Toronto Police Service's Response to Mental Health Crises:

An Investigation of the 2020-2021 Arrests and Strip Search Data Set

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INTRODUCTION

The looming mental health crisis that has gripped North America is not a new occurrence. Rather with the advent of the Covid pandemic, certain inequities in mental health care have come to the forefront and have expressed as a spike in anti-social behaviour, property crime, and random acts of violence. The defunding of mental health institutions in Ontario since the 1990s, coupled with downloading provincial responsibilities to municipalities to deal with mental health issues as community outreach rather than at a mental health institution has only exacerbated this crisis (McCallum, 2016, p.21). And coupled with the surge of the mentally ill triggered by the stress of Covid lockdowns and disruption to their treatments have created a Sisyphean task for most metropolitan areas, including Toronto, to deal with the unintended consequences: the rise of the unhoused, drug addiction, and violent crimes. By default, Toronto Police Services (hereby known as TPS) have been forced to handle these vulnerable people that have slipped through social support. Rather than treating the root of the problem, the lack of mental health services, TPS' approach is triage, which only treats the symptoms: the crimes committed as a result of the mentally ill. While this issue is multifaceted and intersectional including wealth inequalities, racialization, and systemic biases, this investigation hopes to shed light and a better understanding of the mental health crisis that is currently gripping Toronto by isolating key predictors, variances, and tendencies within this TPS dataset.

LITERATURE REVIEW

As stated in the introduction, the Mental Health (hereby known as MH) crisis currently afflicting Toronto citizens is multifaceted. However, a major component of this crisis is the lack of continuous care for individuals suffering from MH breaks or lapses, be it schizophrenia or psychosis. While there is a higher percentage of MH services within Toronto compared to the rest of Ontario, there are still issues with inequalities as outlined by Law and Perlman in their *Exploring Geographic Variation of Mental Health Risk and Service Utilization of Doctors and*

Hospitals in Toronto: “The supply [MH services] was highest in the Toronto Central region of Ontario with 62.7 per 100,000 but these psychiatrists had smaller panels of patients and fewer overall visits per year. Interestingly, within regions, there was also variability in the characteristics of patients who received more outpatient care. In Toronto, patients who had more than 16 visits per year were less likely to have been admitted to inpatient psychiatry in the prior two years and reside in areas of higher income compared to patients with less than four visits per year. Health system inequities could be important in affecting MH, including access to community-based physician care” (Law and Perlman, 2018). The fact that a patient who received 16 visits per year were less likely to receive inpatient psychiatric help indicates a grave flaw in the system. The mentally ill are in a cycle of “catch and release” without any serious long-term care. This poses a serious community safety issue for the downtown core of Toronto.

As outlined in the midterm paper, Division 51’s catchment includes unhoused people, newly arrived immigrants, and drug users that frequent the needle exchange facilities around Moss Park. This area represents a family physician desert whereby the residents are unable to receive adequate follow-up care or continuous care due to a lack of general practitioners. This type of consistent medical treatment for MH issues can result in relapses of schizophrenia and psychosis. As Law and Perlman continue: “This trend is concerning given that contact with a physician or psychiatrist before hospitalization is strongly related to receiving appropriate follow-up care following a first-episode psychosis. Follow-up within 30 days of discharge from the hospital for persons with schizophrenia is associated with a reduced risk of readmission within 30 days. These patterns underscore the importance of having access to outpatient physician care among persons with MH conditions” (Law and Perlman, 2018). To compound matters, nearly 20% of all Ontario physicians are planning to retire within 5 years, and new physicians entering the workforce are not enough to replace these absences (Crawley, 2023). This is another looming crisis that will place more strain on vulnerable people who are most at risk of a MH crisis. Rather than focusing on preventative care, the medical system, like police services, is reacting in a triage environment only dealing with issues once they’ve expressed in a grave matter, i.e. a psychotic break.

There is a prevalence of people suffering from MH episodes and a more pronounced interaction with TPS. In the article, *Interactions between Police and Persons Who Experience Homelessness and Mental Illness in Toronto,* the statistics are quite sobering: "[A] high proportion of participants interacted with police in each year: 55.8% in the year prior to randomization, 51.7% in Study Year 1, and 43.0% in Study Year 2. Most persons with any police interaction had multiple interactions per year, with a median number of days of interactions of 4 (interquartile range [IQR] 2 to 8) in the year prior to randomization, 3 (IQR 1 to 8) in Study Year 1, and 3 (IQR 2 to 8) in Study Year 2" (Kouyoumdjian, Wang, et al., 2019). The study was over the course of three years following a constant sample group that was compared against a randomized group. What is troubling about this study is when it is compared to other regions. There is a higher rate of police interactions from 2009 to 2011 in Toronto of persons with MH episodes compared to British Columbia (Kouyoumdjian, Wang, et al., 2019). One glimmer of hope in this study sheds light on the need for housing. If participants had MH issues and were housed, the rate of police interactions dropped considerably (Kouyoumdjian, Wang, et al., 2019).

Focusing on TPS Division 51, we see that there is in fact a tendency of unhoused individuals with MH episodes and interaction with police that is statistically significantly above average for this catchment when compared to other Toronto neighbourhoods. "[A portion of Division 51's] catchment has a standardized prevalence ratio of MH conditions by a factor of 2.01 - 3.0 for hospital admissions, compared to a standardized prevalence ratio of MH conditions by a factor of 1.01 -2.0 for doctor visits" (Law and Perlman, 2018). This has huge implications for people living in Divison 51's catchment suffering from MH issues being unable to get consistent preventative care and possibly relapsing with a severe MH episode.

In a review of these citations, the literary claims that individuals that are unhoused, unable to secure consistent medical care in the form of a GP or family doctor, and who reside in Toronto are more likely to have numerous police interactions. And as postulated in both Law and Perlman's study and Kouyoumdjian, Wang, et al.'s study, the statistical significance for TPS interacting with the mentally ill is more prevalent when compared to other Canadian regions.

RESEARCH OBJECTIVES AND QUESTIONS

As postulated in the introduction and literature review, the MH crisis afflicting Toronto has been addressed not by routine medical care, but by TPS responding to crimes being committed by the mentally ill in Toronto. As no real Provincial nor Federal intervention has taken place, this report will investigate the frequency and nature of TPS's response to Action at Arrest - Mental Health Instance. And by no means is this report designating these instances in a negative light, rather TPS deeming someone not mentally fit could be the first stages to their recovery and receiving the help they need, albeit outside of an overtaxed medical system.

1) Does Division 51 have a more pronounced presence of Arrest Action - Mental Health Instance compared to other TPS Divisions?
2) What predicting features increase the likelihood of being booked and then categorized as an Action at Arrest - Mental Health Instance by TPS?
3) Does Perceived Race influence being booked and then categorized as an Action at Arrest - Mental Health Instance by TPS?

EDA

Description of Data Set

> Toronto Police Service. (2022, November 10). *Arrests and strip searches (RBDC-arr-TBL-001)*. Toronto Police Service Public Safety Data Portal. Retrieved February 22, 2023, from https://data.torontopolice.on.ca/datasets/TorontoPS::arrests-and-strip-searches-rbdc-arr-tbl-001/about

The Arrests and Strip Searches (RBDC-arr-TBL-001) is a data set produced by the Toronto Police Service. In accordance with the Municipal Freedom of Information and Protection of Privacy Act (MFIPPA), citizens and corporations have a reasonable right to access the information held by local governments and certain institutions. The data set has been deemed 'public' so anyone can access said data set.

The data set contains 65,276 rows and 25 columns/variables and covers 2020-2021.

Null/NaN values were removed.

Please note the below table outlines the specific variables of interest to this report.

Variable	dType	Values
Arrest_Year	int64	Categorical
Arrest_Month	**int64**	**Continous ****
Perceived_Race	object	Nominal
Sex	object	Nominal
Age_group__at_arrest_	**int64**	**Continous****
Youth_at_arrest__under_18_years	object	Binary
ArrestLocDiv	object	Nominal
StripSearch	int64	Binary
Booked	Int64	Binary
Occurrence_Category	object	Nominal
Actions_at_arrest___Concealed	Int64	Binary
Actions_at_arrest___Combative	Int64	Binary

Actions_at_arrest___Resisted__d	Int64	Binary
Actions_at_arrest___Mental_inst	Int64	Binary
Actions_at_arrest___Assaulted_officer	Int64	Binary
Actions_at_arrest___Cooperative	Int64	Binary
SearchReason_CauseInjury	float64	Binary
SearchReason_AssistEscape	float64	Binary
SearchReason_PossessWeapons	float64	Binary
SearchReason_PossessEvidence	float64	Binary
ItemsFound	float64	Binary

****** Denotes that the variable has been processed into a new value to fit the report's statistical models.

Correlation Matrix

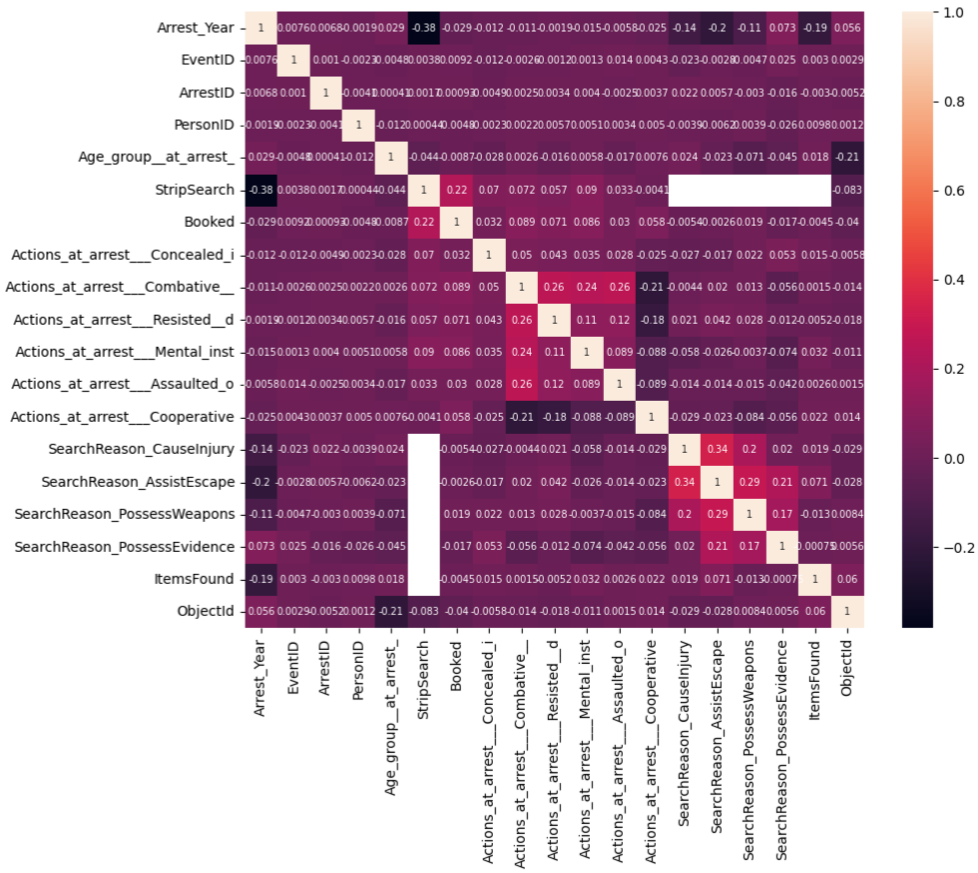

Figure 1

A correlation matrix expressing correlations as a heatmap.

Top 5 positive correlations

SearchReason_CauseInjury	SearchReason_AssistEscape	0.338460
SearchReason_AssistEscape	SearchReason_PossessWeapons	0.290227
Actions_at_arrest___Combative__	Actions_at_arrest___Assaulted_o	0.260223
Actions_at_arrest___Combative__	Actions_at_arrest___Resisted__d	0.260189
Actions_at_arrest___Combative__	Actions_at_arrest___Mental_inst	0.241561

Table 1 Top 5 Positive Correlations between features

Top 5 negative correlations

Arrest_Year	StripSearch	-0.382512
Actions_at_arrest___Combative__	Actions_at_arrest___Cooperative	-0.214554
Age_group__at_arrest_	ObjectId	-0.209104
Arrest_Year	SearchReason_AssistEscape	-0.199185
Arrest_Year	ItemsFound	-0.192501

Table 2 Top 5 Negative Correlations between features

It is interesting to note in Table 1, there exists a correlation between Actions_at_arrest___Combative__ and Actions_at_arrest___Mental_inst.

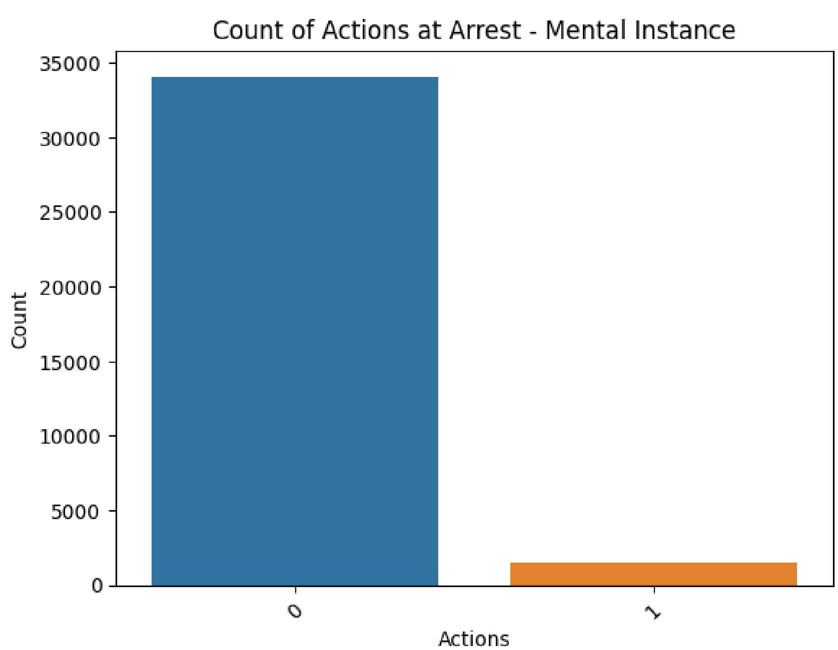

Figure 2

In Figure 2, we see an imbalance in the data for Actions at Arrest - Mental Health Instance. This will need to be corrected when running the Logistic Regression as the model will be unable to learn from so few instances of Actions at Arrest - Mental Health.

Actions at Arrest - Mental Health Instance Count

0 = Not a Mental Health Instance	34084
1 = Yes, a Mental Health Instance	1533

Table 3

Table 3 confirms the imbalance in the data as about ~5% of instances were classified as Actions at Arrest - Mental Health Instance.

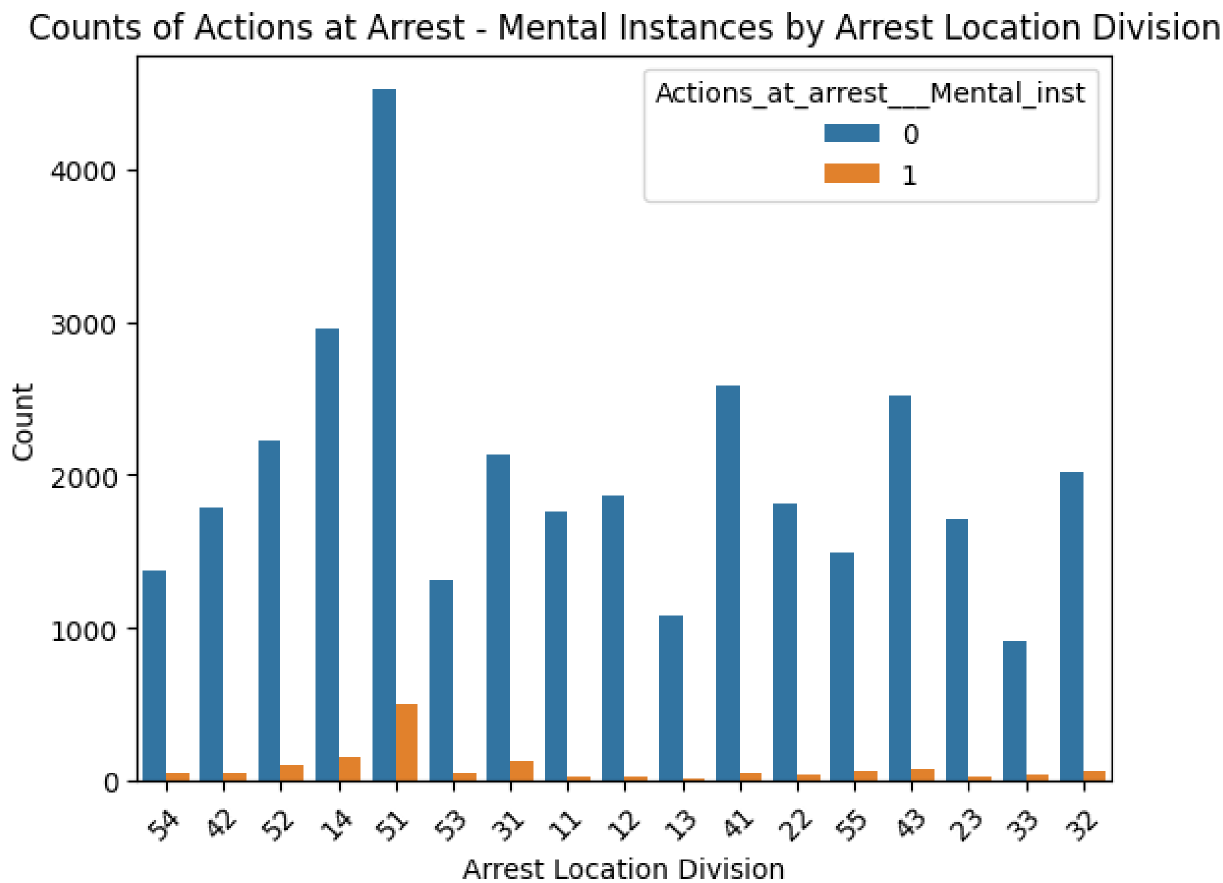

Figure 3

In Figure 3, we can see that Divison 51 has very pronounced Actions at Arrest - Mental Health Instances compared to other TPS Divisions.

Actions at Arrest - Combative Count

0 = No Actions_at_arrest___Combative__	33559
1 = Yes, Actions_at_arrest___Combative__	2058

Table 4

In Table 4, we can see the count similarity between Actions at Arrest - Combative compared to Actions at Arrest - Mental Health Instance.

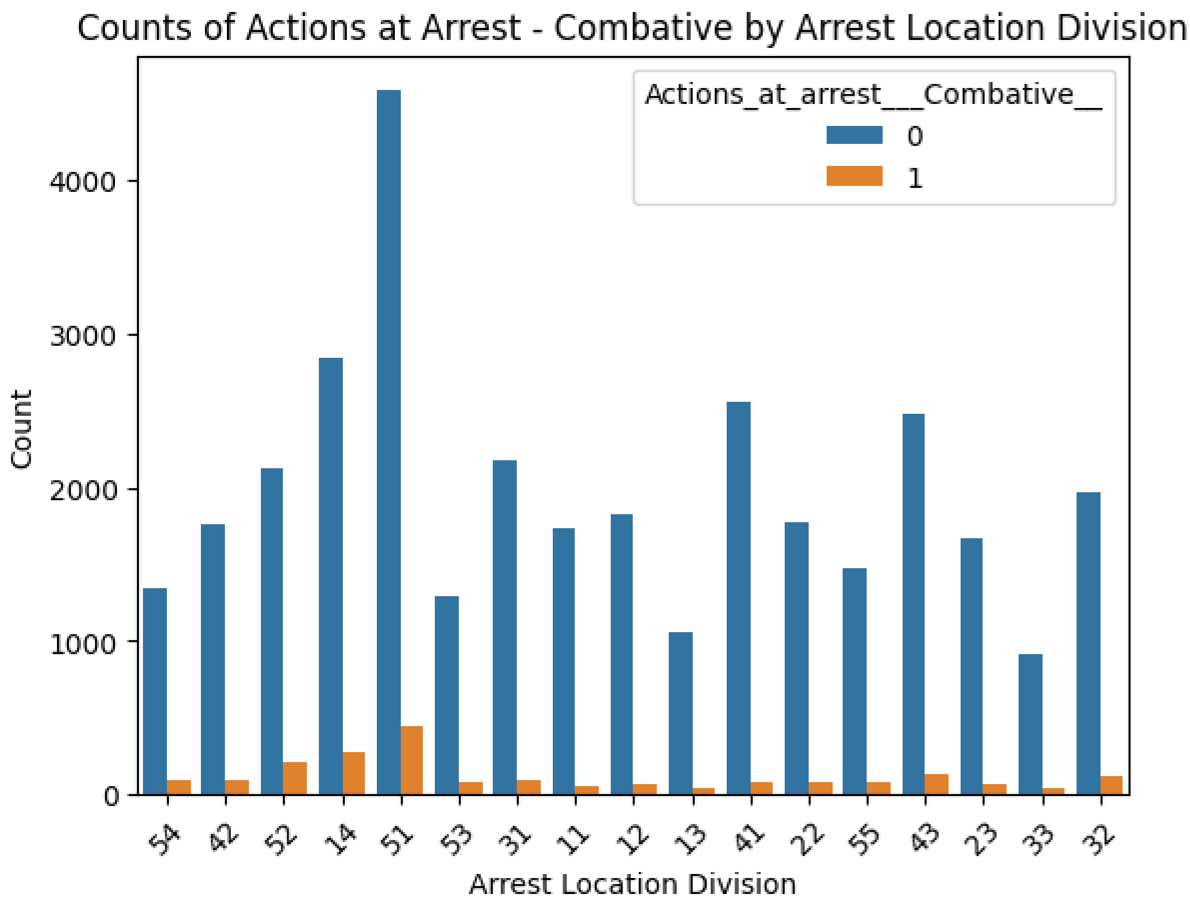

Figure 4

In Figure 4, again we see the similarity to Actions at Arrest - Mental Health Instance compared to Actions at Arrest - Combative Arrest by Location Divison. In both Figure 4 and Figure 3, we see Div 51 has a pronounced count that is closely aligned.

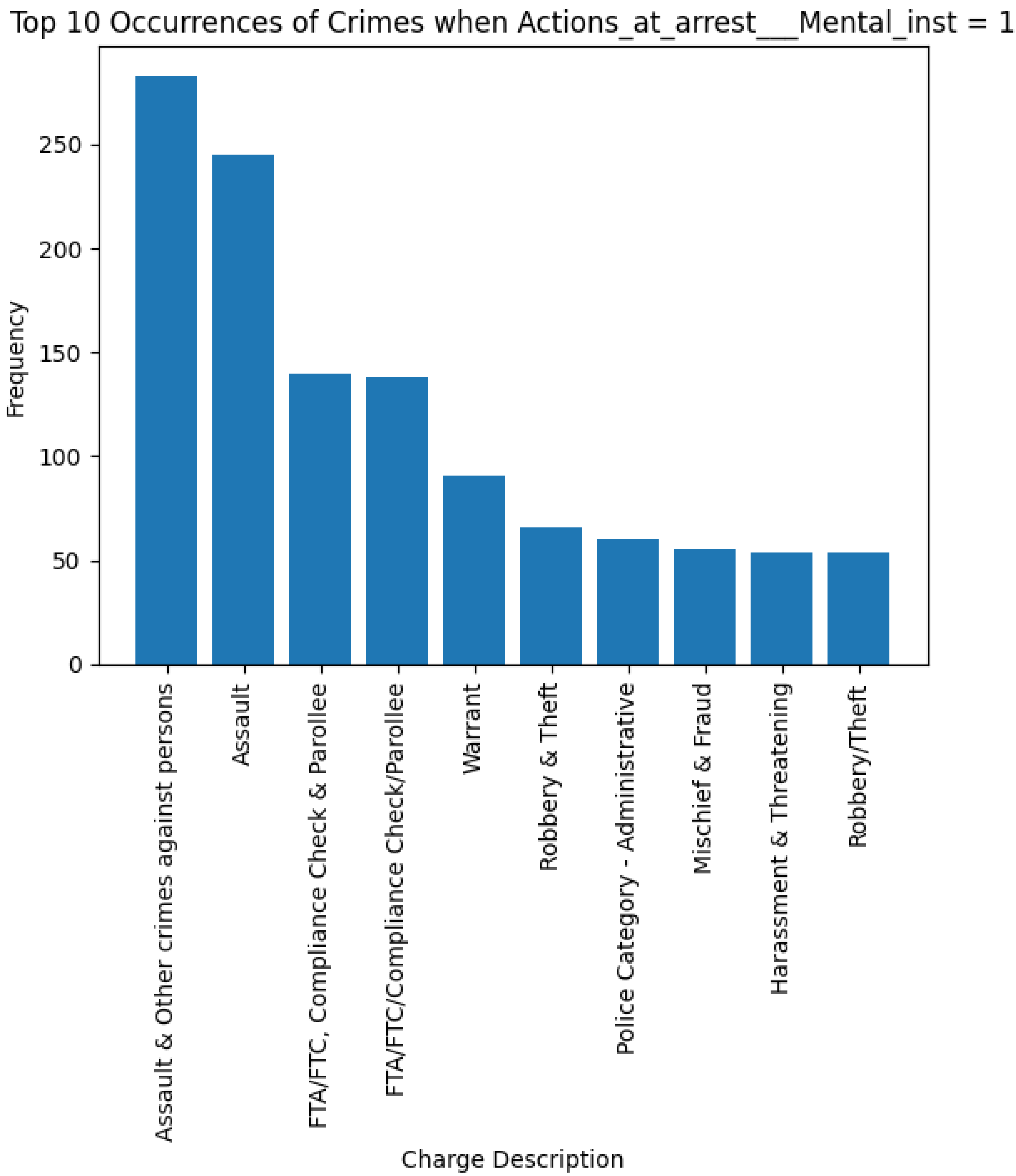

Figure 5

In Figure 5, we see the Occurrence of Crime or "Charge" when Actions at Arrest - Mental Health Instance is true (binary = 1). We can see that Assault is the top crime. This further supports the correlation between Actions at Arrest - Mental Health Instance and Actions at Arrest - Combative. TPS responds to an assualt call by a violent individual, and the officers responding are then presumably assaulted themselves.

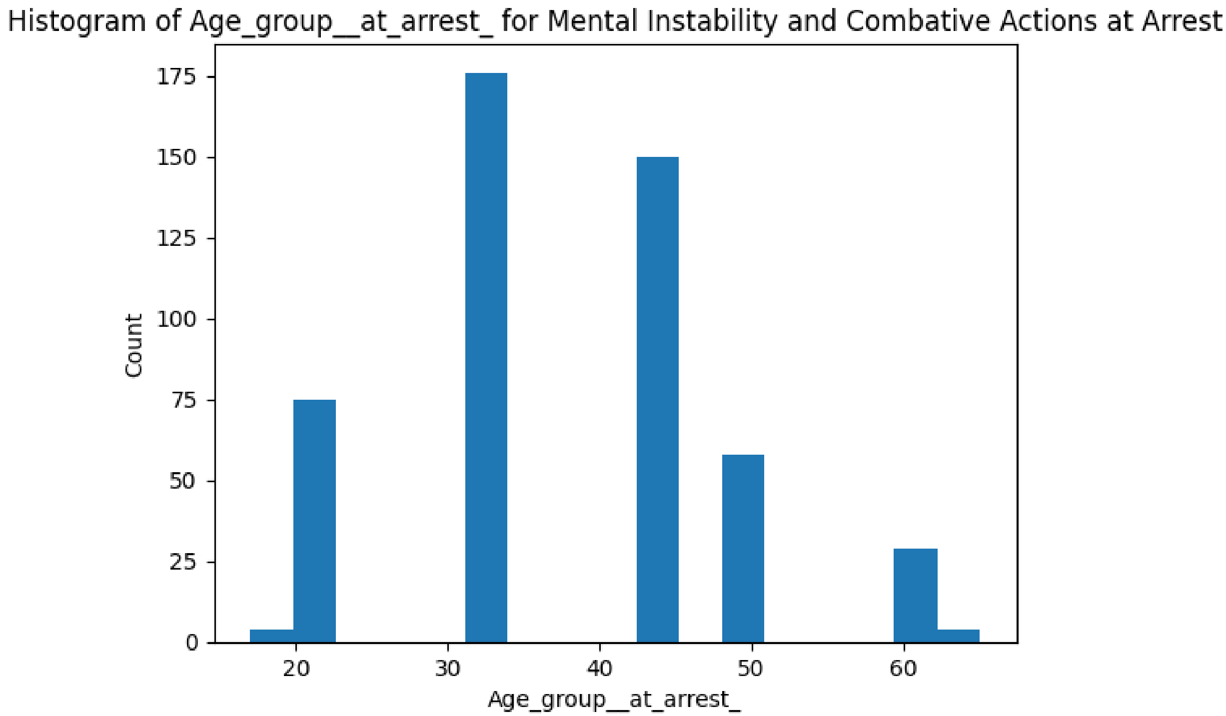

Figure 6

In Figure 6, we see the age distribution of Actions at Arrest - Mental Instance and Combative. Please note the age variable was processed to reflect the mean ages to create a continuous variable. We see that 30s to 40s is the highest group where Mental Health Instance and Combative expresses.

METHODS

Data cleaning and pre-processing

Data cleaning and pre-processing of specific variables were conducted to ensure model fit and the removal of extraneous outliers.

1) All instances of Division XX were removed as this denoted a crime or arrest call conducted outside of the TPS jurisdiction, thus we can infer these instances occurred

outside Toronto proper. This report is only interested in calls or arrests conducted within Toronto city limits.

2) Age_Group_at_arrest_ and Arrest_Month were modified to reflect a continuous value. This was to ensure proper fitting for our models, ex. ANOVA, ANOCA, et al.
    a) Age Group was converted into the mean age of their respective groupings, ex. Aged 18 to 24 years is now 21.5.
    b) Arrest_Month was converted into quarters, ex. Jan–Mar is now 1, reflecting the first quarter of the year.
3) Sex was left to a binary as it was not referring to gender. There were 4 values that were removed and noted as Undefined sex. While it is understood that gender is a construct, in this context of TPS, the sex variable is referring to biological genitalia as this is the classifying factor (Wallace, 2005)

<u>Modeling</u>

To investigate whether there is an upward tendency of police calls resulting in MH crisis overall in TPS and whether Division 51, in particular, has a more pronounced presence of MH crisis, we will conduct a one-way ANOVA test. The dataset is grouped by time slices to generate a new variable 'mental-health crisis-related arrests per quarter' (continuous variable) which will be our dependent variable.

Next, we will focus on the comparison between Division 51 and other divisions in terms of MH crisis-related arrests. We will calculate the proportion of MH crisis-related arrests per quarter for each police division, which will be obtained by dividing the number of 'mental-health crisis-related arrests per quarter' by the total number of 'arrests per quarter'. This proportion will allow for a fair comparison between divisions, accounting for the differences in the total number of arrests.

However, to statistically test, if Division 51 has a more pronounced instance of MH crisis-related arrests than other divisions, we will conduct an Analysis of Variance (ANOVA) test. The dependent variable for this analysis will be the proportion of MH crisis arrests per quarter, and the independent variable will be the ‘Police Division’ categorical variable. The null hypothesis is no statistically significant difference in the mean of MH crisis-related arrests per quarter among the fourteen divisions, keeping a keen eye on the difference in mean for Div 51.

To make sure we have enough samples to measure a medium effect size, we will conduct a power analysis.

For our power analysis, we will define the following:

1) **Effect size:** To select a reasonable effect size for an ANCOVA, we picked a moderate effect size of 0.25. This was decided due to the limited deemed instances of Actions at Arrest - Mental Health Instances within the data set.
2) **Alpha level** (Type I error): We picked the most widely accept alpha level of 0.05.
3) **Power** (1 - Type II error rate): We picked a reasonable and common power level of 0.80, meaning that we have a 80% chance of detecting a true effect.

So our sample size will be ~**63.77**. For reference, our dataset contains 65,276 entries. Of these entries, we have **1533** Actions at Arrest – Mental Health Instance. Our data satisfies our sample requirements.

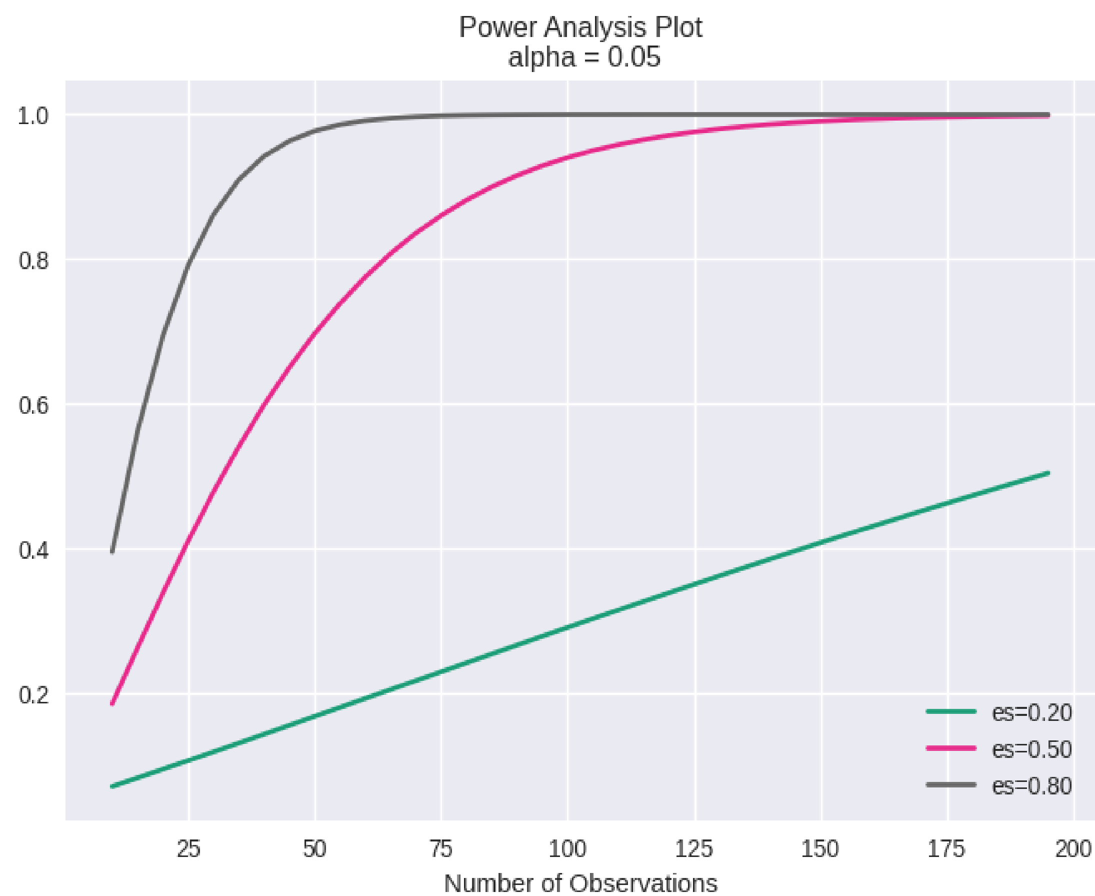

Figure 7

Figure 7, Plot of Power of Analysis for ANCOVA of MH Crisis per Quarter ~ TPS Division + Age.

To investigate the difference that age has on the proportion of MH crisis-related arrests, we conduct an Analysis of Covariance (ANCOVA). The dependent variable for this analysis will be the proportion of MH crisis arrests per quarter, the independent variable will be the TPS Divisions' categorical variable, and the continuous covariate is age. This allows us to assess whether the number of arrests per month differs significantly between mental-health related arrests while controlling for the effect of age. The null hypothesis for this ANCOVA test is there are no statistically significant differences in the proportions of MH crisis-related arrests per quarter between all Toronto police divisions accounting for the effect of 'Age'.

Finally, we will use a logistic regression model to answer whether demographic predictors, specifically perceived race, and other features, influence the likelihood of an individual being categorized as a MH instance. We will employ feature reduction to discover which predicting features increase the likelihood of being categorized as a MH instance in TPS. The dependent variable in the logistic regression model is a binary variable representing whether an arrest was categorized as a MH instance. The independent variables are perceived race, gender, age, crime type and if the person was combative during the arrest. Those are all categorical variables except for age. We will one-hot encode these variables into our logistic regression except for age which is a continuous integer.

The logistic regression model will allow us to calculate the odds ratios for each demographic predictor and other predictive features, which represent the change in odds or likelihood of an arrest being categorized as an MH instance for each unit change in the predictor variable, holding all other variables constant. We can also compare those findings alongside their associated p-values and determine the statistical significance between the demographic predictors and the likelihood of an arrest being categorized as an MH instance within division 51.

During the initial data exploration phase, we discovered that the MH instance dependent variable is heavily unbalanced towards negative cases (i.e. binary = 0 or not a MH instance). This can lead to biased estimates and reduced predictive performance in logistic regression models. To address this issue, we will use SMOTE (Synthetic Minority Over-sampling Technique) to balance the data. SMOTE is a technique used to oversample a minority class, in this case, the MH instance occurring or binary = 1. It can even generate synthetic samples by interpolating between the chosen instance and its nearest neighbours.

RESULTS & DISCOVERIES

To investigate whether there is an upward tendency of police calls resulting in MH instance overall in the Toronto Police Services and whether Division 51 in particular has a more pronounced presence of MH instances, we created a boxplot that shows the proportion of MH crisis related arrests per quarter per division.

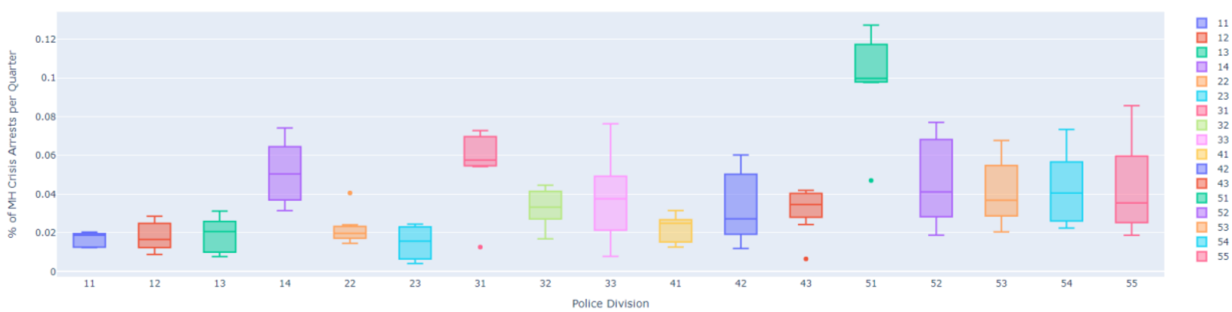

Figure 8

In Figure 8, a visual inspection proves that Division 51 does indeed show positive, supporting evidence for our research question, there is a mean difference in MH instances among the TPS Divisions. We conducted an ANOVA test with the following results:

	F-statistic	p-value
one-way ANOVA	13.3	1.17e-19 (**)

Table 5

Table 5 shows, with statistical significance based on a p-value below our alpha of .05, that the mean proportion of MH instances is not equal amongst all divisions. Therefore, we have significant statistical evidence to reject our null hypothesis that there is no difference in the mean of MH instances among the TPS Divisions. The alternative hypothesis, there is in fact a difference in the mean of MH instances among the TPS Divisions, is accepted.

Table 6 below shows the Tukey Pairwise Test filtered to show Divison 51 mean difference compared to other TPS divisions with the following results:

group1	**group2**	**Mean diff**	**p-adj**	**lower**	**upper**	**reject**
11	51	0.0878	0	0.059	0.1165	TRUE
12	51	0.0824	0	0.0537	0.1111	TRUE
13	51	0.0815	0	0.0528	0.1103	TRUE
14	51	0.0494	0	0.0206	0.0781	TRUE
22	51	0.0786	0	0.0499	0.1073	TRUE
23	51	0.0856	0	0.0569	0.1144	TRUE
31	51	0.0444	0	0.0157	0.0731	TRUE
32	51	0.0674	0	0.0387	0.0961	TRUE
33	51	0.063	0	0.0343	0.0917	TRUE
41	51	0.0783	0	0.0496	0.107	TRUE
42	51	0.0673	0	0.0386	0.0961	TRUE
43	51	0.0687	0	0.04	0.0974	TRUE
51	52	-0.054	0	-0.083	-0.025	TRUE
51	53	-0.059	0	-0.088	-0.031	TRUE
51	54	-0.058	0	-0.087	-0.029	TRUE
51	55	-0.057	0	-0.086	-0.029	TRUE

Table 6

Table 6 is evidence to a p-value below our alpha of .05, therefore there is statistically significant evidence that Divison 51 has a mean difference that is different from all 16 TPS Divisions present in our data set.

Our ANCOVA results are as follows:

Overall Results	R-squared	F-statistic	Log-Likelihood
ANCOVA	0.643	12.48	376.53

Table 7

And our equation coefficients:

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-0.0163	0.057	-0.288	0.774	-0.129	0.096
Division 12	0.0064	0.008	0.762	0.448	-0.010	0.023
Division 13	0.0060	0.008	0.738	0.462	-0.010	0.022
Division 14	0.0390	0.008	4.736	0.000	0.023	0.055
Division 22	0.0102	0.008	1.217	0.226	-0.006	0.027
Division 23	0.0036	0.009	0.414	0.680	-0.014	0.021
Division 31	0.0459	0.009	4.833	0.000	0.027	0.065
Division 32	0.0220	0.009	2.515	0.013	0.005	0.039
Division 33	0.0276	0.010	2.801	0.006	0.008	0.047
Division 41	0.0103	0.008	1.240	0.218	-0.006	0.027
Division 42	0.0217	0.008	2.550	0.012	0.005	0.038
Division 43	0.0210	0.009	2.337	0.021	0.003	0.039
Division 51	**0.0886**	**0.008**	**10.660**	**0.000**	**0.072**	**0.105**
Division 52	0.0352	0.009	4.030	0.000	0.018	0.053
Division 53	0.0296	0.008	3.480	0.001	0.013	0.046
Division 54	0.0305	0.008	3.717	0.000	0.014	0.047
Division 55	0.0310	0.008	3.761	0.000	0.015	0.047
Person_age	0.0007	0.001	0.516	0.607	-0.002	0.004

Table 8, ANCOVA Coefficients Table

In Table 8, the ANCOVA results displays the statistically significant result for Division 51 which is in bold. Division 51 has the largest unit change compared to the other TPS Divisions. There seems to be a relationship between the interactions of MH Instance, Age and Division. Conversely, Age has no statistical significance difference in variance among age groups that have been deemed a MH Instance.

For the Logistic Regression, our first model aims to answer whether demographic predictors, specifically perceived race, influence the likelihood of an individual being booked and then categorized as a MH instance.

	coefficient	**std err**	**Z score**	**P-Value**	**Confidence Interval [0.025**	**Confidence Interval 0.975]**
Black	0.1322	0.016	8.424	0	0.101	0.163
East/Southeast Asian	-0.3325	0.036	-9.178	0	-0.404	-0.262
Indigenous	0.236	0.047	5.002	0	0.144	0.328
Latino	-0.5078	0.058	-8.699	0	-0.622	-0.393
Middle-Eastern	-0.0208	0.039	-0.54	0.589	-0.096	0.055

South Asian	-0.3701	0.041	-9.032	0	-0.45	-0.29
Unknown or Legacy	-0.4827	0.034	-14.32	0	-0.549	-0.417
White	0.0537	0.013	4.079	0	0.028	0.079

Table 9 Coefficient of LR model MH Instance ~ Perceived Race

In Table 9, all race excepted for Middle Eastern has statistical significance as proven by a p-value below our alpha .05.

	Lower CI	Upper CI	Odds Ratio
Black	1.119174	1.182399	1.150352
East/Southeast Asian	0.692081	0.785900	0.737500
Indigenous	1.160113	1.370951	1.261134
Latino	0.600862	0.733572	0.663909
South Asian	0.677057	0.779514	0.726482
Unknown or Legacy	0.537521	0.607156	0.571278
White	1.044795	1.094078	1.069153

Table 10 Confidence Interval and Odds Ratio

In Table 10, the logistic regression model was employed to test the effects of perceived race against the instances of an alleged perpetrator being deemed a MH instance. Of the perceived races, Indigenous and Black have the most pronounced odds compared to the races. Please note, Middle Eastern was omitted due to a p-value above our Alpha of .05.

A person who is Black has an odd ratio that is approximately 1.15 and an Indigenous person's odds ratio is 1.26 when accounting for a Mental Health Instance at the time of the arrest. For each additional Action at Arrest - Mental Health being True or a binary = 1, the increase for the Black person increases by 1.15 and 1.26 for an Indigenous person. This is significant compared to most other races which have a lower odds ratio.

And finally, we have our feature reduction-based logistic regression that aims to discover which predicting features increase the likelihood of being booked and then categorized as a MH instance in TPS the most. We made a total of four iterations:

Iteration	**Features used**	**Worst performing feature (removed)**
1	All	Gender
2	Ethnicity, age, crime type, combative person	Ethnicity
3	Age, crime type, combative person	Age
4	Crime type, combative person	Crime type

Table 11 Feature Selection for Logistic Regression Models

We found that if the person was combative at the time of the arrest had the strongest predictive feature whether the person was then deemed a MH instance.

Feature	**Odds Ratio**
Combative_0	0.709890
Combative_1	7.035851

Table 12 Odds Ratio for Combative at Time of Arrest

In Table 12, A person who is combative has an odd ratio that is approximately 7.03 compared to a person who is not combative with an odds ratio of .71. For each additional Action at Arrest - Comabtive being True or a binary = 1, the increase for the Combative person increases by 7.03 that they will then be deemed a Mental Health instance. An odds ratio this high would confidently state that if a person is combative at the time of booking then they are 7 times more likely to be deemed a Mental Health Instance by TPS.

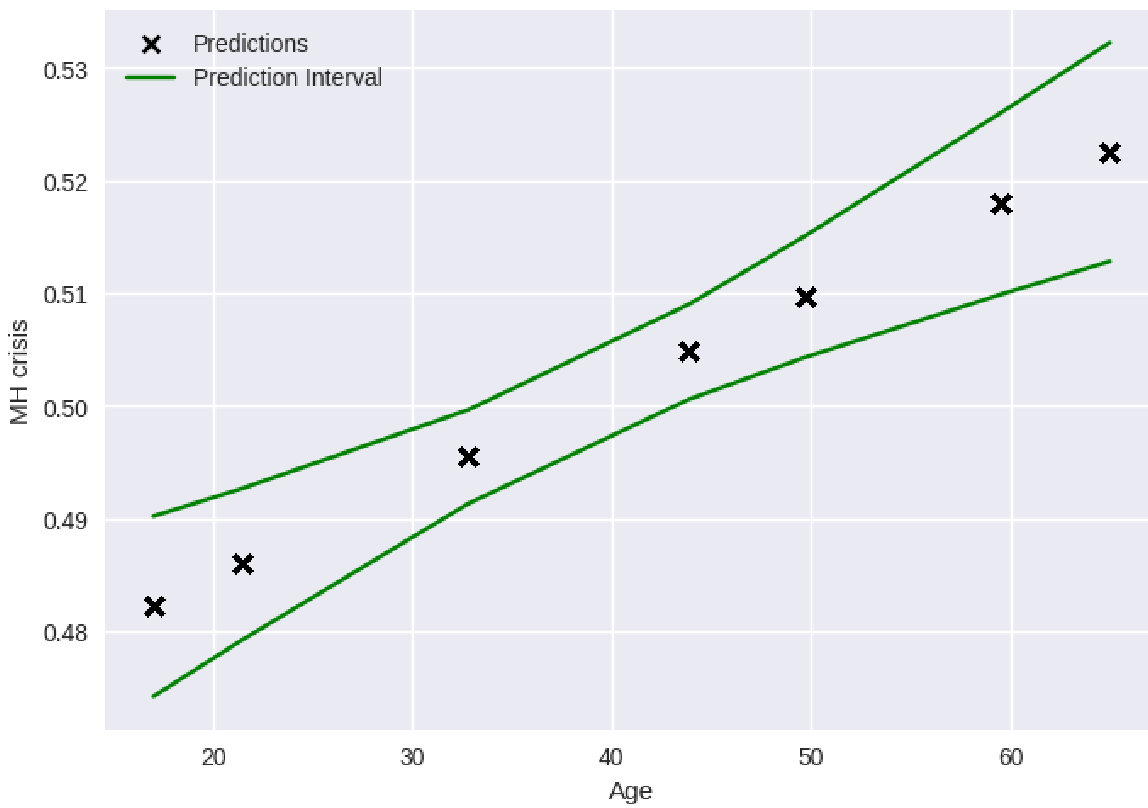

Figure 9 Prediction Interval MH Instance Probability ~ Age

In Figure 9, we see that older individuals have a higher prediction rate of being deemed a MH Instance by TPS compared to someone in their early 20s based off the data set.

	Precision	**Recall**	**F1-Score**	**Support**
0	.59	.96	.73	6829
1	.88	.32	.47	6795

Table 13 Precision, Recall, and F1 Score Logistic Regression Model MH Instance ~ Combative at Arrest

Table 13 presents the strengths and weaknesses of the model. Recall for instances where there was not a MH instance indicates the model can classify these instances the best at 96%. Precisions for instances where there was a MH instance, the model was able to correctly identify these instances 88% of the time. The F1 score which combines both Precision and recall shows the model is best suited to classify instances where there was not a MH instance.

Model Accuracy	.64	13624 rows

Table 14 Accuracy of Logistic Regression Mode MH Instance ~ Combative at Arrest

In Table 14, we see the overall accuracy of the model is 64% which is moderate in classifying both MH instances and no MH instances. The row count was augmented using SMOTE.

True Negatives	6525
False Positives	304
True Positives	2192
False Negatives	4603

Table 15 Confusion Matrix Logistic Regression Model MH Instance ~ Combative at Arrest

From Table 15, we see that the model best-classified instances that were True Negative than True Positive. This could be because of the imbalance in the data. While SMOTE did help increase our accuracy, there are still limitations to this method. The False Negative could also be because of the SMOTE data augmentation. More data would be needed to get better results.

DISCUSSION

To answer whether there is an upward tendency of police calls resulting in MH instance in Division 51, we aggregated our results to show with statistical significance that there is a mean difference of proportional arrests that are MH instances between divisions because our ANOVA test came out with a p-value < 0.05. Furthermore, we have shown with the Tukey's test that Division 51's mean MH crisis arrests in particular are not equal to the mean MH crisis arrest of all other divisions in Toronto.

Based on the ANCOVA results, we can make multiple statistically significant conclusions.

- Overall Model Significance: The F-statistic is 12.48, with a p-value of 3.89e-19, which is statistically significant at our alpha of 0.05. This indicates that, after controlling for age, there is a significant difference in the proportion of mental-health instance-related arrests per quarter among the different police divisions which is aligned with our ANOVA and Tukey test.
- The coefficient for Division 51 is 0.0886, with a p-value less than 0.001. This suggests that Division 51 has a significantly higher proportion of mental-health crisis-related arrests per quarter compared followed by Division 31 with a coefficient of 0.0459 and a p-value also less than 0.001.
- Other Divisions: Several other divisions also show statistically significant differences. For example, Division 14, Division 31, Division 32, Division 33, Division 42, Division 43, Division 52, Division 53, Division 54, and Division 55 all have statistically significant coefficients. These findings suggest that there are differences in the proportion of mental-health crisis-related arrests per quarter among these divisions as well, but all with coefficients less than almost half the size of Division 51.
- Age: The coefficient for age is 0.0007, with a p-value of 0.607. This indicates that, after controlling for the effect of police divisions, age does not have a statistically significant effect on the proportion of MH instance arrests per quarter.
- Model Fit: The adjusted R-squared value is 0.591, which implies that the model explains about 59.1% of the variation in the proportion of MH instance arrests per quarter. Although not perfect, this suggests that the model does a moderate job of capturing the relationships in the data.

Finally, looking at our logistic regression which aimed to investigate the influence of perceived race on the likelihood of an individual being categorized by TPS as having a mental health instance during an arrest and which features are the strongest predictors of a MH instance outcome. We have discovered the following:

- "Indigenous", "Black" and "White" are positively correlated with the outcome of being a MH instance-related arrest and they are all statistically significant.
  - "Indigenous" individuals have the highest log odds of being categorized as having a MH instance related arrest compared to the remaining ethnicities with a p-value < 0.001 and coef = 0.2360. Closely following by "black" with coef = 0.1322, p-value < 0.001 and finally "white" with coef = 0.0537, p-value < 0.001.
  - Odds Ratio for Black individuals is 1.15.
  - Odds Ratio for Indigenous individuals is 1.26.
- "Latino", "South Asian" and "East/southeast Asian" have a lower odds ratio of being categorized as a MH instance while in custody, and the results are all statistically significant for those three ethnicities.
  - "Latino" individuals have the lowest log-odds of being categorized as MH instance arrest compared to the rest of the ethnicities with coef = -0.5078, p-value < 0.001. Followed by "South Asian" and "East/Southeast Asian" with coef = -0.3325, p-value < 0.001 and coef = -0.3701, p-value < 0.001 respectively.
- "Middle-eastern" individuals had a p-value of 0.589 which is greater than our alpha of 0.05, so we cannot make a conclusion.
- The Occurance of Crime is not a good predicating factor to determine whether or not an individual will be deemed a MH instance while in the custody of TPS. However, it is important to note that in our EDA we discovered that Assault is the top occurrence of crime for a call to TPS that results in the perpetrator being then classified as a MH instance.
- The prediction interval for MH instance controlled for Age shows that the data reflecting older individuals, ages > 50 have a greater certainty of being classified than an individual in their 20s as a MH instance with our Logistic Regression Model. This claim is also supported by our findings in EDA Figure 6 visualizing the age distribution of individuals deemed to be a MH instance.

While conducting a feature reduction analysis, we discovered that the strongest predictor is whether the individual is combative or not. Closely followed by the occurrence of crime and then by age. Gender is not a strong predictor of MH crisis-related arrest.

CONCLUSION

As supported by our literature review claims and this report's statistical findings, our research questions were answered. There is in fact a difference in mean counts of MH instances at Division 51 compared to all other TPS divisions present in the data set. The logistic regression proved that perceived race, in all races except Middle Eastern individuals, is a predicting feature for a MH instance, while being combative in the custody of TPS had the highest predicting outcome for MH instances. So what does this all mean? Vulnerable individuals that live within Division 51's catchment have a greater likelihood of being classified as a MH instance while in TPS custody. Racialized individuals, specifically Black and Indigenous, have higher odds of being classified as a MH instance. But by far, a person who is combative while in the custody of TPS is seven times more likely to be classified as a MH instance versus someone who is not combative. As Figure 5 visualizes in the EDA section, the occurrence of crime - Assault is the majority of crimes charged to individuals that were then classified as a MH instance. This supports the high odds ratio between an individual being combative while in TPS custody and then being classified as a MH instance.

Without supporting data that specifies the type of combative behaviour, it's hard to discern the circumstances. But this does indicate that a troubled individual is unaware of the repercussions of striking an officer, thus this could be interpreted as a better outcome for the individual rather than being punished further with a heftier sentencing. They are not cognizant of their actions and need help. But by the same token, what is the outcome for the individual being classified as a combative and MH instance? Without a more robust MH system that offers to house the individual, there could be a cycle of "catch and release" of individuals that are then placed back into the current community outreach system i.e. shelter system or on the streets. For Division 51's catchment where continuous medical care is lacking, as is the case in most of Ontario, individuals are treated in a triage manner at St. Michael's emergency room. And as our literature review has claimed along with the current status in Toronto, community outreach for mentally ill individuals without consistent and proper care and housing will only result in the individual relapsing into another possible psychotic break, thus the cycle continues for TPS services to respond to calls regarding a crime related to a MH instance – in most cases, the call would be responding to an assault. Summarizing the findings, a person suffering from a MH crisis receives government services, most likely TPS, if they commit an assault, are racialized, and were combative while in custody. This is an ominous finding that classifies a vulnerable segment of the population that is ignored until they become violent.

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