The Effects of Crime type and Race on Strip Searches

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1. Introduction

Power and control have historically been points of tension in criminal justice systems throughout the world. Unfortunately, figures of authority have been known to misuse their station to enact power and command control over incarcerated individuals or potential prisoners. The infamous Stanford Prison Experiment by Philipp Zimbardo (1973), showed us that anyone who is given the tools and environment to fill the role of a figure of authority is capable of doing harm towards people. Although this experiment has been criticized for its disregard for research ethics, it remains as a powerful reflection of what is happening with our current justice system. Aside from assuming the role of an authority figure, a recent study showed that officers who experience higher levels of stereotype threat, moments where individuals are in situations that activates negative stereotypes about their group, also showed increased rates of support for use coercive policing (Trinker, Kerinson, & Goff, 2019). Seeing multiple excessive use of force cases portrayed in the media is now not so surprising knowing these mechanisms are playing in the background. In Ontario alone, an 18.2% increase in use of force cases was observed in a span of ten years, from 2010 to 2020 (Wortley et. al, 2021, p.19). One such operationalization of use of force is strip searching.

In 2001, Ian V. Golden appealed his police assault charge to the Canadian Supreme Court, where he was strip searched three times throughout his arrest (R V. Golden, 2001). Although he was found guilty, his police assault charges were dropped in the light of the officers' excessive use of force. According to the Canadian Civil Liberties Association, Ontario's criminal system's usage of strip searches are dehumanizing and invasive in nature. In their recent constitutional challenge to the Supreme Court they describe strip searches as " unreasonable, overly broad, and grossly disproportionate to the purpose of the legislative scheme" (Canadian Civil Liberties Association v. Canada, 2022). Furthermore, officers have also found ways to circumvent regulations that are meant to protect inmates from excessive use of strip searches by distorting the meaning of strip searches within their domain (Daems, 2014). Additionally, research also shows that strip searches are disproportionately used against racially marginalized groups, specifically Afro Caribbeans (Newburn, Shiner, & Hayman, 2004). In tandem with that, Newburn et. al (2004) explained that strip search percentage is much higher in crimes where there is perceived obfuscation of evidence (i.e. drug related crimes). Knowing that race and crime type are predictors for strip search rates, our research aims to contextualise these findings in Toronto and find a potential interaction between the two. We aim to answer these research questions:

RQ1: Does perceived race influence strip search rates in Toronto?
RQ2: Does crime type influence strip search rates in Toronto?
RQ3: Do perceived race and crime type of arrested individuals influence strip search rates in Toronto?

To do so, we explored the Toronto Police *Arrests and Strip Searches* Database, which documents strip searches throughout the greater Toronto Area from 2020 - 2021. Our results showed that there is a significant difference in strip search rates between race groups, especially between Asian (East, Southeast, South Asian, and Middle Eastern) and Indigenous individuals. Similarly, results showed that there is a significant difference between crime type levels: Property, Violent, and Other. However no significant interaction between the two predictors was found.

2. EDA

2.1 Data Cleaning

The first thing we did was to pick variables that would help us explore our research questions. We isolated the 'Arrest_Year' ,'Perceived_Race', 'Sex','Age_group__at_arrest_', 'Occurrence_Category', and 'StripSearch' variables, which we renamed to Year, Race, Sex, Age, Crime_Type, and Strip for easier reference. Besides variables that are directly included in the research questions, we also include sex and age to see some demographic differences that could provide nuance to our analysis if needed.

We aggregated levels within our predictor variables Race and Crime_Type. In the original data set Race has 8 levels and Crime_Type has 30 levels. As a public safety record, such a detailed record is a good thing; however, in this report, we simplified these two variables. For the race, we combine different levels into White, Black, Asian, Latino, Indigenous, and Unknown or legacy. This is quite conventional in crime and race research (especially the ones who were largely investigating the dichotomy between White and Black groups. For the crime type, we followed a paper that explored crime types (Pratt & Cullen, 2005) to create three levels: Property crime, Violent crime, and Other crime. The specific classification of different levels into these categories follows (NIJ, 2023). Please see appendix for the specific aggregation of the Race and Crime_Type.

The last step we did is to find a variable that can be used as the dependent variable in the following analysis. In the beginning, we thought that the count of strip searches could be a good variable, reflecting the number of strip searches in Toronto. However, we soon realized that if the total number of strip searches is not controlled, the comparison of the count would not be fair. Therefore, we choose to calculate the proportion of strip searches as the dependent variable, which is defined as :

$$\sum_{count} of\ strip\ searches\ (within\ each\ predictor\ levels) \div \sum_{total\ count} of\ arrests$$

To create this new variable, we grouped the original dataset by the variables we picked in the first step, except Strip. Then we calculated the count of strip searches (entries that had a ‘1’ in the Strip column) and total arrests for each combination of levels. Finally, we divided these two values to compute the proportion of strip searches per group. We thought that this was a fairer comparison and reflection of how much strip searches occur within a specific group rather than relying on the count variable as it is directly affected by the magnitude of the populations or sample size of each level within the Race and Crime_Type categories.

2.2 Descriptive Statistics

2.2.1 Race Descriptive Statistics

First we wanted to see the general trends of Crime Type and Race within the context of number of strip searches and proportion of strip searches. You can see in Figure 1 that when raw counts were of strip searches there is a disproportionate amount of White individuals represented by the largest bar.

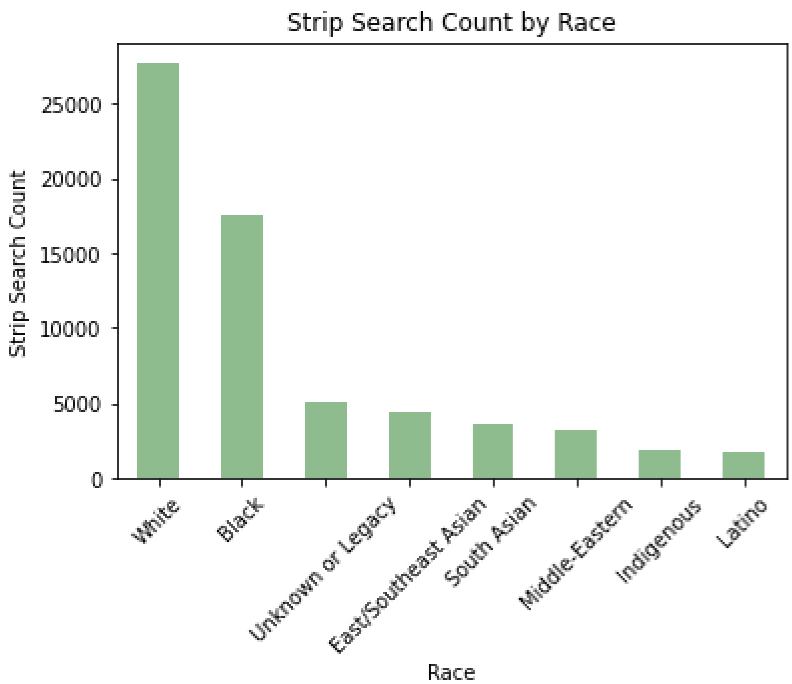

Figure 1. *Strip Search counts groups by Original Perceived Race Counts*

Even after we formed the Race group, we still saw a disproportionate amount of White individuals represented in strip counts (Figure 2). Looking at the summary of descriptive statistics in Table 1, White arrests account for 27635 out of 65083 arrests, which accounts for 42% of all arrests made by the Toronto Police from 2020 - 2021.

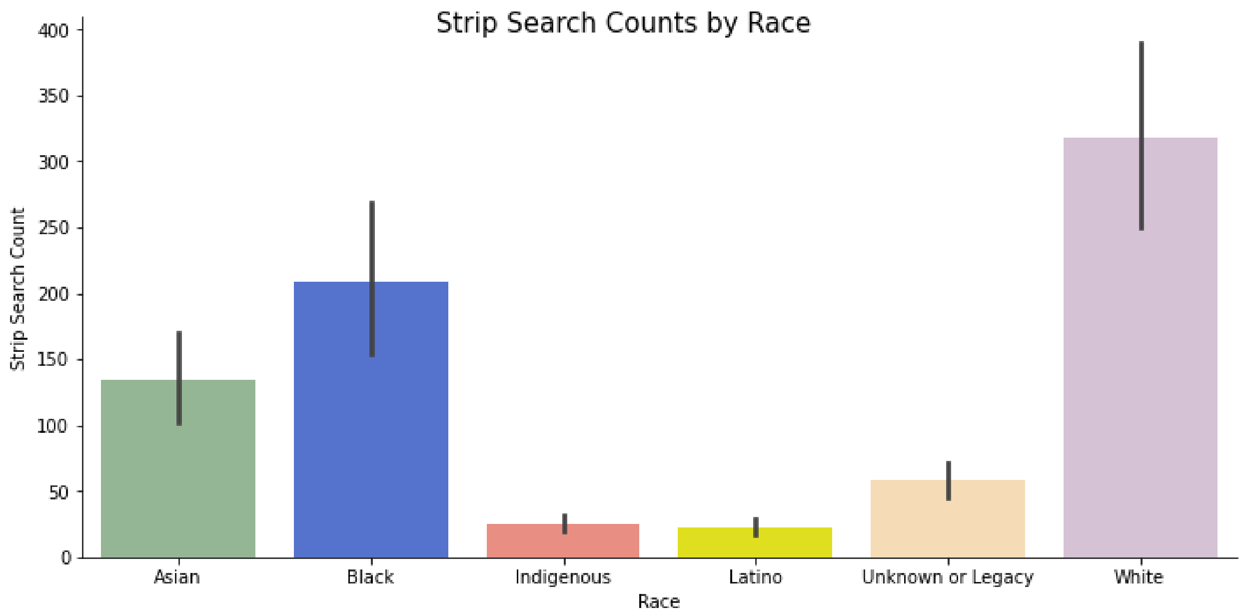

Figure 2. *Strip Search counts plotted with combined Race groups*

This further supported our assumption that the raw counts would not be able to provide us with a fair comparison between groups. The graph could just be reflecting that there are just a lot more White people who live in Toronto.

Table 1. *Summary of Descriptive Statistics for Proportion of Strip Searches grouped by Race*

Race	Mean	StDev	Strip Searches	Total Arrest
Asian	0.06	0.07	826	11232
Black	0.10	0.11	2434	17487
Indigenous	0.13	0.18	306	1926
Latino	0.08	0.11	132	1759
Unknown	0.08	0.11	535	5044
White	0.10	0.11	3566	27635

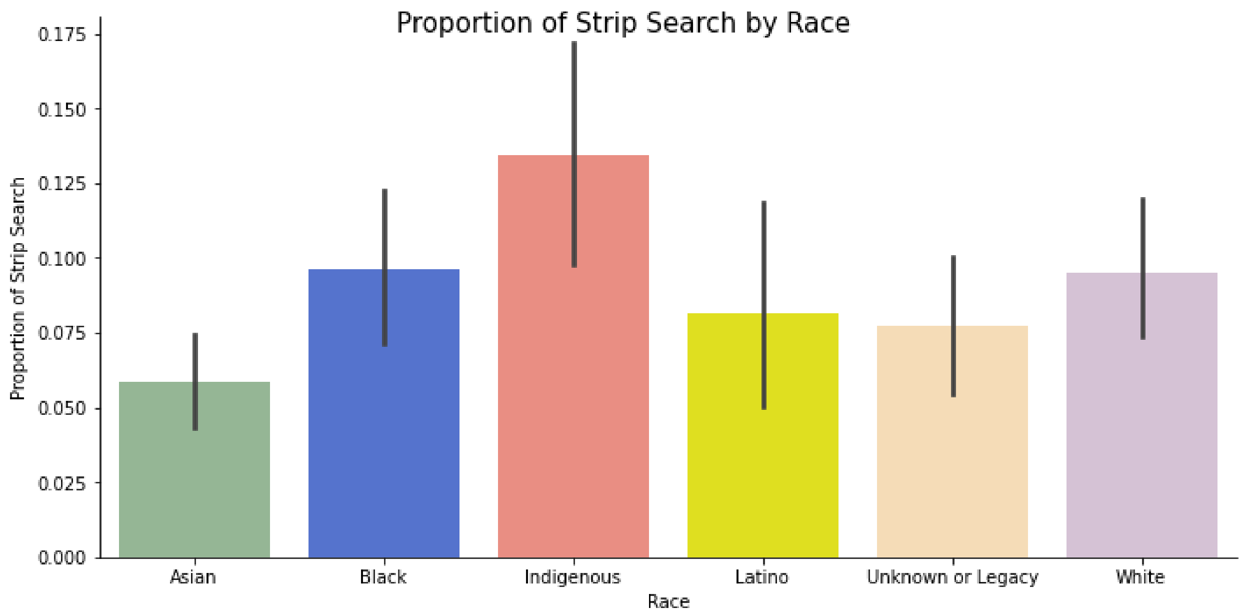

Figure 3. *Proportion of Strip Searches grouped by Race*

Figure 3, which shows the proportion of strip searches by race, shows a more nuanced representation of how strip searches are distributed between the different racials groups in the dataset. The graph shows that Indigenous people, who account for the second smallest racial group for all arrests (3%), have the highest proportion of strip searches p = 306/1962 (0.16) among all races. While the Asian group, which is 17%, have the lowest proportion of strip searches p = 826/11232 (0.07).

2.2.2 Crime Type Descriptive Statistics

Figure 4 below represents the strip search counts across the pre-processed crime types. We can see that the top two crimes with the most strip searches are Assault-based (Violent crime). The crimes that yielded the least strip searches were Homicide (Violent) and Crimes against Children (Other).

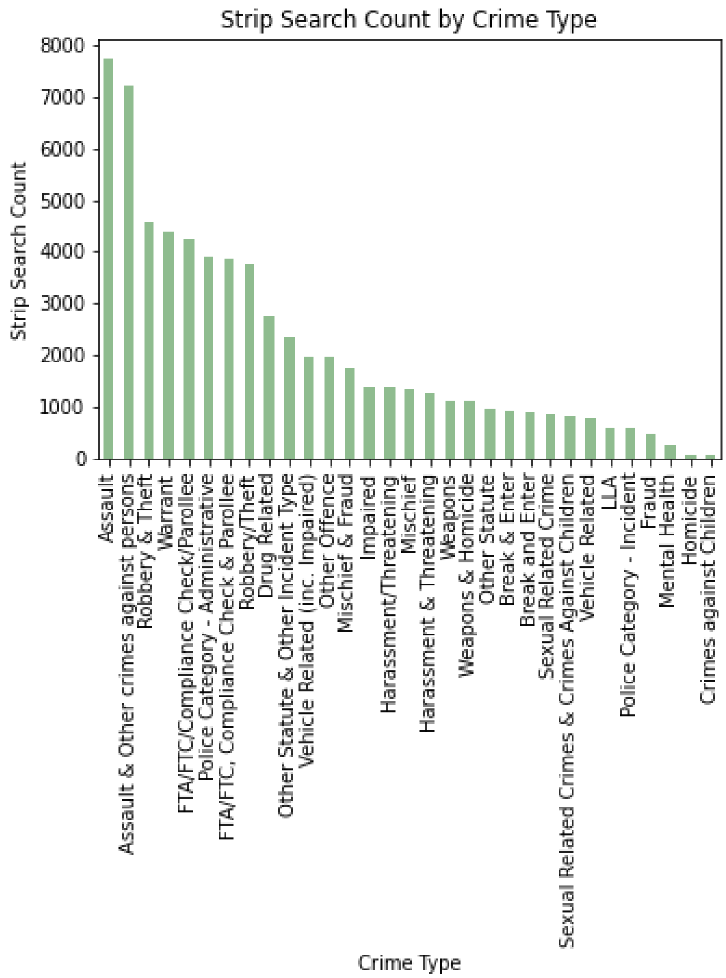

Figure 4. *Strip Search counts groups by Original Perceived Race Counts*

We also plotted Crime Type by proportion of strip searches (Figure 5) and found that there is a higher proportion of strip searches for Other crimes, non-property or non-violent crimes, compared to Property and Violent crimes. Property crimes have the lowest proportion of strip searches among the three categories. This is further supported with the calculated means (Table 2) showing the same pattern, where the average proportion of strip searches related to property crimes are 6 %.

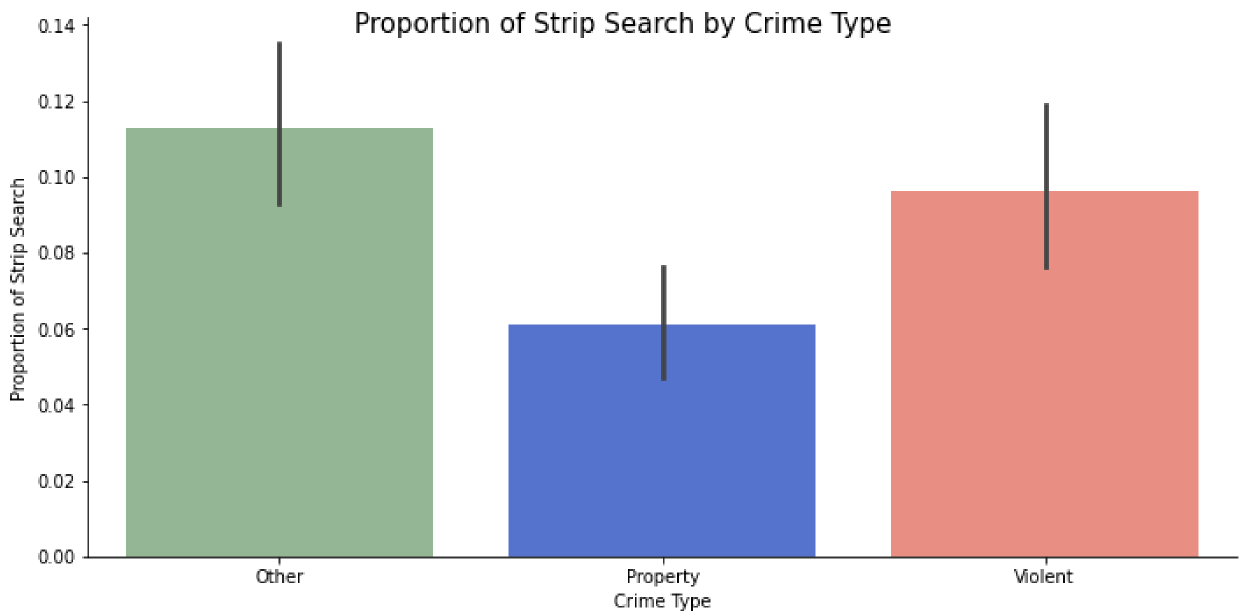

Figure 5. *Proportion of Strip Searches grouped by Crime Type*

Table 2.

Summary of Descriptive Statistics for Proportion of Strip Searches grouped by Crime Type

Crime Type	Mean	StDev	Strip Searches	Total Arrest
Other	0.11	0.14	3401	23806
Property	0.06	0.10	1714	17748
Violent	0.10	0.14	2684	23529

2.2.3 Plotting Race and Crime Type Together

Figure 6 shows the distribution of the proportion of strip searches by race, grouped by crime type. In this plot, we are trying to find if there is a pattern that comes up when plotting the two predictors together. The graph indicates that the Other crime graph reflects a higher level of proportion of strip searches across all races compared to Property and Violent crimes. It is evident that throughout all three graphs, the Indigenous group experiences the highest amount of strip searches amongst all other races. Conversely, the Asian group shows the smallest proportion of strip searches overall.

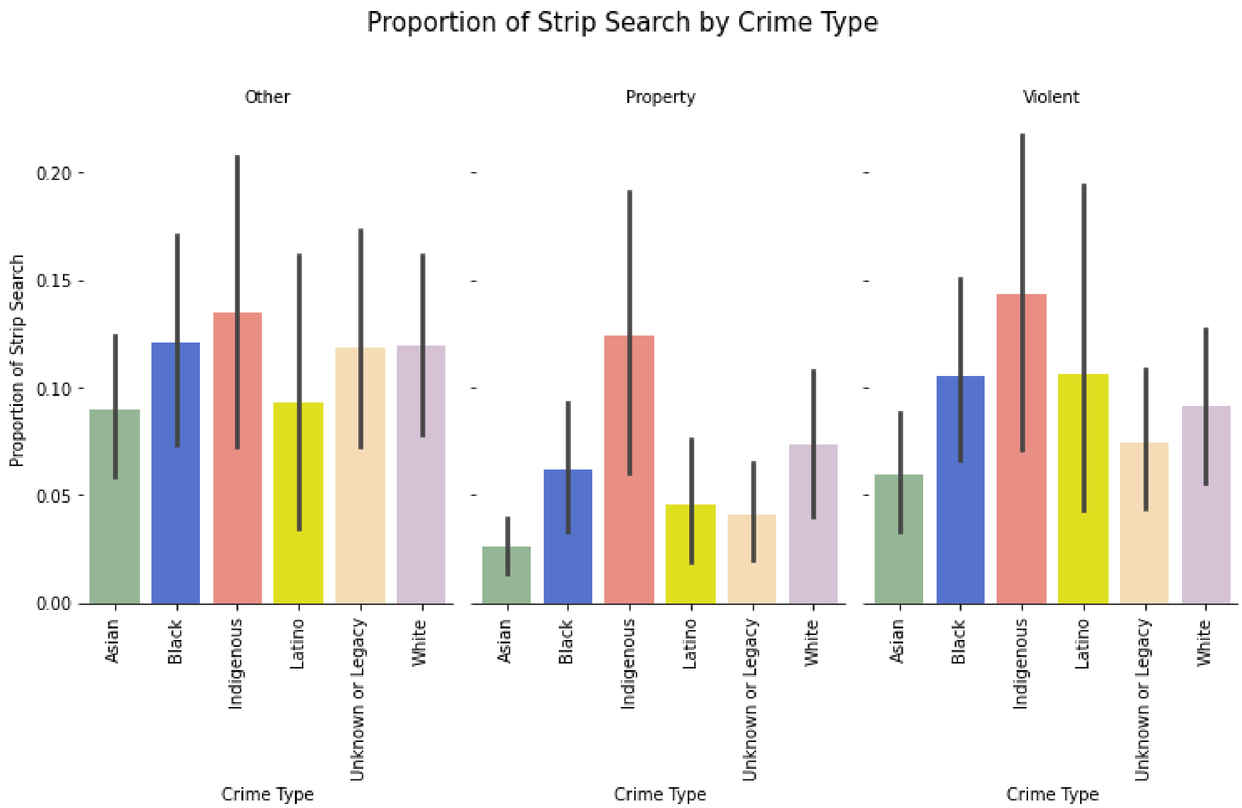

Figure 6. *Proportion of Strip Searches by Race, grouped by Crime Type*

Finally, we also wanted to see the shape of the dataset as it pertains to strip search counts after the data was grouped by Race and Crime Type. Figure 7 is a right-skewed histogram, meaning that a lot of the Strip Search counts per group are on the lower end of the range.

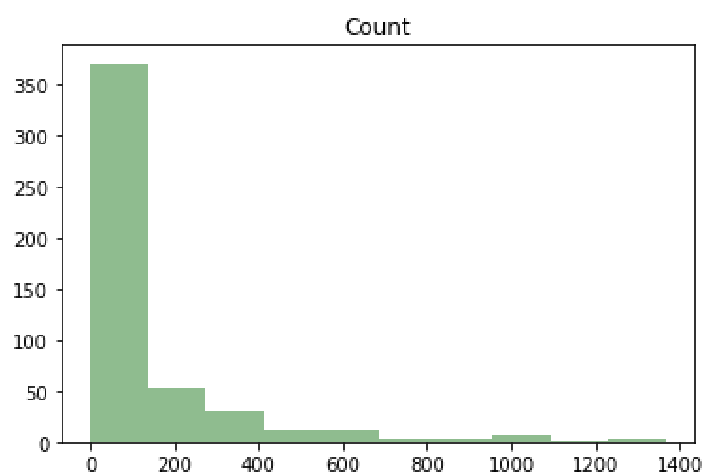

Figure 7. *Histogram of Strip Search Counts*

2.3 T-Tests

From the EDA, we saw that there are differences in mean proportions of strip searches within the different predictors of Race and Crime Type. The graph shows that the Indigenous group had the highest proportion of strip searches amongst all the racial groups, while the Asian group had the lower average proportion of strip searches. Similarly, Property crimes represent the lowest proportion of strip searches within the three crime types. We wanted to further investigate whether these differences are significant. To examine that, we conducted two one-tailed two sample t-tests with Bonferonni corrections between the different levels of Race and Crime Types.

2.3.1 Race t-tests

For the Race predictor we wanted to understand race influences the proportion of strip searches. The hypotheses we tested were:

H0 (null hypothesis): The mean proportion of strip searches of the six racial groups, Asian, Black, Indigenous, Latino, Unknown, and White, are equal.
HA (alternative hypothesis): The mean proportion of strip searches of the six racial groups, Asian, Black, Indigenous, Latino, Unknown, and White, are not equal.

In the initial t-test, the results indicated that there were 4 comparisons that produced significant differences in mean proportions of strip searches. At an $\alpha = 0.05$, the proportion of strip searches in the Asian group ($M = 0.06$, $SD = 0.07$) were significantly lower compared to the proportion of strip searches of the Indigenous ($M= 0.13$, $SD = 0.18$), $p = 0.01$, and Black ($M= 0.10$, $SD= 0.11$), $p = 0.01$ groups. Additionally, the Indigenous group's ($M = 0.13$,$SD = 0.18$) mean proportion of strip searches were significantly higher than the Latino ($M = 0.08$, $SD = 0.16$) and Unknown ($M = 0.07$, $SD = 0.11$) groups. However, since we did 15 t-tests we also corrected the p-value using the Bonferroni correction. After this correction, with an adjusted alpha level of .0003 per test (0.05/15) none of the comparisons yielded a significant difference. Thus we cannot reject the null hypothesis. Full results are in the appendix (Table 3).

2.3.1 Crime Type t-tests

Similarly we conducted t-tests to find if there are significant differences between mean proportion of strip searches between the three different crime types: Other, Property, and Violent. After calculating each group's mean proportions of strip searches, we found that Property crimes had the lowest proportion of strip searches amongst the three crime type levels. To explore this relationship further, we conducted three t-tests with Bonferroni correction testing these hypotheses:

H0 (null hypothesis): The mean proportion of strip searches of the three crime types, Other, Property, and Violent, are equal.
HA (alternative hypothesis): The mean proportion of strip searches of the three crime types, Other, Property, and Violent, are equal.

The initial t-test results indicate that the proportion of strip searches for Property crimes (M = 0.06, SD = 0.10) is less than the proportion of strip searches for Other crimes (M = 0.11, SD = 0.14), p-value = 0.001 and Violent crimes (M = 0.10, SD = 0.14), p-value = 0.02 . Even after the Bonferonni correction, with an adjusted alpha level of 0.016 (0.05/3), the results suggested that individuals who commit Other crimes are more likely to experience strip searches in proportion to individuals who committed Property, p-value = 0.0003, or Violent crimes, p-value = 0.01. Accordingly, we are able to reject the null hypothesis. Full results are in appendix (Table 4).

3. Method

3.1 Data Description

The dataset we analysed for this report was the *Arrests and Strip Searches (RBDC-ARR-TBL-001),* taken from the Toronto Police Service, Public Safety Data Portal (*Arrests and Strip Searches,* 2021). It includes all recorded information related to all arrests and strip searches that officers from Toronto Police Service conducted from 2020 to 2021 (arrests that are not in Toronto are identified with an 'xx' entry in the 'ArrestLocDiv' variable). It contains 65276 rows and 25 columns. The variables represented are year, month, IDs (i.e., event

ID, arrest ID, person ID, and information ID), race, sex, age group, youth, location, strip search, booked, crime type, etc. The dataset also included observational data of strip search reasons and actions in arrest coded as binary categories. Aside from ID and Time variables, all of the data were categorical in nature.

3.2 Analytic Approach

In order to answer our research questions and investigate the patterns we found through our exploratory data analysis, we performed multiple one-way ANOVAs to check for any significant differences between the average proportion of strip searches (outcome variable) and the levels within the Race and Crime Type predictors. After that, we ran Tukey's HSD post-hoc tests, when our main ANOVA test produced significant results, to check which specific levels were significantly different from other levels in a given categorical variable. Lastly, we conducted a two-way ANOVA and graphed an interaction plot to investigate the interaction between Crime Type and Race.

4. Results and findings

4.1 One-way ANOVAs and Tukey's tests

Based on the pre-processed data set, we first conducted a two one-way ANOVAs: race vs. the proportion of strip searches and crime type vs. the proportion of strip searches. Following each one-way ANOVA, we also conducted a Tukey's post-hoc test to see if we can reject the null hypothesis in the corresponding one-way ANOVA. The results are given as follows.

4.1.1 Race

The null hypothesis of this one-way ANOVA between race and the proportion of strip searches is that the proportion of strip searches is identical across different races.

The analysis of variances showed that race significantly influenced the mean proportion of strip searches ($F = 3.20$) with a p-value = 0.008, which is smaller than the alpha level of 0.05. Thus, we have enough evidence to reject the null hypothesis and claim that there is at least one race has a significantly different proportion of strip searches from other races.

The post-hoc analyses using the Tukey's HSD test, showed that among all comparisons, only the Asian (M = 0.06, SD = 0.07) group's mean proportion of strip searches was significantly different from the Indigenous groups (M= 0.13, SD = 0.18), p-value = 0.002. Thus, with an alpha level of $\alpha = 0.05$, we are able to reject the null hypothesis. All other pairwise comparisons do not show a statistically significant difference.

4.1.2 Crime Type

The null hypothesis of the one-way ANOVA between crime type and the proportion of strip searches is that the proportion of strip searches is identical across different crime types.

Similarly, the analysis of variance for crime type indicated that crime type significantly influenced the mean proportion of strip searches (F = 7.19), p-value = 0.001. With our alpha level of $\alpha = 0.05$, we are able to reject the null hypothesis and claim that there is at least one crime type's proportion of strip searches is different from other races.

To investigate this further, we also used the Tukey's HSD test to identify which crime type yields a different proportion. The results suggest that, for the pairwise comparison, there is a significant difference between the proportion of strip searches between Other (M = 0.11, SD = 0.14) crime type and the Property (0.06, SD = 0.10) crime type, as well as the Violent (M = 0.10, 0.14) crime type and the Other crime type. Lastly, the results showed that there is no significant difference between the mean proportion of strip searches between Other and Violent crime types.

4.2 Two-way ANOVA and interaction plots

The past sections looked at Race and Crime Type as individual predictors to the proportion of strip searches. To explore if Race and Crime Type have a significant interaction or are influencing the proportion of strip searches together, we performed a two-way ANOVA. The main effects test results indicated that both Race (p-value = 0.007) and Crime Type (p-value =

0.008) have a significant impact on the proportion of strip searches. However, the two-way analysis of variances did not show a significant interaction between Race and Crime Type F(10, 478) = 0.36, p-value = 0.96.

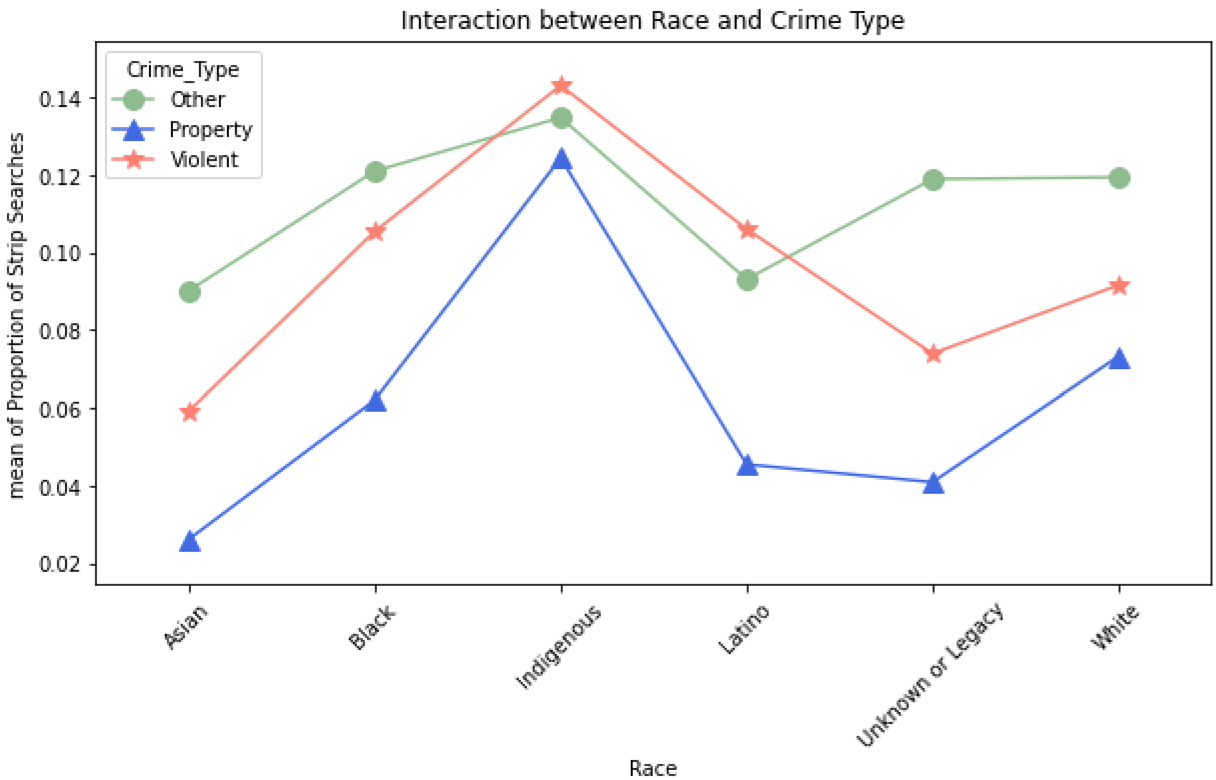

Figure 8. *Interaction Plot for Proportion of Strip Searches by Race and Crime Type*

Although there is no significant interaction between the Race and Crime Type, the interaction plot (Figure 8) shows some intersections between Other and Violent crimes, while Property crimes are parallel to both. This suggests that there might be some observable patterns of levels of proportion of strip searches within different racial groups who committed Other or Violent crimes.

5. Discussion

Our analysis of variances show that race does impact the number of strip searches, which indicates potential discrimination by the police showing different treatment of strip searches on different racial groups. This supports previous research that found that police tend to target specific race groups during arrests (Newburn, Shiner, & Hayman, 2004). Unlike the findings of previous research where the Black people tend to be targeted by the authorities, our post hoc test indicates that the major difference in proportion of strip searches is between Asian and Indigenous groups, where Indigenous people tend to be strip searched more. Other groups faced similar rates of strip searches regardless of their race.

Additionally, our results showed that the proportion strip searches are also impacted by the type of crime that an individual commits. Tukey's test indicates that when an arrest is related to a Property crime, the strip search proportion is significantly lower than if someone commits Violent or Other crimes. This is in contrast with previous research explaining that people who commit Property crimes usually experience more strip searches compared to Other and Violent crimes because the police suspect that the individual is concealing evidence (Newburn, Shiner, & Hayman, 2004). This is perhaps due to our interpretation of what property crime means. In categorizing crimes in the dataset, we consulted the National Institute of Justice (NIJ, 2023), where drug-related crimes were not categorized under the Property crime, contrasting from the study mentioned above. Drug crimes represented the 9th highest strip searched crime type in the dataset (Figure 4)

Lastly, although we suspected that there could be patterns after seeing some in our EDA (Figure 6), our two-way ANOVA between race, crime type, and the proportion of strip searches, indicated that there is no significant interaction between race and crime type.

5.1 Limitations:

All the data in the dataset were originally categorical in nature and had to be transformed for our analysis. This is a large limitation as it left us to make a lot of assumptions in how we wanted to represent the data in our research. The people who collected and used this data, the Toronto

Police, might also have a different data schema than us or the other researchers in literature. Additionally, fitting categorical data into analyses like ANOVAs and t-tests, which are for continuous data, is not the conventional way to do these investigations. A dataset like this could possibly yield more accurate results when run through a Chi-Square test, where two categorical predictors are compared.

Another limitation with our data is that our sample data did not fit a normal distribution. After running a Shapiro-Wilks test, for all levels of the two predictors, the p-values were less than 0.05. This meant that we were able to reject the null hypothesis for the test indicating that our data is not normalized. This could have affected our ANOVA results and could be the reason why our residuals errors were quite high (Table 7).

Additionally, the fields in the dataset can also be misleading. The Race predictor was originally called “Percieved_Race". This means that the officer who collected the information about the individual assumed the person’s race upon arrest. This was not a self report, which could have been more accurate. Additionally, individual “Person_IDs” fields are captured multiple times within the dataset, possibly as a repeat arrest for the same person. Unfortunately, unique “Person_IDs” do not all have the same value in their ‘Percieved_Race’ field. We interpreted this in two ways: 1) the “Person_ID” was used twice for two different people or 2) the officers who noted the arrest were not able to assume the same race.

6. Conclusion

In this report, we focused on a dataset retrieved from the Toronto police service on the arrest information between 2020 to 2021. Based on the dataset and a literature review, we tried to answer three research questions: 1) in Toronto, does race influence the proportion of strip searches? 2) In Toronto, does crime type influence the proportion of strip searches? and 3) in Toronto, to what extent do race and crime type influence the proportion of strip searches? After our EDA and statistical analyses, we uncovered that in Toronto, both race and crime type influence the proportion of strip searches individually. However, there are no significant interactions between these two variables.

Moving forward with these findings, we could do further exploration into the dataset by testing for the multiple effect sizes that Race and Crime Type have on strip searches to see how "meaningful" the differences these predictors have on the outcome or the magnitude of differences they produce. Additionally, our research focused on the proportion of strip searches at a given time. We can explore the dataset's other categorical variables that indicate reasons for strip searches and actions during arrest. This can give a more nuanced picture of the motivations of officers and the reactions of people who were arrested in Toronto, adding to a greater understanding of the arrest protocols in Toronto. We can also look at other well researched predictors like Gender, Year, and Age, as they influence Booking and Arrest rates.
Although we found that there is no significant interaction between the two predictors, there could still be some patterns that are worth studying.

Our research only sheds some light on a limited cross-section of the Toronto Police Service operations, however we were able to unveil that Race and Crime Type affected strip searches in Toronto. This indicates that racial profiling and crime type based discrimination could potentially be happening in Toronto, especially amongst Indigenous folks. It is important for us to further examine our authorities' biases through studies like this in order to create policies driven by equity and justice, rather than prejudice.

7. References:

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Appendix:

T-Test Results Tables

Table 3. *T-test results for Race and proportion of Strip Search*

Race 1	Race 2	Statistic	p-value	p-value (Corrected)
Asian	Black	-2.54	0.01	0.18
Asian	Indigenous	-3.57	0.01	0.01
Asian	Latino	-1.17	0.24	1.00
Asian	Unknown	-1.35	0.18	1.00
Asian	White	-2.61	0.10	0.15
Black	Indigenous	-1.62	0.11	1.00
Black	Latino	0.68	0.49	1.00
Black	Unknown	1.11	0.27	1.00
Black	White	0.07	0.95	1.00
Indigenous	Latino	1.94	0.05	0.82
Indigenous	Unknown	2.49	0.01	0.21
Indigenous	White	1.73	0.07	1.00
Latino	Unknown	0.18	0.86	1.00
Latino	White	-0.65	0.51	1.00
Unknown	White	-1.09	0.28	1.00

Table 4. *T-test results for crime type and proportion of strip search*

Type 1	Type 2	Statistic	p-value	p-value (Corrected)
Other	Property	3.97	0.01	0.01
Other	Violent	1.09	0.28	0.83
Property	Violent	2.65	0.01	0.03

Tukey's HSD Tables:

Table 5. *Tukey's tests for race vs. the proportion of strip search*

Group 1	Group 2	Mean diff	P-value	Lower	Upper	Rejection
Asian	Black	0.0377	0.391	-0.0184	0.0938	False
Asian	Indigenous	0.0759	0.0025	0.0183	0.1334	True
Asian	Latino	0.0228	0.8485	-0.0342	0.0797	False
Asian	Unknown or Legacy	0.019	0.9	-0.0368	0.0747	False
Asian	White	0.0366	0.4162	-0.019	0.0922	False
Black	Indigenous	0.0382	0.4061	-0.0194	0.0957	False
Black	Latino	-0.0149	0.9	-0.0719	0.042	False
Black	Unknown or Legacy	-0.0187	0.9	-0.0745	0.037	False
Black	White	-0.0011	0.9	-0.0567	0.0545	False
Indigenous	Latino	-0.0531	0.0986	-0.1115	0.0053	False
Indigenous	Unknown or Legacy	-0.0569	0.0523	-0.1141	0.0003	False
Indigenous	White	-0.0393	0.362	-0.0964	0.0178	False
Latino	Unknown or Legacy	-0.0038	0.9	-0.0604	0.0528	False
Latino	White	0.0138	0.9	-0.0427	0.0703	False
Unknown or Legacy	White	0.0176	0.9	-0.0377	0.0729	False

Table 6. *Tukey's tests for crime type vs. the proportion of strip search*

Group 1	Group 2	Mean diff	P-value	Lower	Upper	Rejection
Other	Property	-0.0519	0.001	-0.0848	-0.019	True
Other	Violent	-0.0167	0.4567	-0.0496	0.0161	False
Property	Violent	0.0352	0.0314	0.0025	0.0679	True

Table 7. *Two-way ANOVA Results*

predictor	sum_sq	df	F	PR(>F)
C(Race)	0.257399	5.0	3.230002	0.007039
C(Crime_Type)	0.231017	2.0	7.247340	0.000793
C(Race):C(Crime_Type)	0.057601	10.0	0.361408	0.962479
Residual	7.618384	478.0	NaN	NaN