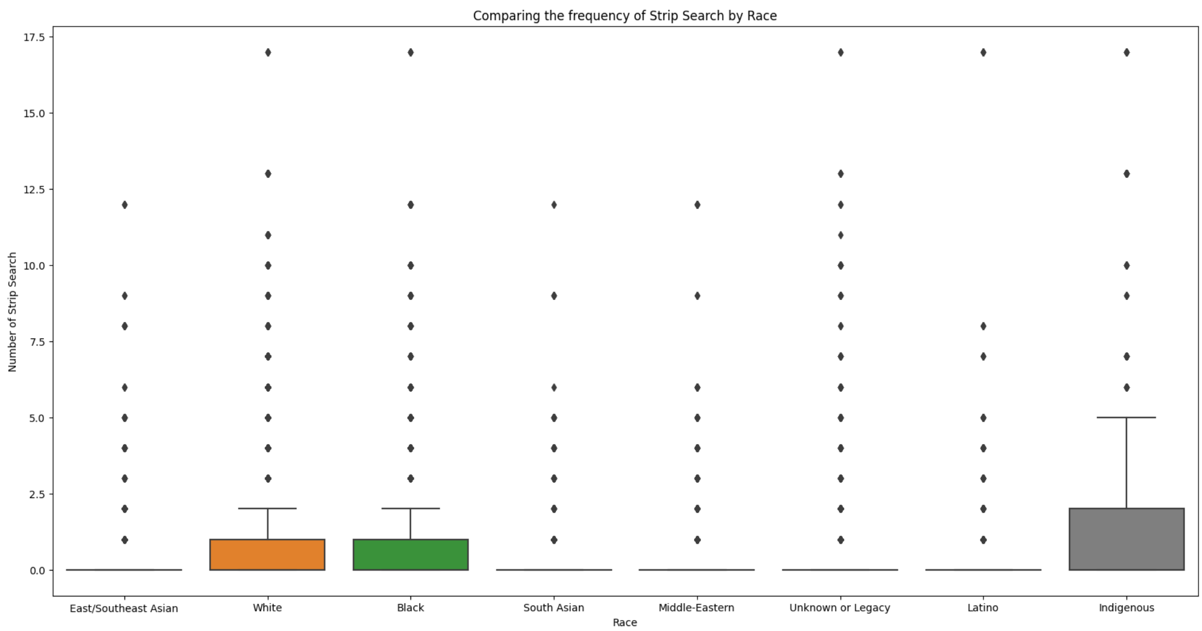


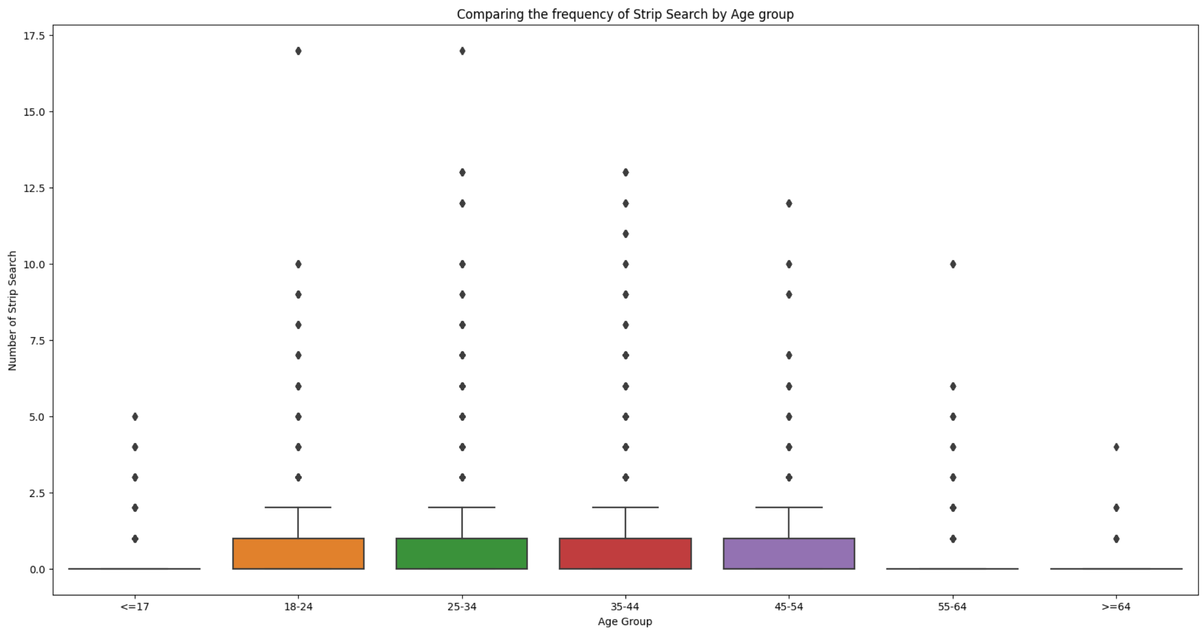
The Histogram of Number of ItemsFound
Frequency
0
10000
20000
30000
40000
50000
60000
0
2
4
6
8
10
12
Number of Items Found


Boxplot Showing Distribution of Number of Arrest
50
40
30
20
10
0
0

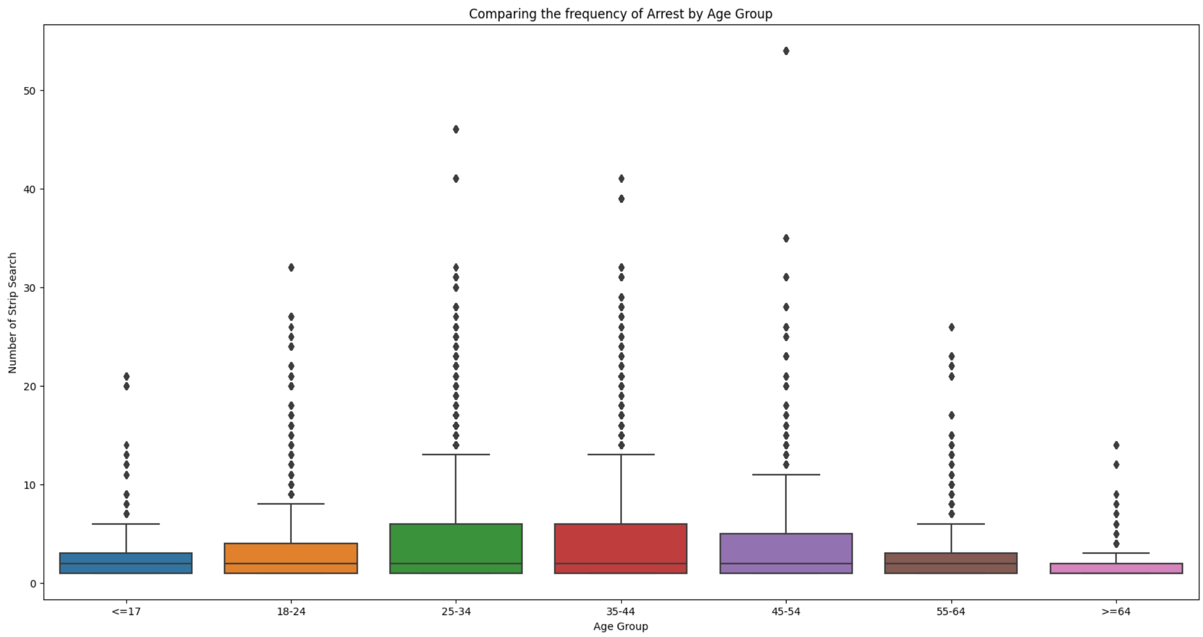

Boxplot Showing Distribution of Number of Strip Search
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0


Comparing the frequency of Arrest by Race
Number of Arrest
0
10
20
30
40
50
East/Southeast Asian
White
Black
South Asian
Middle-Eastern
Unknown or Legacy
Latino
Indigenous
Race


Comparing the frequency of Strip Search by Race
Number of Strip Search
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
East/Southeast Asian
White
Black
South Asian
Middle-Eastern
Unknown or Legacy
Latino
Indigenous
Race



Comparing the frequency of Strip Search by Age group
Number of Strip Search
Age Group
<=17
18-24
25-34
35-44
45-54
55-64
>=64



Comparing the frequency of Arrest by Age Group
Number of Strip Search
Age Group
<=17
18-24
25-34
35-44
45-54
55-64
>=64