Analyzing the Relationship between Arrests, Strip Searches, and Other Factors: A Study of the Toronto Police Service

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Introduction:

Arrests and strip searches are two common practices within the criminal justice system that have been subject to debate and controversy. When a person is arrested, they are taken into custody by law enforcement officials, and if there is a suspicion that the person may be carrying contraband or weapons, a strip search may be conducted. A strip search involves the removal of all clothing and may include a visual inspection of the person's body cavities. Meanwhile, some people argue that strip searches are a violation of personal privacy and dignity and may be used excessively or unnecessarily in some cases. There have been cases where strip searches have been conducted on individuals who were arrested for minor offences or who posed no threat to themselves or others. Additionally, there have been instances where strip searches have been used to humiliate or intimidate individuals. In recent years, there have been more concerns about strip searches. One concern is about the high strip search rate of the Toronto police service. McNeilly's 2019 report indicates, "Each year, well over 22,000 strip searches are conducted by police officers in Ontario, the majority by the Toronto Police Service." (Wendy, 2020). This raises public doubts about whether Toronto police officers use strip checks rationally and follow the relative rules. Several studies demonstrate the persistence of illegal and brutal strip-searching by Canadian police (Monika, 2022). Thus, understanding the potential relation between strip searches and other factors is essential to improve the current situation and reduce the occurrence of illegal and brutal strip searches.

In this research, we are trying to determine the possible relationships between strip searches and other factors with the data collected by the Toronto Police Service. We mainly focus on three research questions, which are the occurrence of strip searches in relation to location divisions and gender and the relation of strip searches with other factors. By answering these research questions, the aim is to provide insights into potential patterns or biases in the use of strip searches in law enforcement, which can inform discussions on policy changes and reforms. For example, by examining the occurrence of strip searches in relation to location divisions and gender, the study can provide insights into potential disparities or biases in the use of strip searches across different groups. This can help identify areas where policies or procedures may need to be improved to ensure more equitable treatment for all individuals.

Literature Review:

In recent years, there has been a growing concern about the use of strip searches in law enforcement. Strip searches are highly invasive and can be traumatic experiences for individuals who undergo them. The literature suggests that strip searches are often used in cases where there is a suspicion that a person is hiding drugs or weapons on their body (Durose et al., 2011). However, some argue that strip searches are overused and can be used as a form of intimidation or humiliation (Kang-Brown et al., 2019). Additionally, there are concerns that strip searches are disproportionately used on marginalized communities, such as people of color and LGBTQ individuals (Human Rights Watch, 2013).

Research has shown that strip searches are more likely to occur in certain locations, such as jails and prisons (Durose et al., 2011). This suggests that there may be institutional factors at play that contribute to the use of strip searches. Additionally, research has found that strip searches are more likely to be conducted on individuals who are male (Kang-Brown et al., 2019). This may be due to the stereotype that men are more likely to engage in criminal activity or carry weapons.

There is also evidence to suggest that strip searches may be related to other factors, such as the severity of the offense or the presence of drugs or alcohol (Human Rights Watch, 2013). In some cases, strip searches may be conducted as part of a larger effort to prevent contraband from entering a correctional facility. However, there are concerns that this practice may violate the Fourth Amendment, which protects individuals from unreasonable searches and seizures (Kang-Brown et al., 2019).

Overall, the literature suggests that strip searches are a controversial and highly debated practice in law enforcement. While there may be some legitimate reasons for conducting strip searches, such as preventing contraband from entering correctional facilities, there are concerns that strip searches may be overused and disproportionately applied to certain groups. Further research is needed to better understand the factors that contribute to the use of strip searches and to determine whether alternative search methods may be more effective and less invasive.

Exploratory Data Analysis:

For the study, we used the arrest and stripped searches dataset gathered from the Toronto Police Service (Toronto Police Service, 2022) to explore the potentially correlated variables and set up the research objective and questions accordingly. In the following sections, we present the process of data cleaning formatting and finding relationships by various data visualization approaches, including bar charts and box plots. Since the dataset is primarily composed of categorical variables, we perform multiple rows and column merging to introduce the continuous variables for further analysis.

a. Data cleaning

The first step in the data-cleaning process is to clarify the dimensions and variables contained by the data frame after reading the CSV file using pandas packages (Figure 1). Using the shape method, we found the dataframe containing 65276 rows of data with 25 variables.

After examining the content, we found there are a large amount of null values, and string values such as "XX" appear in columns. The density of null value appeared high for columns under the categories "SearchReson_XX," while "XX" appears in the "ArrestLocDiv" column representing arrest events that happened outside the Toronto designated divisions. For the "SearchReason" columns, there are three possible values: 0, 1 and NAN, where 0 represents the specific search event that happened during the arrest and 0 if there was a search event but not the specific search type. Eventually, "NAN" stands for no search event that occurred during the arrest. Since we focused on the accumulated number of strip searches that happened during the year, it is appropriate to set all the "NAN" to 0, representing that the specific event did not occur. For the "Youth_at_arrest_under_18_years" column, we replaced the string variable with integers 1 and 0 for easy determination. Next, when examining each variable, we found unique variables such as "EventID," "ArrestID," and "PersonID" not applicable as we were interested in the general pattern relationship over the years rather than a particular event. Therefore we decided to drop these columns.

b. Exploration of relationships

Our general goal at the stage was to explore variables that have relationships with the merged number of searches set as the dependent variable. Before collapsing the search column to create continuous variables, we first made horizontal bar counts plots for the variable we were interested in.

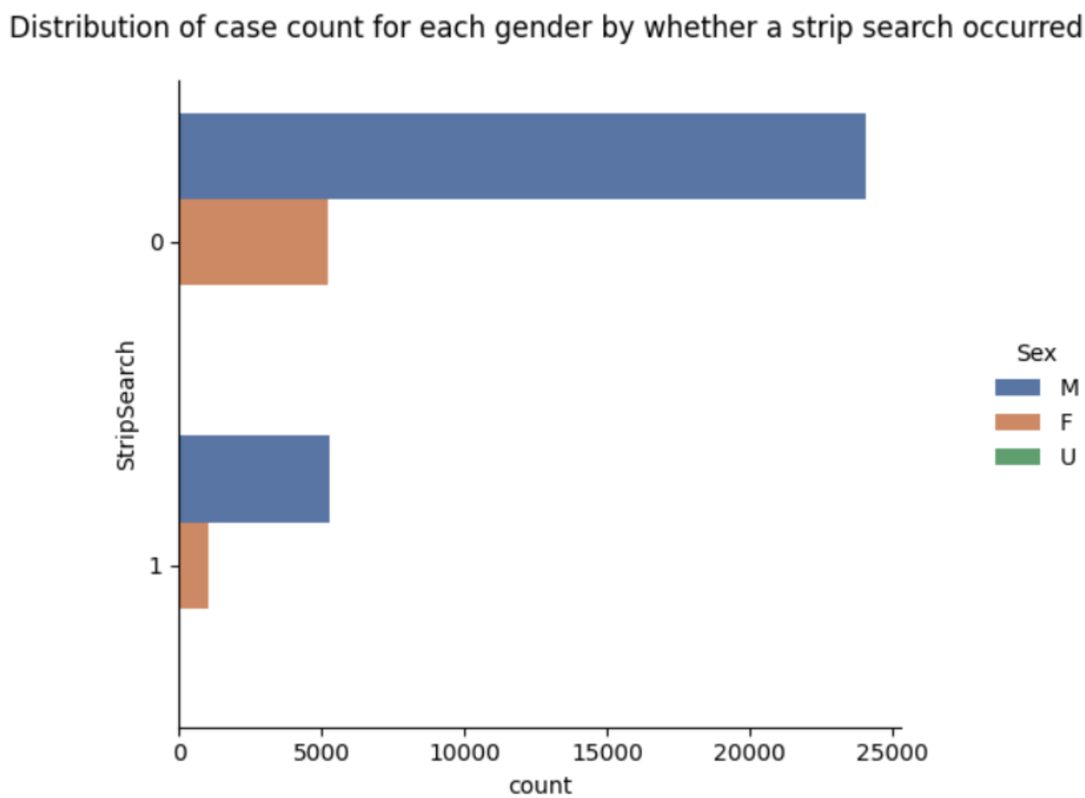

Figure 1: The case count in sex by if the strip search happened labelled in colours.

As shown in figure 1, the male's total number of arrest reports is much more than female. The distribution of the happenings of strip search is approximately similar for both genders. There are also several cases for another gender type, which is unknown. However, this type only has 9 records in total. Because its small data size can not provide enough evidence to support a relationship, we will not discuss this gender in the following paragraphs. The percentage of strip search is around 12.38% for males and 10.17% for females. The slight difference in the percentage of strip search can not represent the strong relationship between strip search and sex. As a result, we are going to take further analysis about the relationship between strip search and sex. First, we need to think about the effect of the year.

	StripNum_20_M	StripNum_21_M	StripNum_20_F	StripNum_21_F
Count	17	17	17	17
Mean	286.76	27.12	55.35	5.67
Std	231.27	33.42	55.13	6.52
Min	69	4	11	1
25%	167	6	25	2
50%	220	11	38	3
75%	274	31	69	6
Max	1049	108	241	23

Table 1: Statistical description of a table categorized the number of strip searches into two columns according to variable sex and year.

We then rearrange the original table — select and categorize columns in the number of strip searches conducted by the sex of the suspect and the year the case was raised in all divisions. From table 1, examining evidence from the mean, minimum and maximum, we see that mean search cases raised for males were considerably higher than for females and males were also shown to have a higher standard derivative of 231.3 and 33.4 compared to females [55,1, 5.7]. We also observed a dramatic drop in strip search numbers across the year for both sexes. Figure 2 illustrates the density distribution across divisions for different sex and years. For both years, males and females share a similar drop in group mean. Especially for females, because of the low base search value in 2020, the drop illustrated as shape nail-shaped rise near the zero. Except for the female curve for 2021, the other three categories seem to show a standard bell-shaped curve, meaning that while the mean is high in density, there are few extreme cases. There are some outliers that indicate the unusually high number of cases in some divisions. However, we decided not to treat these divisions as outliers considering the population density distribution in Toronto (the population tends to be concentrated in the downtown area.) Overall, there seems to be a strong relationship between sex and the number of strip searches based on the count of found items.

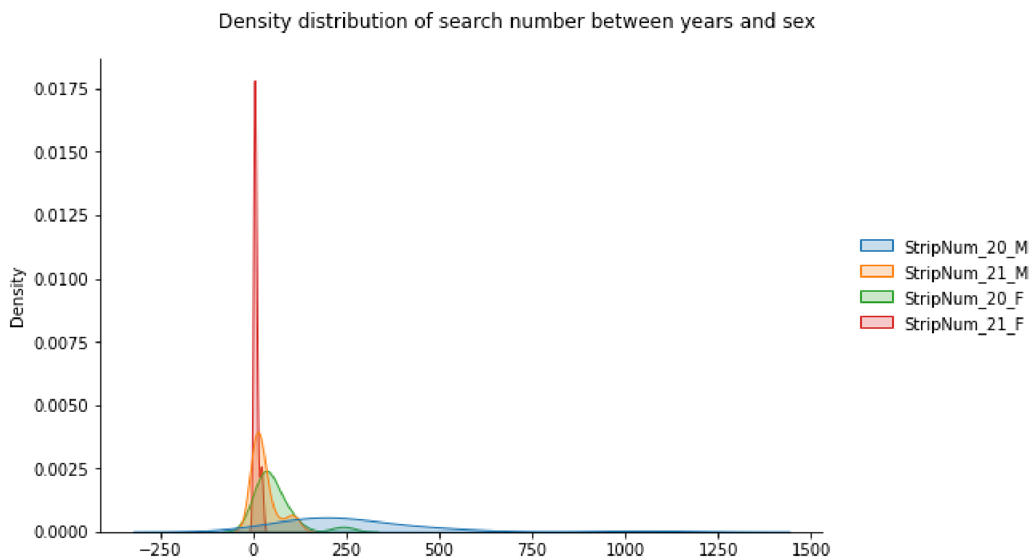

Figure 2: Density distribution of search number between years and sex.

In Figure 3, we then switch the topic from sex to the arrest location division. We see a similar distribution for the percentage of strip search. However, there are significant differences between different arrest location divisions. In division 51, it has the largest records of arrest and the highest chance to get strip searches, which is more than 5000 and around 21.4% respectively. Meanwhile, division 33 has the smallest number of records and the lowest percentage of strip search. There seems to be a relationship between division and strip search.

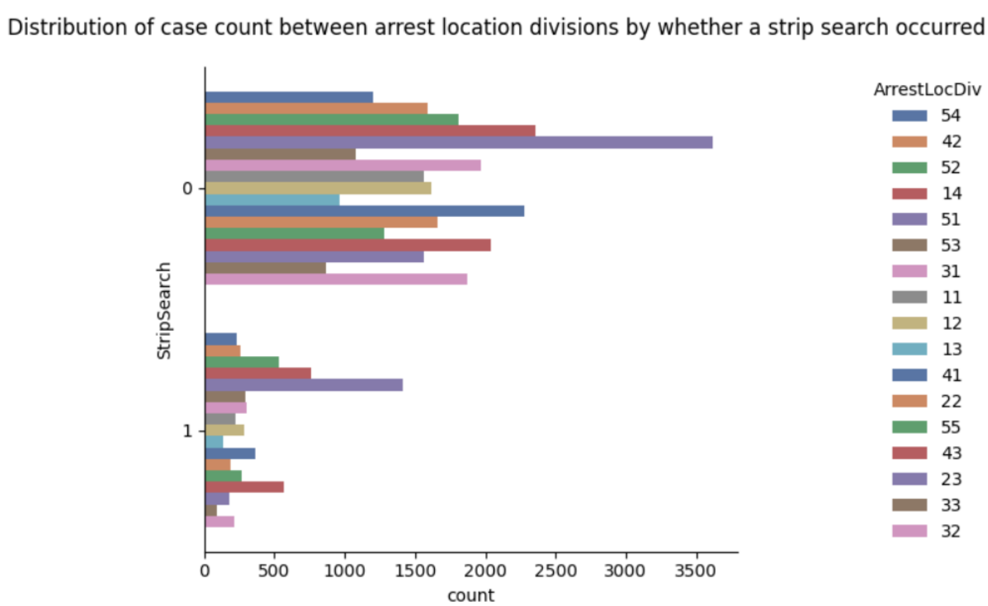

Figure 3: The distribution of case count for each arrest location divisions by strip search.

It is not enough to prove the relationship with only one graph. The distribution of case count for arrest location divisions does not have significant differences in all divisions between strip search. Therefore, we create another figure adding the attribute “Items Found” to figure out if there exist any changes. The figure below shows the number of cases that find the items during the strip search. We can clearly find that the chance of finding an item in strip search has dramatical difference for some divisions. In division 51, the percentage of finding an item in strip search is almost close to 50% and these percentages of other divisions are also larger than their percentage of strip search. Generally, we think there is a strong relationship between the division and strip search based on the item found attribute.

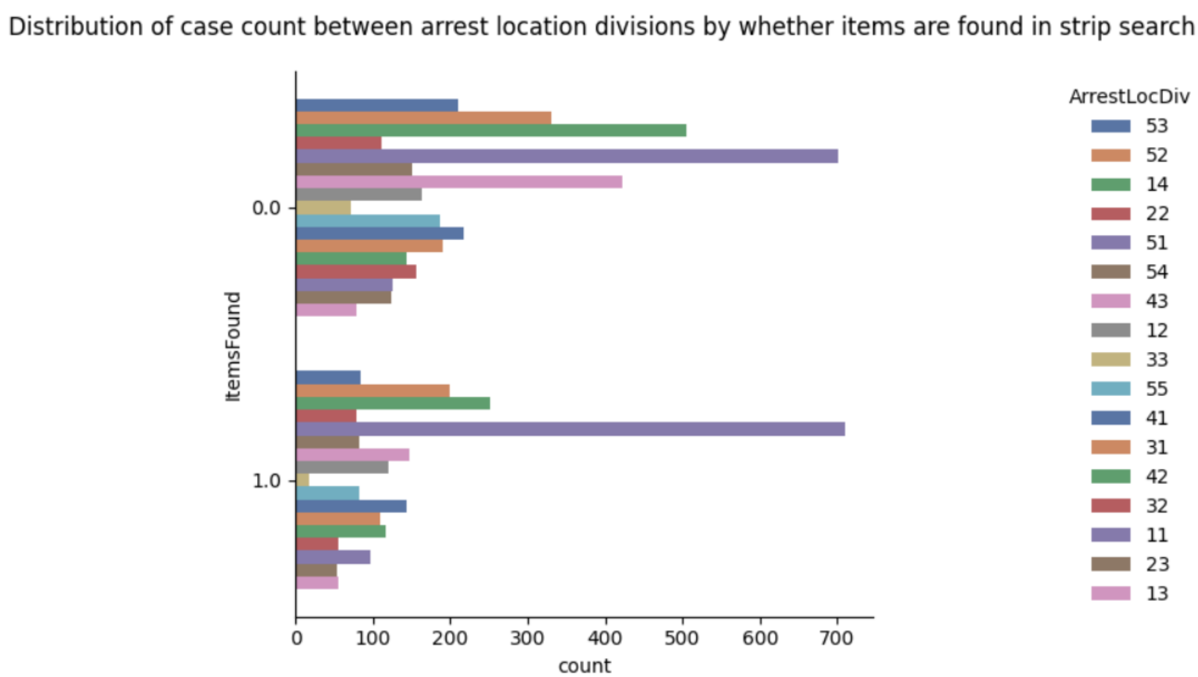

Figure 4: The distribution of case count for each arrest location divisions by whether there are items found during the strip search.

Further, arrest count and strip search numbers categorized by other factors were also examined. The graph (Figure 5) shows that white and black race groups have considerably higher case counts than others, and fewer strip search events occurred in 2021 than in 2020. There was not sufficient support to relate race with the high strip search number, for we also observed a high proportion of cases with no search conducted for the two races and in fact, according to the demographic composition of Toronto in 2016, white accounted for 50.2 percent of the total population. However, it is a surprise that East Asian and South Asian race group has extremely low crime rate compared to other race groups, as they together took 23 percent of the population (East Asian 12.7%, South Asian 12.3%) and only account for 5.33 percent of the cases reported, and 3.46 percent of the cases reported with a search conducted. In comparison, the black race group seems to have a relatively high case number reported (31.44%), considering its population proportion.

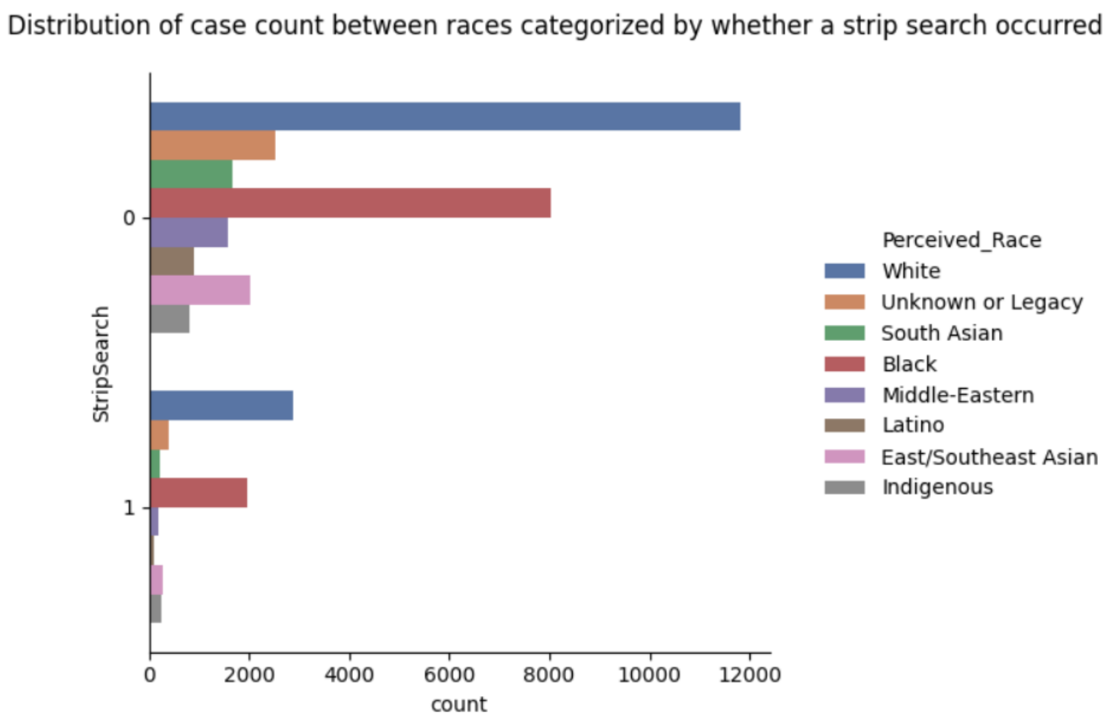

Figure 5: The distribution of case count for race categories by strip search.

In figure 6, it shows the distribution of strip search results for different occurrence categories. From the table, we can see that the majority of occurrences (over 95%) for most categories of crimes did not involve a strip search. However, there are some categories where Strip Searches were more likely to occur, such as Break & Enter (46.29% of occurrences involved a Strip Search) and Weapons (41.72% of occurrences involved a Strip Search). On the other hand, there are some categories where Strip Searches were much less likely to occur, such as Crimes against Children (0% of occurrences involved a Strip Search) and Fraud (0.21% of occurrences involved a Strip Search). It's important to note that these results do not necessarily indicate a causal relationship between the occurrence of a particular category of crime and the likelihood of a strip search. Rather, they provide information about the frequency of strip searches in relation to different categories of crimes. Other factors, such as the specific circumstances of each incident, may also influence the decision to conduct a strip search.

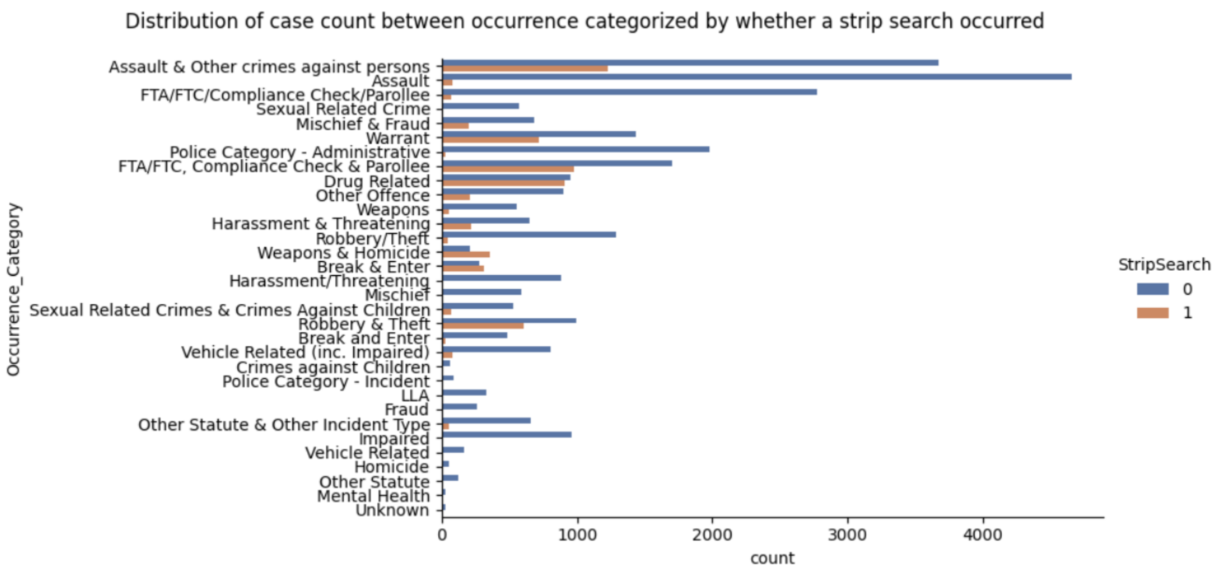

Figure 6: The distribution of case count for occurrence categories by strip search.

The graph below shows that out of a total of 62,276 arrests, 54,713 (87.9%) did not involve a youth under 18 years old and did not result in a strip search, while 7,521 (12.1%) did not involve a youth under 18 years old but did result in a strip search. Among arrests that involved a youth under 18 years old, 2,762 (90.8%) did not involve a strip search, while 280 (9.2%) did involve a strip search. This figure provides insight into the relationship between youth arrests and strip searches, indicating that strip searches are more likely to occur during arrests of individuals who are not youth under 18 years old.

Generally, we can find that there are 5 factors that can affect the occurrence of strip search, which are sex, division, youth, race and occurrence categories. For example, Assault & Other crimes against persons, Break & Enter, and Robbery & Theft have relatively high percentages of StripSearches associated with them (19.72%, 46.29%, and 17.71%, respectively), while Crimes against Children and Fraud have very low percentages of StripSearches associated with them (1.35% and 0.21%, respectively). These findings suggest that there may be certain factors that increase the likelihood of a StripSearch occurring, such as the type of occurrence or the age of the person being arrested. However, further analysis would be needed to fully understand the relationship between these variables and the likelihood of a StripSearch occurring.

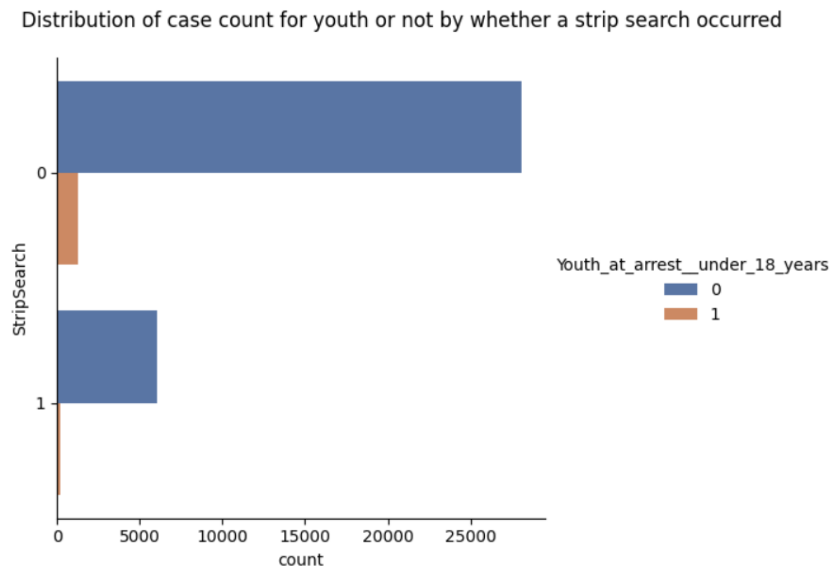

Figure 7: The distribution of case count for youth or not by strip search.

c. Tests and hypotheses

Since we are interested in if differences in divisions or sex affect the number of strips each conducted when accounting for the items found. We perform power analyses prior to the ANCOVA test. The first hypothesis is stated as:

H0: There is no significant difference in the number of strip searches conducted across divisions when accounting for the items found.

H1: There is a significant difference in the number of strip searches conducted across divisions when accounting for the items found.

For the power analysis, we calculate the effect size of the explanatory variable using Cohen's D metric, followed by computing the required sample size using the obtained effect size and establishing the statistical power at 80%. Start with the first set of hypotheses, to explore whether differences in divisions affect the number of strips each conducted when accounting for the items found, we calculated and obtained the effect size to be approximately 0.069, and the required sample size was shown to be 15.8 rounded to 16 for the number of districts in the sample. Since there are in practice 17 districts present in the dataset, it is plausible to expect a great possibility of obtaining correct rejection with less Type 1 error.

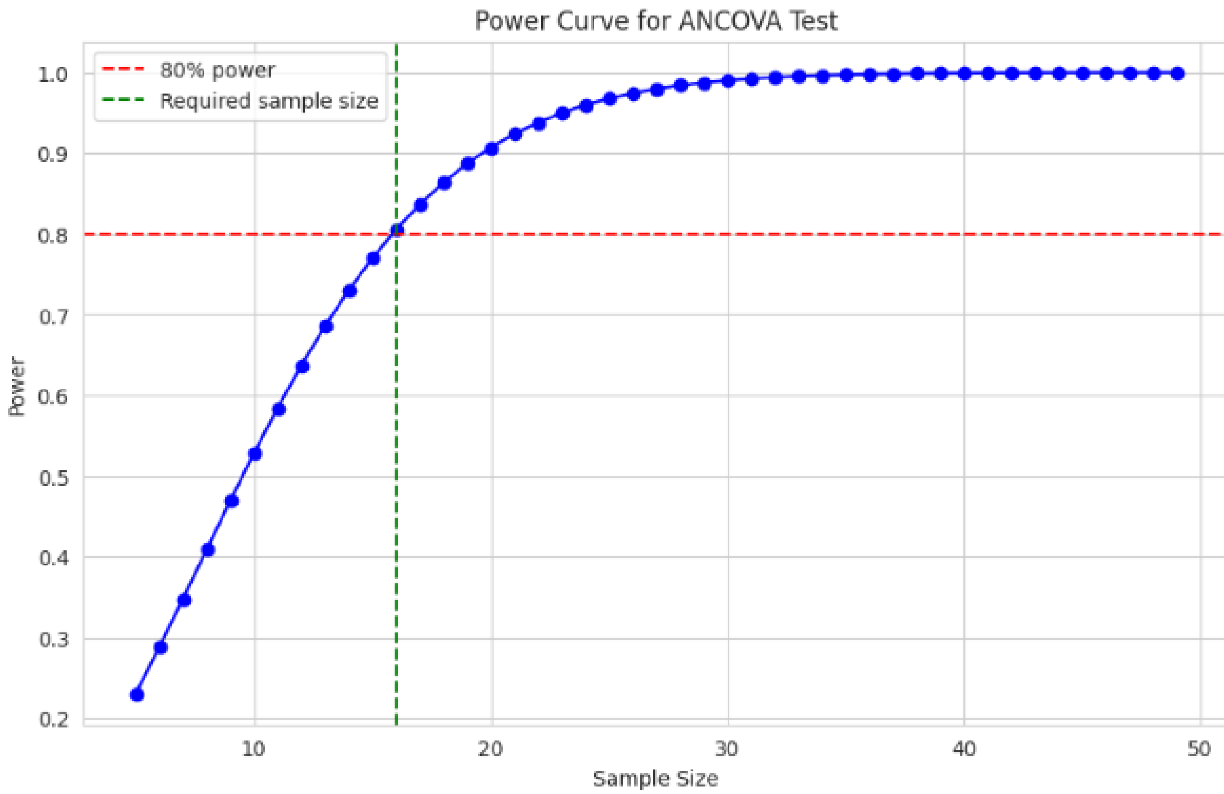

Figure 8: The power curve for divisions, the plot gives power versus sample size, where the green dash line represents the required sample size with the desired 80 percents power

For the relationship between sex and search count, we proposed the following hypothesis:

H0: There is no significant difference in the number of strip searches conducted between different sexes when accounting for the items found.

H1: There is a significant difference in the number of strip searches conducted between different sexes when accounting for the items found.

For the second hypothesis researching whether sex affects the number of strips each conducted when accounting for the items found, the result indicates an effect size of 0.6. Moreover, the required sample size is 34 for males, while a sample size of 42 is required for females. This outcome is significant because the dataset contains sample sizes of 114 and 281 for the respective groups, which can influence the reliability of the results.Figure 8 gives the relationship between sample size and statistical power for divisions.

For the logistic regression, we perform a chi-squared test to examine the association between variables with hypotheses as follows:

H0: There is no significant association between the strip search and each of the factors being analyzed.

H1: There is a significant association between the strip search and each of the factors being analyzed.

The chi-squared tests revealed significant associations between strip searches and Perceived_Race (p=2.37e-63), Sex (p=0.0030), Youth_at_arrest__under_18_years (p=0.0044), and ArrestLocDiv (p=1.53e-194). Moreover, the observed distribution of the data is very unlikely to have occurred by chance alone for strip searches and ItemsFound (p=0.0) or Occurrence_Category (p=0.0), assuming the null hypothesis is true. These findings suggest that factors such as race, sex, age, number of items found, the occurrence category, and arrest location division all play a role in the likelihood of strip searches. Figure 8 gives the relationship between sample size and statistical power for both sexes.

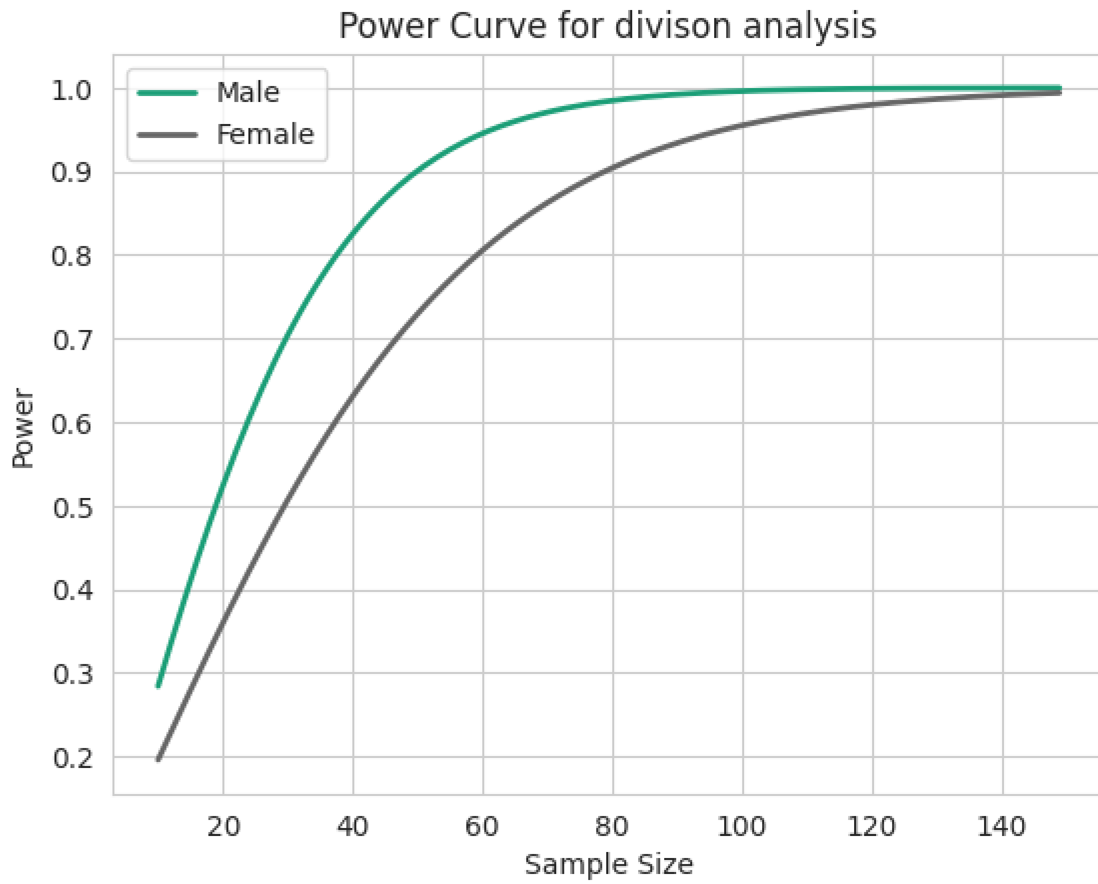

Figure 9: The power curve for males and females, the plot gives power versus sample size

Method:

a. Dataset Description

In this study, we analyze the dataset, which includes information on all arrests made by the Toronto Police Service between January 2020 and December 2021. It includes data on the location and time of the arrest, the nature of the crime, the age, gender and race of the person being arrested, and other relevant information about arrest and strip search. This dataset totally has 65276 records of the arrest with 24 attributes. One of the key features of this dataset is that it includes information on strip searches conducted by police officers during the arrest process. The information is basically divided into four search reasons and if there are items found. Another key feature is a wide range of offences, which contains 31 categories, from relatively minor offences to serious crimes. It also involves indicators of whether a person was booked at a police station within 24 hours following a particular arrest event and the six possible actions at arrest.

b. ANCOVA and Logistic Regression

As for our study, the dataset is composed of primarily categorical variables, and we aimed to analyze the relationship between these categorical variables and the continuous variable we created for the counts of strip searches and items found during the search. To assist with the analysis using the ANCOVA test, we employed power analysis to determine the effect size and required sample size required for adequate statistical power. Power analysis is crucial for estimating the sample size needed to detect an effect, reducing the chance of Type II errors, and ensuring the reliability of the results. Furthermore, we chose ANCOVA to investigate the relationship as it is a technique that combines ANOVA and regression, which was used to examine the differences between group means while controlling for potential confounding variables.

For categorical data analysis, the chi-squared test was employed to support logistic regression. The chi-squared test was used to determine the association between categorical variables by comparing the observed frequencies with expected frequencies. It helps us to identify the potential relationships among categorical variables that may be useful or can be eliminated from subsequent logistic regression analysis.

We further utilized logistic regression, a type of regression analysis that deals with categorical dependent variables, to model the relationship between a binary outcome and a set of independent variables, which may be categorical or continuous. Since the regression required solely numerical input, we applied one-hot encoding and label encoding to convert the non-numeric category values and replace the text with either a binary form or integers. This method allows us to determine the probability of a particular outcome based on the values of predictor variables and to understand the relationship between the independent variables and the binary dependent variable. By combining power analysis, ANCOVA, chi-squared test, and logistic regression, our study aimed to provide a comprehensive understanding of the relationships between the variables and the factors influencing strip searches and items found.

For assessing the performance of the algorithms, we used a confusion matrix for the accuracy checking which yields the true positive, false positive, true negative, and false negative in a two dimensional matrix. The dataset is split into a 20-80 test-train ratio for the training process.

Results:

the main focus of ANCOVA is on determining whether there is a significant difference in the adjusted means of the dependent variable across the levels of the independent variable, after controlling for the effects of one or more covariates. For the first hypothesis, we are interested in whether differences in divisions affect the number of strips each conducted when accounting for the items found. Since the p-value (0.002) is less than the common significance level of 0.05, there is a significant effect of ArrestLocDiv on the dependent variable after controlling for ItemsFound. The partial eta-squared (np2) of 0.154166 indicates that 15.42% of the variance in the dependent variable can be explained by the arrest location, after controlling for ItemsFound.

Source	p-unc	np2
ArrestLocDiv	2.000351e-03	0.154166
ItemsFound	9.719754e-127	0.930910

Table 2: output from ANCOVA test, where 'p-unc' stands for Uncorrected p-values, and 'np2' stands for Partial eta-squared

For the second hypothesis, we looked into whether sex affects the number of strip searches conducted when accounting for the items found. Since the p-value (3.757714e-08) is much smaller than the common significance level of 0.05, we can conclude there is a significant effect of sex on the dependent variable after controlling for ItemsFound. The partial eta-squared (np2) of 0.123567 indicates that 12.36% of the variance in the dependent variable can be explained by Sex, after controlling for ItemsFound.

	Lower CI	Upper CI	OR
Intercept	0.10162279779285635	0.12967122381385549	0.114793521407733

Perceived_Race	0.9867718128587676	1.0068283407940761	0.9967496310924602
Sex	1.043136205348104	1.230386491527407	1.1328992434826084
Youth_at_arrest__under_18_years	0.6224869743232557	0.8750372137639134	0.738037443234522
Occurrence_Category	1.0010477328828296	1.0070939786776272	1.004066304660796
ArrestLocDiv	1.0115557831809068	1.0157094432658358	1.0136304856144647

Table 3: Confident interval for columns, where CI stands for confident interval, OR stands for odds ratio

Moving the logistic regression model, after converting non-numerical variables into numerical category variables with one hot encoding and label encoding, we split the data frame into test and training sets and performed regression accordingly. The logistic regression results show associations between the independent variables and StripSearch while controlling for other variables in the model. All variables except race (p=0.526) demonstrate a statistical significance, which is positive (Sex, occurrence category, arrest location) or negative (age) association with the number of strip searches conducted. In particular, we found age and arrest location has an extremely small p-value (<0.001), which implies a strong association with the independent variable. For our data frame, almost all variables are binary or are not ordinal, therefore we did interpret the result in terms of the log odds of variables. Table 2 gives the confidence interval (Lower CI and Upper CI) of each of the target variables researched, which we can see the likelihood (OR) of strip search occurring affected by each category while holding the others. As a result, we found sex has the highest likelihood (1.13) of affecting the strip search number compared to other variables.

From the prediction interval plot (Figure 10), we can find the 95 percent prediction interval across all divisions, where the probability ranges from 0 to 1. We can see the lower and upper boundary of the prediction interval from the shaded band. Figure 11 gives the number of data which fall into the four classes. According to the outcomes, we see there were 5756 samples correctly predicted as false (True negative), but there are also 1004 false negative results. 150 instances were falsely predicted as positive (False positive), and there are 216 instances correctly predicted as positive (True positive). Overall the metric omits a 83.8 percent of accuracy.

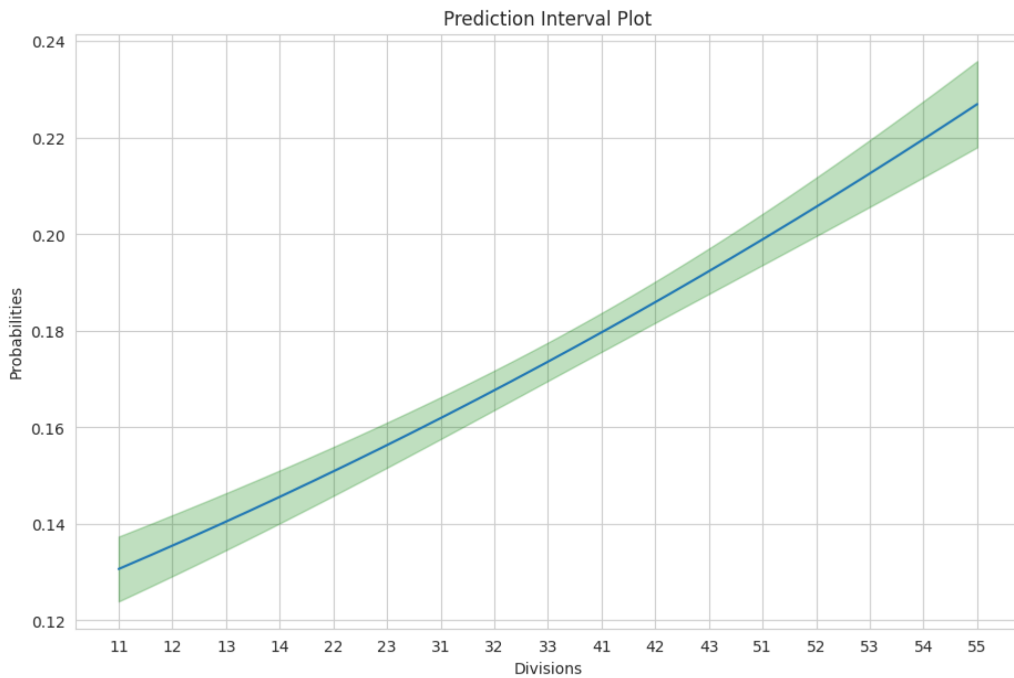

Figure 10: The estimated probabilities of strip search based on the divisions, along with their 95% prediction intervals.

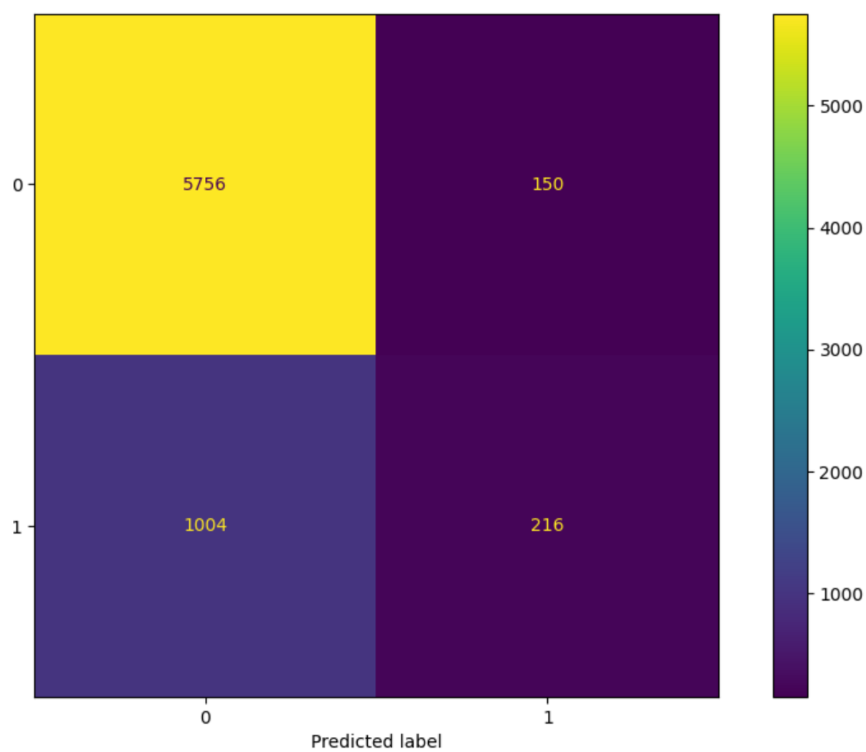

Figure 11: confusion matrix based on the prediction compared to the test set

Discussion:

For the first research question, we are interested in how the differences in divisions affect the number of strips search conducted when accounting for the items found. From the one-way ANCOVA test, we hypothesized the physical location of where the case raised has a determinate effect on the number of strip searches that will be conducted when accounting for the number of items found during the search. According to the outcome, we did observe a p-value lower than the set significant level, which implies a statistically significant association with the strip search cases. Meanwhile, we need to highlight that the location can be a relatively abstract term to be considered as an affecting factor. As a comprehensive factor, the overall citizen behavioural quality associated with physical geography can include various factors like average population distribution and economic status, which are further affected by transportation, division planning, racial preference, etc. While we shall also consider divisions with higher population density will generally have high crime rates due to the increased frequency of human-to-human interactions.

For the second question, we ask whether sex has a significant effect on the number of strips search conducted when accounting for the items found. We found an extremely low p-value from the ANCOVA test, indicating a significant relationship between the number of strip searches and the sexual identity of the suspects. The expected outcomes align with the commonly perceived concept of a male-dominated societal structure, meaning males have taken the majority in occupations. A similar pattern reflects in our study, and males have an overwhelmingly higher search number than females. However, we recognized that setting the search number as an identifier for criminal activity may not be robust, neither the dramatic difference between search numbers between sex can conclude the crime pattern difference regarding sex. If male and female were acting as pair (common law, couple, marriage), we expect male tend to have more criminal activities, if there is any, with higher exposure, compared to female. Yet, it does not imply females possess less intention to commit or support crime. Therefore, further investigations are necessary to identify such patterns unbiasedly.

Lastly, we performed logistic regression to explore the topic of how do factors of perceived race, sex, age, occurrence category, and the arrest location affect the number of strip searches conducted. The outcome suggests the relationship with the strip search amount of all factors except race is statistically significant. It is sane to re-examine our database, in which we found the sample size of the white and black ethnic groups are noticeably more prominent than the others. This might introduce bias in the result. Despite the limited sample available, we do observe a lower count for Asian groups, which might raise some insight into how regional culture affects the crime rate. Moreover, aligning with the previous conclusion, arrest location was found to have a significant relationship with extremely low p-value, as well as the high odds ratio for sex.

Conclusion:

Based on our analysis, we found that there is a significant difference in the number of strip searches conducted based on the division where the arrest occurred, even when controlling for the items found. Specifically, we found that Division 51 had a higher mean number of strip searches conducted compared to the other divisions. Furthermore, we also found that sex was a significant predictor of the number of strip searches conducted, even when controlling for the items found. Females were less likely to undergo strip searches compared to males. Our logistic regression analysis also showed that age and arrest location were strongly associated with the number of strip searches conducted. Specifically, we found that younger individuals and those arrested in Division 51 were more likely to undergo strip searches. Additionally, we found that the occurrence category (i.e., reason for arrest) was also a significant predictor of strip searches, with those arrested for drugs being more likely to undergo strip searches compared to other reasons. It is worth noting that the logistic regression model did not show a significant association between perceived race and strip searches. However, this does not necessarily mean that there is no racial bias in strip searches, as other factors that were not included in our analysis could be influencing the decision to conduct a strip search.

For future analysis, it would be interesting to explore the potential impact of other factors, such as the arresting officer, on the decision to conduct a strip search. It would also be important to investigate whether there are any racial biases in the decision to conduct strip searches, which could involve gathering additional data on the race of the arresting officers and other relevant contextual factors. Additionally, it would be beneficial to further explore the reasons for the differences in strip search rates across divisions and to consider possible interventions to reduce disparities in strip search rates.

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