**THE POTENTIAL FOR MACHINE LEARNING IN MENTAL HEALTH POLICING: PREDICTING OUTCOMES OF MENTAL HEALTH RELATED CALLS FOR SERVICE**

**THE POTENTIAL FOR MACHINE LEARNING IN MENTAL HEALTH POLICING: PREDICTING OUTCOMES OF MENTAL HEALTH RELATED CALLS FOR SERVICE**

**By DANIEL PEARSON HIRDES, B.A.**

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**LAY ABSTRACT**

The study goal was to predict outcomes following police interactions with persons with mental illness (PMIs). Additionally we compare the predictive validity of logistic regression and Random Forests learning algorithms. Classification approaches were applied to outcomes following police interactions with PMIs, including: high risk of harm to self, high risk of harm to others, and high risk of failure to care for self within 24 hours and 72 hours of initial police contact. The study also sought to determine if the predictive accuracy of Random Forests was sensitive to the police service community. Variation in predictive accuracy was assessed between a merged data set (13 communities) and 3 community-specific data. The study found that the predictive accuracy of the classification approaches on outcomes was modest. Random Forests exhibited greater predictive validity than logistic regression. The performance of the Random Forests suggested that performance was not sensitive to police service context.

**ABSTRACT**

My objective was to predict outcomes following police interactions with PMIs, and compare the predictive accuracy of logistic regression models and Random Forests learning algorithms. Additionally I evaluated if predictive accuracy of Random Forests changed when applied to merged versus region-specific data. I conducted a retrospective cohort study of reports completed by police in 13 communities between 2015 and 2018. 13,058 reports were analyzed. Random Forests learning algorithms were compared against logistic regression models for predictive accuracy in a merged dataset (13 communities) and 3 regional datasets. Outcomes for prediction were high risk of harm to self, risk of harm to others, and risk of failure to care for self within 24 and 72 hours following police contact. Random Forests learning algorithms were trained on merged and regional datasets, and compared against merged and regional holdout datasets. Performance was compared by area under the curve. For Random Forests learning algorithms, confusion matrix statistics were calculated for each outcome and predictive utility was examined by calculating conditional probabilities.   
Prediction accuracy was modest across all methods. Random Forests achieved better predictive accuracy than logistic regression. Random Forests accuracy varied between merged and regional holdout data. Sensitivity of Random Forests learning algorithms were moderate (74% average, 6 outcomes, merged holdout set). Specificity was low (53% average, 6 outcomes, merged holdout set). Conditional probabilities were modestly improved by the use of the Random Forests learning algorithm. The rareness of the target outcomes created a situation where even predictions with moderate likelihood ratios had only modest predictive value. Though the Random Forests learning algorithms did outperform the logistic regression learning algorithms, the clinical significance of those benefits were limited when conditional probabilities were calculated.These findings are limited to the outcomes considered, and may not apply to more common outcomes.

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# Abbreviations and Symbols

1. ACC – Accuracy
2. AIC – Akaike Information Criterion
3. AOR – Adjusted Odds Ratio
4. AUC – Area Under Curve
5. BMHS – Brief Mental Health Screener
6. CEW – Conducted Energy Weapon
7. CI – Confidence Interval
8. CID – Crisis Intervention and De-escalation
9. CIT – Crisis Intervention Team
10. CMHA – Canadian Mental Health Association
11. COAST – Crisis Outreach and Support Team
12. CTO – Community Treatment Order
13. EDP – Emotionally Disturbed Person
14. EMS – Emergency Medical Services
15. FN – False Negatives
16. FNR – False Negatives Rate
17. FP – False Positives
18. FPR – False Positives Rate
19. IMIM – Incident Management Intervention Model
20. IMPACT – Integrated Mobile Police and Crisis Team
21. MDT – Mobile Data Terminal
22. MCIT – Mobile Crisis Intervention Team
23. MCRRT – Mobile Crisis Rapid Response Team
24. MCSCS – Ministry of Community Safety and Correctional Services
25. MCT – Mobile Crisis Team
26. M-HEART – Mental Health Engagement and Response Team
27. MHU - Mental Health Unit
28. NPV – Negative Predictive Value
29. PACT – Police and Crisis Team
30. PMI – Persons with Mental Illness
31. PPV – Positive Predictive Value
32. SIU – Special Investigations Unit
33. TN – True Negatives
34. TNR – True Negatives Rate
35. TP – True Positives
36. TPR – True Positives Rate

# 1| Introduction

## 1.1| Mental Health Crisis Response in Canada

### 1.1.1| Epidemiology of Mental Health in Canada

A 2017 report by the Mental Health commission of Canada estimated some 7.5 million Canadians (1 in 5 Canadians) were facing some form of mental health problem (*Strengthening the Case for Investing in Canada's Mental Health System: Economic Considerations*, 2017). The report found the disorders most common amongst Canadians are anxiety and mood disorders (12.3% of total population) followed by substance abuse (5.6%) and cognitive impairment (2.4%). Mental health problems are so prevalent that for the under 65 age group, mental illness makes up 38% of all reported illness.

In 2013 a similar report found that as much as 21.4% of the Canadian working population was experiencing mental health problems. The estimated cost to Canadians, including employer costs, disability insurance, income support, social programs, lost tax revenue and caregivers’ costs is over $50 billion (*Making the Case for Investing in Mental Health in Canada*, 2013).

Accurate estimates of the costs to Canadian law enforcement have proved challenging due to the problem of correctly identifying mental health as a factor in each call. A comprehensive study of the London Police Service found that the cost associated with mental health accounted for between 3 – 9% of the police service’s annual budget (Hartford, 2005). An internal review by the Vancouver Police Department suggests that as much as 49% of all calls for service involve mental health, accounting for an estimated $9 million dollars (equivalent to 90 full-time Officers) in staff time and resources annually (Wilson-Bates, 2008).

### 1.1.2| De-institutionalization of the Canadian Mental Health System

In 1848, the first Asylum (then named the “Provincial Lunatic Asylum”) was opened in Saint John, New Brunswick (*Fonds ID81 - Provincial Lunatic Asylum*, 2018). The opening of the first asylum marked the beginning of a period for mental health services in Canada that was widely criticized for the cruel and inhumane treatment of the patients.

Following significant pressure from civil rights groups in the 1960’s and political pressures in the 1970’s, the asylum system in Canada was abandoned in favour of mental health care that emphasized outpatient services (Richman, 1983). Between 1964 and 1979 the number of psychiatric beds reduced from 4 for every 1000 Canadians to less than 1 (Sealy, 2004). Although the large-scale reduction of inpatient beds suggests the process of deinstitutionalization is complete, the system intended to replace it is widely considered to be inadequate. Major concerns with the current system are a lack of integration between services (police, hospitals, community mental health providers, etc.) and a persistent negative stigma surrounding mental health and mental health treatment (Spagnolo, 2014).

Many have noted that the financial and legal motivations were the major drivers behind deinstitutionalization – not the health care needs of persons with mental illness (Sealy, 2004). By 1960, only 0.4% of Canadians were receiving care in mental institutions, and among them the likelihood of discharge was very small. Those that were discharged would receive care out in the community, but hospitals quickly identified chronic patients (those who could not be admitted for long term inpatient services, but were insufficiently supported in the community) as a persistent problem (Richman, 1983).

Deinstitutionalization of mental health care in Canada is widely considered to be a major cause of the frequency of police contact with persons with mental illness (Iacobucci, 2014). Persons with mental illness were found to be 3.1 times more likely to interact with police than the general population, and twice as likely to have repeat contact with police (Hartford, 2005). Persons with mental illness were also twice as likely to be charged or arrested than the general population, with a large majority (~40%) of charges involving minor offences (Hartford, 2005). A study by Brink, 2011 found police to be involved in 3 out of 10 care pathways (the steps by which a person receives healthcare services) for persons with mental illness, and 1 in 7 referrals to psychiatric emergency services. Of interactions between police and persons with mental illness, approximately 25% were initiated by police, 15% by the person with mental illness, and 20% by the family of the person with mental illness. About 50% of these calls resulted in transport or referral to health care, with 40% of the calls being resolved through informal actions (Brink, 2011). In summary, the planned shift from inpatient beds to outpatient services has instead largely shifted the burden of care onto law enforcement.

### 1.1.3| Mental Health Law Related to Policing in Canada

With the de-institutionalization of mental health care in Canada, provincial mental health legislation was amended to support the renewed focus on treatment in the community (Frankenburg, 1982). Although the provinces and territories of Canada share many common elements between their mental health acts, there exists nuanced differences between each act that dictate the powers and responsibilities of police Officers, herein referred to as “peace Officers.” These laws relevant to policing are as follows:

#### 1.1.3.1| Alberta

Peace Officers in Alberta have the authority to apprehend persons with mental illness under the Mental Health Act of Alberta in situations where a person with mental illness is found to be non-compliant with a Community Treatment Order (CTO) (Section 9.6.1), a Judge has issued a warrant for apprehension (Section 10.2) or through the Peace Officer’s power under Section 12.1.

Section 9.1.1 through 9.5 details the conditions under which a Community Treatment Order may be placed upon person with mental illness, the contents of the Community Treatment Order, and the duration amendment and cancellation of the Community Treatment Order. If an individual is found to be non-compliant with the Community Treatment Order, a psychiatrist may issue an order under Section 9.6.1 that authorizes the apprehension of the individual by Peace Officers.

Section 10.1 through Section 10.7 details the conditions in which a person may give information to a Judge of the Provincial Court that provides evidence that a person is (Section10.2.a.i) likely to cause harm to the person or others or to suffer substantial mental or physical deterioration or serious physical impairment or (Section 10.2.a.ii) subject to a community treatment order and is not complying with the community treatment order. The evidence may be used by the judge to issue a warrant authorizing peace Officers to apprehend that person for examination.

Section 12.1 details the Peace Officer’s power to apprehend a person with mental illness. The condition of which are that (Section 12.1.a) “a person is suffering from a mental disorder” and (Section 12.1.b.i) the person is “likely to cause harm to the person or others or to suffer substantial mental or physical deterioration or serious physical impairment” or (Section 12.1.b.ii) “subject to a community treatment order and is not complying with the community treatment order” (Mental Health Act, 2016).

#### 1.1.3.2| British Columbia

Peace Officers in British Columbia have the authority to apprehend persons with mental illness under the Mental Health Act of British Columbia under Emergency Procedures (Section 28.1) and with authorization of a Judge’s warrant under Section 28.3.

Section 28.1 through Section 28.2 details the conditions in which a person may be apprehended by a police officer where the person is (Section 28.1.a) acting in a manner likely to endanger that person’s own safety or the safety of others, and (Section 28.1.b) is apparently a person with a mental disorder.

Section 28.3 through Section 28.7 details the conditions in which a person may give information to a judge of the Provincial Court that provide evidence that the person matches the conditions set out in Section 22.3.a.ii and as a result the judge may issue a warrant (Section 28.4) authorizing the apprehension of the individual by a peace officer (Section 28.5) (Mental Health Act, 2018).

#### 1.1.3.3| Manitoba

Peace Officers in Manitoba have the authority to apprehend persons with mental illness under the Mental Health Act of Manitoba in situations where a physician had made an application for involuntary assessment (Section 8.1), a warrant has been issued by a justice (Section 9.2), or under the Peace Officer’s Powers (Section 12.1).

Section 8.1 through Section 9.2 details the conditions under which a physician may apply for an involuntary assessment (Section 8.1) if the physician is of the opinion that the person (Section 8.1.a) is suffering from a mental disorder, (Section 8.1.b) because of the mental disorder, is likely to cause serious harm to himself or herself or to another person, or to suffer substantial mental or physical deterioration; and (Section 8.1.c) is unwilling to undergo or is not mentally competent to consent to a voluntary psychiatric assessment, and which authorize detention an assessment by a peace officer (Section 9.1.a) for not more than 72 hours (Section 9.1.b).

Section 10.1 through Section 11.3 details the conditions in which any person may apply to a justice for an order that another person be examined by a physician (Section 10.1) and where the judge may issue an order if the justice has reasonable grounds to believe that the person (Section 11.1.a) is apparently suffering from a mental disorder; (Section 11.1.b) because of the mental disorder, is likely to cause serious harm to himself or herself or to another person, or to suffer substantial mental or physical deterioration; (Section 11.1.c) needs a medical examination to determine whether he or she should undergo a psychiatric assessment; and (Section 11.1.d) refuses to be medically examined. If an order is issued, peace Officers are authorized to apprehend the individual for immediate examination by a physician (Section 11.2.a, Section 11.2.b).

Section 12.1 through Section 12.2 detail the peace Officers power to take into custody where (Section 12.1.a) the peace officer believes on reasonable grounds that the person (Section 12.1.a.i) has threatened or attempted to cause bodily harm to himself or herself, (Section 12.1.a.ii) has behaved violently towards another person or caused another person to fear bodily harm from him or her, or (S.12.1.a.iii) has shown a lack of competence to care for himself or herself; (S.12.1.b) the peace officer is of the opinion that the person is apparently suffering from a mental disorder of a nature that will likely result in serious harm to the person or to another person, or in the person's substantial mental or physical deterioration; and (S.12.1.c) the urgency of the situation does not allow for an order for an examination under section 11 (The Mental Health Act, 2018).

#### 1.1.3.4| New Brunswick

Peace Officers in New Brunswick have the authority to apprehend persons with mental illness under the Mental Health Act of New Brunswick in situations where a physician has issued a certification for examination for involuntary assessment (Section 7.1.1), a warrant has been issued by a judge (Section 9.1), or under the Peace Officer’s Powers (Section 10).

Section 7.1.1 through Section 7.1.7 details the conditions in which a physician may issue a certificate for involuntary examination if the physician is of the opinion that (Section 7.1.1.a) may be suffering from a serious mental illness of a nature or degree so as to require hospitalization in the interests of the person’s own safety or the safety of others, and (Section 7.1.1.b) is not suitable for admission as a voluntary patient. And that peace officer or any other person may take the person into custody and take that person to a psychiatric facility for examination (Section 7.1.4.a).

Section 9.1 through Section 9.5 details the conditions in which any person may give information to a judge of the Provincial Court as evidence that a examination of another person is necessary and (Section 9.1.1) an order for examination may be directed at one or more peace Officers authorizing the peace Officers to enter the persons dwelling for the purposes of immediately transporting that person to a psychiatric facility for examination (Section 9.5).

Section 10 details the conditions in which a Peace Officer may take a person into custody for examination if the officer has reasonable grounds to believe that (Section 10.a) has threatened or attempted, or is threatening or attempting, to cause harm to himself or herself, (Section 10.b) has behaved or is behaving in a way that causes or is likely to cause another person harm or is causing another person to fear harm from the person, (Section 10.c) has shown or is showing a lack of competence to care for himself or herself, and if the peace officer is of the opinion that the person is apparently suffering from a serious mental illness of a nature or degree that likely will result in harm to the person or harm to another person and that it would not be reasonable to proceed in accordance with section 9 (Mental Health Act, 2017).

#### 1.1.3.5| Newfoundland and Labrador

Peace Officers in Newfoundland and Labrador have the authority to apprehend persons with mental illness under the Mental Health Act of Newfoundland and Labrador in situations where a warrant has been issued by a judge (Section 19), or under the Peace Officer’s Powers (Section 20).

Section 19 details the conditions in which a Judge may order an Involuntary Psychiatric assessment on the grounds that person (Section 19.a) has a mental disorder (Section 19.b) as a result of disorder has caused or is likely to cause harm to self, others, or is likely to suffer substantial physical or mental deterioration or physical impairment and (Section 19.c) refuses to submit to psychiatric assessment. Following the release of this order a peace officer must apprehend and transport the person to psychiatric facility (Section 19.4.a).

Section 20 details the conditions in which a Peace Officer may apprehend a person if the officer has reasonable grounds to believe that (Section 20.a) has a mental disorder (Section 20.b) as a result of disorder has caused or is likely to cause harm to self, others, or is likely to suffer substantial physical or mental deterioration or physical impairment and (Section 20.c) refuses to submit to psychiatric assessment and it is not feasible to apprehend under Section 19 (Mental Health Care and Treatment Act, 2006).

#### 1.1.3.6| Northwest Territories

Peace Officers in the Northwest Territories have the authority to apprehend persons with mental illness under the Mental Health Act of the Northwest Territories in situations where a justice has issued an order for involuntary apprehension (Section 11.6), or under the Peace Officer’s Powers (Section 12.1).

Section 11.2 through Section 11.8 details the conditions in which any person may apply to a justice for another person to be examined involuntarily if they have reasonable grounds to believe that (a) the other person is suffering from a mental disorder; (b) because of the mental disorder, the other person (i) is likely to cause serious harm to himself or herself or to another person, or to suffer substantial mental or physical deterioration, or serious physical impairment, or (ii) has recently caused serious harm to himself or herself or to another person, or has threatened or attempted to cause such harm; and (c) the other person has refused to undergo or appears not to be mentally competent to consent to an examination by a health professional to assess the mental state of that person.

Section 12.1 through Section 12.3 details the conditions in which a peace officer may, without a justice’s order, apprehend a person convey him or her for immediate psychiatric evaluation if the peace officer has reasonable grounds to believe that (Section 12.1.a) the person is suffering from a mental disorder; (Section 12.1.b) because of the mental disorder, the person (Section 12.1.b.i) is likely to cause serious harm to himself or herself or to another person, or to suffer substantial mental or physical deterioration, or serious physical impairment, or (Section 12.1.b.ii) has recently caused serious harm to himself or herself or to another person, or has threatened or attempted to cause such harm; (Section 12.1.c) the person should be examined by a health professional to determine whether an involuntary psychiatric assessment of the person is required; (Section 12.1.d) the person is unwilling to undergo or appears not to be mentally competent to consent to an examination by a health professional to assess the mental state of the person; and (Section 12.1.e) by reason of exigent circumstances, it would be impracticable to obtain an order under subsection 11.6 (Mental Health Act, 2018).

#### 1.1.3.7| Nova Scotia

Peace Officers in Nova Scotia have the authority to apprehend persons with mental illness under the Mental Health Act of Nova Scotia in situations where two physicians have signed certificates for involuntary assessment (Section 10.1), a judge has issued an order for involuntary apprehension (Section 13.4), or under the Peace Officer’s Powers (Section 14).

Section 10.1 details the conditions in which two certificates for involuntary psychiatric assessment by physicians authorize (Section 10.1.a) any peace officer to take the person into custody and transport to a facility for involuntary psychiatric assessment.

Section 13.4 details the conditions in which a judge may issue an order for the medical examination where the judge has reasonable grounds to believe that the person (Section 13.4.a) has a mental disorder; (Section 13.4.b) will not consent to undergo a medical examination by a physician; and (Section 13.4.c) as a result of the mental disorder, (Section 13.4.c.i) is threatening or attempting to cause bodily harm to self or has recently done so, or has recently caused bodily harm to self, (Section 13.4.c.ii) is behaving violently or is threatening violence towards another person or has recently done so, or (Section 13.4.c.iii) shows or has recently shown a lack of ability to care for himself or herself and is likely to suffer impending serious physical impairment or impending serious mental deterioration, or both. Following such an order (Section 13.5.a) a member of a police force named in the order shall take that person into custody and transport that person to a facility for medical examination.

Section 14 details the conditions in which a peace officer may take a person into custody for a medical examination by a physician if the peace officer has reasonable grounds to believe that (Section 14.a) the person apparently has a mental disorder; (Section 14.b) the person will not consent to undergo medical examination; (Section 14.c) it is not feasible in the circumstances to make application to a judge for an order for a medical examination pursuant to Section 13; and (Section 14.d) the person, (Section 14.d.i) as a result of the mental disorder, is threatening or attempting to cause bodily harm to himself or herself or has recently done so, has recently caused bodily harm to himself or herself, is behaving violently or is threatening violence towards another person or has recently done so, (Section 14.d.ii) as a result of the mental disorder, shows or has recently shown a lack of ability to care for himself or herself and is likely to suffer impending serious physical impairment or impending serious mental deterioration, or both, or (Section 14.d.iii) is committing or about to commit a criminal offence (Mental Health Act, 2004).

#### 1.1.3.8| Nunavut

Peace Officers in Nunavut have the authority to apprehend persons with mental illness under the Mental Health Act of Nunavut in situations where a judge has issued an order for involuntary apprehension (Section 9), or under the Peace Officer’s Powers (Section 11).

Section 9.1 through Section 9.8 detail the conditions in which a person may make an application to a justice

for an order to have another person undergo a psychiatric assessment by a medical practitioner and (Section 9.6) where if the justice of the opinion that the person who is the subject of the application is apparently suffering from a mental disorder of a nature or quality that will likely result in (Section 9.6.a) serious bodily harm to that person, (Section 9.6.b) serious bodily harm to another person, or (Section 9.6.c) imminent and serious physical impairment of that person, the justice may issue an order authorizing apprehension of the person by a peace officer (Section 9.7, Section 9.8) for transport to a facility for immediate psychiatric assessment.

Section 11.1 through Section 11.2 detail the conditions in which a peace officer is authorized to apprehend an individual where the officer has reasonable cause to believe that the person (Section 11.1.a) has threatened or attempted or is threatening or attempting to cause bodily harm to himself or herself, (Section 11.1.b) has behaved or is behaving violently towards another person or has caused or is causing another person to fear bodily harm from him or her, or (Section 11.1.c) has shown or is showing a lack of competence to care for himself or herself, and, if based on the information before the peace officer, the peace officer is of the opinion that the person is apparently suffering from a mental disorder of a nature or quality that will likely result in (Section 11.1.d) serious bodily harm to that person, (Section 11.1.e) serious bodily harm to another person, or (Section 11.1.f) imminent and serious physical impairment of that person, and the circumstances are such that to proceed under section 9 would be unreasonable or would result in a delay that would likely result in serious bodily harm to that person or to another person or in imminent and serious physical impairment of that person, the peace officer may take that person in custody without delay to a medical practitioner or a hospital within the Territories for psychiatric assessment by a medical practitioner.

Of note, Section 12.1 empowers civilians with the unique power to conduct an apprehension if a peace officer is unavailable and it would be unreasonable to wait for the arrival of such an officer

(Consolidation of Mental Health Act, 2003).

#### 1.1.3.9| Ontario

Peace Officers in Ontario have the authority to apprehend persons with mental illness under the Mental Health Act of Ontario in situations where a judge has issued an order for involuntary apprehension (Section 16), under the Peace Officer’s Powers (Section 17), or where the person has breached the terms of a Community Treatment Order (Section 33).

Section 16.1 through Section 16.4 details the conditions in which information may be brought before a justice of the peace and where the judge may deem that the person (Section 16.1.a) has threatened or attempted or is threatening or attempting to cause bodily harm to himself or herself; (Section 16.1.b) has behaved or is behaving violently towards another person or has caused or is causing another person to fear bodily harm from him or her; or (Section 16.1.c) has shown or is showing a lack of competence to care for himself or herself, and in addition based upon the information before him or her the justice of the peace has reasonable cause to believe that the person is apparently suffering from mental disorder of a nature or quality that likely will result in, (Section 16.1.d) serious bodily harm to the person; (Section 16.1.e) serious bodily harm to another person; or (Section 16.1.f) serious physical impairment of the person, the justice of the peace may issue an order for the examination of the person by a physician. The order provides sufficient authority for a peace officer to apprehend the person and transport them for immediate psychiatric evaluation (Section 16.3).

Section 17 details the conditions in which a peace officer has the authority to conduct an involuntary apprehension if the officer has reasonable grounds to believe that a person is acting or has acted in a disorderly manner and has reasonable cause to believe that the person, (Section 17.a) has threatened or attempted or is threatening or attempting to cause bodily harm to himself or herself; (Section 17.b) has behaved or is behaving violently towards another person or has caused or is causing another person to fear bodily harm from him or her; or (Section 17.c) has shown or is showing a lack of competence to care for himself or herself, and in addition the police officer is of the opinion that the person is apparently suffering from mental disorder of a nature or quality that likely will result in, (Section 17.d) serious bodily harm to the person; (Section 17.e) serious bodily harm to another person; or (Section 17.f) serious physical impairment of the person, and that it would be dangerous to proceed under Section 16.

Section 33.1 through Section 33.9 details the conditions in which a peace officer may be authorized to conduct an apprehension (Section 33.3.3) if the person has failed to comply with the Community Treatment Order (Section 33.3.1) (Mental Health Act, 2015).

#### 1.1.3.10| Prince Edward Island

Peace Officers in Prince Edward Island have the authority to apprehend persons with mental illness under the Mental Health Act of Prince Edward Island in situations where a physician has issued an order for involuntary apprehension (Section 6.1), a judge has issued an order for involuntary assessment (Section 7.1), or under the Peace Officer’s Powers (Section 8).

Section 6.1 details the conditions in which a physician may make an application for a person to undergo psychiatric assessment if the person (Section 6.1.a) is suffering from mental disorder of a nature or degree so as to require hospitalization in the interests of the person’s own safety or the safety of others; and (Section 6.1.b) is refusing or is unable to consent to undergo psychiatric assessment. (Section 6.3.a) An application is sufficient authority for a peace officer apprehend the individual and take the person to any psychiatric facility for psychiatric assessment*.*

Section 7.1 details the conditions in which a judge may issue an order for the involuntary psychiatric examination of a person if the judge has reasonable cause to believe that the person (Section 7.1.a) is suffering from a mental disorder of a nature or degree so as to require hospitalization in the interests of the person’s own safety or the safety of others; and (Section 7.1.b) is refusing or is unable to consent to undergo psychiatric examination. Such an order provides peace Officers with sufficient authority to apprehend the person and transport that person to a psychiatric facility for examination.

Section 8.1 details the conditions in which a Peace Officer may take a person into custody and take him or her forthwith to a place for involuntary psychiatric examination if the peace officer has reasonable grounds to believe that (Section 8.1.a) the person is suffering from mental disorder of a nature or degree so as to require hospitalization in the interests of the person’s own safety or the safety of others; (Section 8.1.b) the person is refusing or unable to consent to undergo psychiatric examination; and (Section 8.1.c) the urgency of the situation does not allow for a judicial order for psychiatric examination (Mental Health Act, 2018).

#### 1.1.3.11| Quebec

Peace Officers in Quebec have the authority to apprehend persons with mental illness under the Act Respecting the Protection of Persons whose Mental State Presents a Danger to Themselves or Others under the Peace Officer’s Powers (Section 8).

Section 8 details the conditions in which a peace officer may, without the authorization of the court, take a person involuntarily to a psychiatric facility (Section 8.1) at the request of a member of a crisis intervention unit who considers that the mental state of the person presents a grave and immediate danger to himself or to others; (Section 8.2) at the request of the person having parental authority, the tutor to a minor or any of the persons where no member of a crisis intervention unit is available in due time to assess the situation. In such a case, the peace officer must have good reason to believe that the mental state of the person concerned presents a grave and immediate danger to himself or to others. (ACT RESPECTING THE PROTECTION OF PERSONS WHOSE MENTAL STATE PRESENTS A DANGER TO THEMSELVES OR TO OTHERS, 2018)

#### 1.1.3.12| Saskatchewan

Peace Officers in Saskatchewan have the authority to apprehend persons with mental illness under the Mental Health Act of Saskatchewan in situations where a judge has issued an order for involuntary apprehension (Section 19), under the Peace Officer’s Powers (Section 20), or where the person has breached the terms of a Community Treatment Order (Section 24).

Section 19.1 through Section 19.2 details the conditions in which a person may lay an information before a judge of the Provincial Court of Saskatchewan if that person believes on reasonable grounds that another person who refuses to submit to a medical examination is (Section 19.1.a) suffering from a mental disorder; and (Section 19.1.b) is in need of examination to determine whether he or she should be admitted to a mental health centre and in which the judge of the Provincial Court of Saskatchewan may issue a to apprehend the person (Section 19.2) to be taken to a place where he or she may be examined by a physician.

Section 20.1 through Section 20.2 details the conditions in which a Peace Officer may apprehend a person without a warrant and convey that person to a place where he or she may be examined by a physician if the peace officer has reasonable grounds to believe that the person is (Section 20.1.a) suffering from a mental disorder; and (Section 20.1.b) likely to cause harm to himself or herself or to others or to suffer substantial mental or physical deterioration if he or she is not detained in a mental health centre.

Section 24.3.1 through Section 24.3.4 details the conditions in which a community treatment order may be applied to a person and in which a person refusing to be examined under that Community Treatment Order may be apprehended and conveyed to a place where the examination is to occur (The Mental Health Services Act, 2017).

#### 1.1.3.13| Yukon

Peace Officers in Yukon have the authority to apprehend Persons with mental illness under the Mental Health Act of Yukon in situations where a judge has issued an order for involuntary apprehension (Section 6), under the Peace Officer’s Powers (Section 8), or where the person has breached the terms of a Community Treatment Order (Section 33).

Section 6.1 details the conditions in which a judge may issue an order for the involuntary examination by a physician of the person alleged to be mentally disordered if the judge believes on reasonable grounds that the person will not consent to an examination by a physician and that at least one of the following conditions applies (Section 6.3.a) As a result of a mental disorder the person, (Section 6.3.a.i) is threatening or attempting to cause bodily harm to themselves, or has recently done so, (Section 6.3.a.ii) is behaving violently towards another person, or has recently done so, or (Section 6.3.a.iii) is causing another person to fear bodily harm, or has recently done so, and the person is likely to cause serious bodily harm to themselves or to another person; or (Section 6.3.b) As a result of a mental disorder, the person shows or has recently shown a lack of ability to care for themselves and is likely to suffer impending serious physical impairment. Following the release of such an order a Peace Officer is authorized to apprehend the person (Section 6.5) for involuntary examination.

Section 8.1 details the conditions in which a Peace Officer may take a person into custody if at least one of the following conditions applies (Section 8.1.a) The peace officer believes on reasonable grounds that the person as a result of a mental disorder (Section 8.1.a.i) is threatening or attempting to cause bodily harm to themselves or has recently done so, (Section 8.1.a.ii) is behaving violently towards another person or has recently done so, or (Section 8.1.a.iii) is causing another person to fear bodily harm or has recently done so, and the peace officer further believes on reasonable grounds that the person as a result of the mental disorder is likely to cause serious bodily harm to themselves or to another person; or (Section 8.1.b) The peace officer believes on reasonable grounds that the person as a result of the mental disorder shows or has recently shown a lack of ability to care for themselves and the peace officer further believes on reasonable grounds that the person as a result of the mental disorder is likely to suffer impending serious physical impairment   
(Mental Health Act, 2002).

### 1.1.4| Major Inquests in Canada

Although most police calls involving mental health are resolved peacefully, incidents resulting in the use of deadly force continue to occur. Between 1990 and 2016 Officers have fatally shot 142 persons with mental illness in Ontario alone (McNeilly, 2017). These incidents, reviewed by the Special Investigation Unit and Office of the Chief Coroner, have resulted in more than 550 recommendations (Dubé, 2016) to police that have shaped mental health response protocols and police training.

Almost every inquest into the death of persons related to a mental health crisis has recommended changes to the training of police Officers, including the recognition of mental health, methods of communication, methods of de-escalation and disengagement (*Inquest into the death of: Douglas Clive Minty*, 2014; *Inquest into the death of: Matthew Henry Roke*, 2014; *Inquest into the death of: Mladen (Steve) Mesic*, 2014; *Inquest into the death of: Evan Thomas Jones*, 2012; *Inquest into the deaths of: Reyal Jardine Douglas, Sylvia Klibingaitis and Michael Eligon*, 2014; *Inquest into the death of: Michael MacIsaac*, 2017; *Coroner's Report into the death of Robert Dziekanski*, 2007).

The topic of conductive energy weapons (non-lethal projectile weapons that apply an electric current to the target) has also been considered in many inquests. In some cases where use of conductive energy weapons may have been used instead of lethal force, recommendations suggested expanding use of the tool as part of crisis de-escalation (*Inquest into the death of: Matthew Henry Roke*, 2014; *Coroner's Report into the death of Robert Dziekanski*, 2007). In other inquests where the officer’s use of conductive energy weapons were criticized, recommendations have urged review of the effects of conductive energy weapons (*Coroner's Report into the death of Robert Dziekanski*, 2007) and changes to the national use of force framework to better integrate conductive energy weapons (*Inquest into the deaths of: Reyal Jardine Douglas, Sylvia Klibingaitis and Michael Eligon*, 2014).

Other major patterns in the recommendations resulting from inquests include expanding the use of mobile crisis resources (*Inquest into the deaths of: Reyal Jardine Douglas, Sylvia Klibingaitis and Michael Eligon*, 2014; *Inquest into the death of: Evan Thomas Jones*, 2012), integrating de-escalation and communication into the national use of force framework (*Inquest into the death of: Michael MacIsaac*, 2017), improving access to mental health data for responding Officers (*Inquest into the death of: Mladen (Steve) Mesic*, 2014; *Inquest into the death of: Evan Thomas Jones*, 2012), training dispatchers to recognize mental health calls and convey mental health information to responding Officers (*Inquest into the deaths of: Reyal Jardine Douglas, Sylvia Klibingaitis and Michael Eligon*, 2014; *Inquest into the death of: Mladen (Steve) Mesic*, 2014) and increased collaboration and communications between law enforcement and health care agencies (*Legistlative Assembly of Ontario Committee Transcript 1993-May-31*, 1993; *Inquest into the deaths of: Reyal Jardine Douglas, Sylvia Klibingaitis and Michael Eligon*, 2014; *Coroner's Report into the death of Robert Dziekanski*, 2007).

For the most part, these recommendations have been implemented by police services across Canada, though the rate of adoption and completeness of the implementation varies service by service. In most cases the implementation of the recommendations is dependent on what resources are available to the police service (e.g., funding for a mobile crisis resource).

### 1.1.5| Police Interactions with Persons with Mental Illness in Canada

#### 1.1.5.1| Response to Mental Health Crisis Calls

Along with the deinstitutionalization of the mental health system came the modern principle that Canadians should have the right to refuse treatment (except in some extreme circumstances) (Health Care Consent Act, 1996). As result persons with mental illness in a state of crisis frequently end up in contact with police (Iacobucci, 2014). Though estimated rates of contact vary between agencies, generally services report that between 7% to 30% of calls involve a person with mental illness (Coleman, 2010). For larger services such as Toronto Police Service, this could mean as many as 20,000 mental health crisis calls per year (Iacobucci, 2014). Though it is widely accepted that mental health response has become part of standard policing (a study by Cotton (2010) found that 80% of Officers felt that response to Persons with mental illness was part of the job), police still lack awareness of resources that are available in their community. Until recently, collaboration between police services and mental health agencies has been limited. To further complicate the issue, many psychiatric facilities report experiencing significant pressure to discharge patients resulting from an insufficient number of beds. As a result, police spend a significant amount of time returning recently discharged patients to the hospital (Iacobucci, 2014). During his investigation into Toronto Police Service’s response to mental health calls, Justice Iacobucci concluded that “police Officers … form a part of the spectrum of care, in tandem with other participants in the mental health system.” The end result is that Canadian police have become part of the community working together to address mental health concerns rather than a solitary organization for law enforcement (Coleman, 2010).

When responding to a person with mental illness in a state of crisis, Officers must determine whether apprehension under the mental health act is necessary. Though the mental health law varies province by province, all provinces allow for Officers to conduct an involuntary apprehension in response to a perceived immediate risk of harm to self or others. If an apprehension is not warranted, the officer will have at his / her disposal options that range from allowing the person to remain on scene to transport or referral to non-emergent support services in the community (depending on the resources available in each community, and the relationships that have been established). In cases where the officer deems an apprehension is warranted, the officer must transport that individual to emergency psychiatric services for evaluation. The involuntary apprehension process has been the source of much frustration for both police and health care staff, as hospital wait times place significant burden on police patrol resources and patients brought by police are frequently not admitted. A study by (Hoffman, 2013) found that as much as 54.9% of persons brought by police and determined to be of high risk were subsequently not admitted.

Generally speaking, the current approach lacks a comprehensive strategy for response to and treatment of mental illness (Iacobucci, 2014).

#### 1.1.5.2| Impact of Mental Health Calls on Police Resources

Though cost estimates related to mental health crisis response vary between services, it is widely accepted that the increase in police contact with persons with mental illness following deinstitutionalization has placed substantial demands on police resources. The impending shift to rely on policing was evidently not considered during the process of deinstitutionalization, as a review of government documents revealed little investigation into the effects on policing (Cotton, 2010).

Recent studies indicate that Officers will interact with persons with mental illness approximately 40 times per year (Cotton, 2010) and that 1 in 50 calls a service responds to will involve mental health, with 1 in 100 of all calls resulting in apprehension (Iacobucci, 2014). Though most services have come to accept mental health response as part of their standard operating procedures, 50% of Officers report feeling that persons with mental illness take a disproportionate amount of time (Cotton, 2010).

In addition to the frequency of mental health calls, the legal obligations placed on Officers by the various mental health acts mean that Officers in remote locations may be required to transport persons with mental illness great distances for treatment. In an interview with one member of the RCMP “D” Division, I was informed of calls in the northern regions of Manitoba that had resulted in extraction by float plane to a regional airport, transport by car for over 10 hours, and an additional 8 hour wait at the psychiatric hospital. Including the costs of chartering the planes, paying the officer’s overtime, and the amortized cost of the police resources used, each of these calls was estimated to cost well over $10,000.

Recent studies have indicated that the number of police interactions with Persons with mental illness will likely continue to increase and place additional pressure on police budgets. One such increase was documented in London Ontario, where police reported a 134% increase in costs related to Persons with mental illness between 2000 and 2011 (Heslop, 2011).

#### 1.1.5.3| De-Escalation of Mental Health Crisis and the National Use of Force Framework

Although ‘de-escalation’ is used a general term to describe many policing techniques, de-escalation as it relates to the National Use of Force Framework (See Appendix 1) has been the subject of much discussion. The National Use of Force Framework was developed as reference for Officers during training (*A National Use of Force Framework*, 2000) and provides guidance on when different levels of force may be applied. The framework has been criticized for not depicting other options (e.g., tactical repositioning) that may allow Officers to de-escalate interactions with persons with mental illness without the use of force (Dubé, 2016). For example, the RCMP’s Incident Management Intervention Model (IMIM) (See Appendix 2) includes references to tactical considerations, perceptions and tactical repositioning (*Incident Management Intervention Model*, 2017) implying that time and distance are also important tools for de-escalation.

#### 1.1.5.4| Use of Conductive Energy Weapons

Conductive Energy Weapons were first made available to Canadian law enforcement Officers in 2004, but were initially only permitted for use by patrol supervisors and specialized units (Dubé, 2016). Following a number of recommendations from inquests into the death of persons with mental illness (McNeilly, 2017) conductive energy weapons were eventually permitted for use by all front line Officers in 2013 (Iacobucci, 2014).

Also frequently referred to by the brand name ‘TASER’, conductive energy weapons are classified as a less lethal use of force option that can be used to de-escalate high risk situations (O'Brien, 2014). Though several variants of conductive energy weapons exist, the weapons generally function by passing a current between conductive darts that are propelled into the target (axon, 2018). The electric current is thought to incapacitate the target for a brief period in which police Officers may then contain the situation.

Officers are permitted to apply a conductive energy weapon if the officer believes that there is an immediate need to control the situation. As per the National Use of Force Framework, officer’s are required to explore other methods of de-escalation, including but not limited to verbal commands before deploying the conductive energy weapon (Iacobucci, 2014). Specifically, the Ontario Ministry of Community Safety and Correctional Services guidelines for use of a conductive energy weapon are as follows:

“1. The officer believes a subject is threatening or displaying assaultive behaviour or, taking into account the totality of the circumstances, the officer believes there is an imminent need for control of a subject;   
  
and

2. The officer believes it is reasonably necessary to use a conducted energy weapon, which may involve consideration of the following factors:

i) whether efforts to de-escalate the situation have been effective;

ii) whether verbal commands are not practical or are not being followed;

iii) the risk of secondary injury (e.g., as a result of a fall); and

iv) the conducted energy weapon’s capabilities in relation to the context and environment.”

(*Report of the Ontario Human Rights Commission on police use of force and mental health*, 2018)

Although specific guidelines for use of conductive energy weapons exist, research has noted that conductive energy weapons were more than twice as likely to be deployed to control a mental health related emergency compared to situations involving criminal arrests (O'Brien, 2014). In addition to the high frequency of use against Persons with mental illness, conductive energy weapons have also been known to be a risk factor for sudden unexpected deaths (often when applied in addition to physical restraints and drug intoxication) (O'Brien, 2014) as well as smaller risks such as falls or ocular perforation. Despite these outcomes, a before and after study of police services using conductive energy weapons found that the deployment of conductive energy weapons reduced rates of suspect and officer injuries and reduced rates of injuries requiring medical attention (O'Brien, 2014).

### 1.1.6| Police Resources for Mental Health Calls

In response to the growing resources demands of mental health related calls for service, police services have adopted several new strategies for managing mental health calls. Though mental health training still tends to be limited (Cotton, 2010), most services have designated a mental health resource officer to act as a liaison with mental health services in the community. Several other law enforcement driven mental health initiatives have been highlighted recently (*Community Service Officer*, 2019), including the emergence of co-response and crisis intervention teams, situation tables and mental health courts. Though these initiatives have proven successful in many communities, their availability varies substantially between each community.

#### 1.1.6.1| Co-Response / Mobile Crisis Teams

Mobile Crisis Teams (MCT), sometimes known as co-response teams, typically pair a uniformed officer with a psychiatric nurse or social worker to respond to known mental health calls. The first Mobile Crisis Team, thought to be the “Car 87” program, was developed by Vancouver Coastal Health and Vancouver Police Department in 1984 (Iacobucci, 2014). Shortly afterwards the “Memphis Model” of Mobile Crisis Teams was developed in Memphis, Tennessee in 1988. News of the success of the Mobile Crisis Team programs has become wide spread, and the model has spread rapidly across Canada (*Police and Crisis Team (PACT),* 2018).

Though the concept at its core (pair an officer and a health practitioner together) is standardized, the implementation of the model varies substantially between each community. In the communities included in my study alone I found there to be 5 different names for the Mobile Crisis Teams, and 6 different models. These included Mobile Crisis Rapid Response Teams (MCRRT), Mental Health Engagement and Response Teams (M-HEART), Integrated Mobile Police and Crisis Team (IMPACT), Crisis Outreach and Support Teams (COAST) and Police and Crisis Teams (PACT).

Protocols surrounding Mobile Crisis Teams vary between each community. Some Mobile Crisis Teams respond directly to calls from dispatch where the call is known to involve a person in crisis (Cotton, 2010), others provide services only as secondary response after Officers have arrived on scene and established control over the safety of the situation (Iacobucci, 2014). Other communities may use Mobile Crisis Team resources to conduct proactive outreach to prevent future crisis calls (Savage, 2018). Depending on the community, Officers may be uniformed or not, use marked or unmarked cars, and be accompanied by a social worker, nurse practitioner, or psychiatrist.

Research suggests that Mobile Crisis Teams are effective at reducing the time Officers spend on scene (2 hours 45 minutes down to 2 hours 16 minutes) and in generating greater engagement with outpatient contacts within the community (Kisely, 2010). The teams are also known for allowing healthcare to conduct comprehensive needs assessments on scene without requiring apprehension and transport of the person with mental illness (Farrell, 2005). Officers accepted into Mobile Crisis Teams have usually completed additional training such as Crisis Intervention and De-Escalation (CID) (see Appendix 3) and have been selected for outstanding performance during prior mental health related calls for service (Iacobucci, 2014).

#### 1.1.6.2| Hub Model / Situation Tables

The Hub model, also known as situation tables, connectivity tables, or community response teams, is a model for multi-agency collaboration within a community to address the needs of persons at an acute risk of harm. The Hub model is designed to address individuals who are at an elevated risk on a case-by-case basis, working upstream of emergency response to plan interventions. These interventions involve multiple agencies and are designed to respond to acute needs within the community on short notice.

Participating agencies within a community will typically meet twice a week to review clients identified as having complex needs and elevated risk (*Risk-Driven collaborative intervention: A preliminary impact assessment of Community Mobilization Prince Albert’s Hub Model*, 2014). The process of identifying vulnerable individuals between agencies can follow privacy regulations through use of the Four Filter Process (Russell, 2014). The first step in the model is an internal review conducted by each agency in which the agency determines if the acutely-elevated risk can be handled without the support of other agencies. If the risk cannot be mitigated alone, the individual may be brought to Hub. The next step is a discussion process, which includes identifying the individual through use of the Four Filter Process and sharing information between appropriate agencies to plan support for the individual. The final step is a multi-agency intervention to offer support to the individual in a non-coercive manner. The results of the intervention are then reviewed by the Hub (*Technology-enabled Hubs in remote communities: A review of research and practice*, 2016).

Individuals that meet the Hub definition for acutely-elevated risk meet these criteria:

1. There is significant interest at stake,
2. There is a high probability of harm occurring,
3. There is significant intensity of harm, and
4. The risk is multi-agency in nature.

The primary mission of the Hub model is to:

1. Identify acutely-elevated risk in the community and rapidly mobilize integrated, multi-agency support for the individual at risk.
2. Provide short-term intervention to bridge at risk community members into longer term solutions.

(*Prince Albert Hub – The Community Mobilization Prince Albert (CMPA)*, 2018)

The Hub model has been credited with providing several benefits for communities. Most significant is its ability to bridge silos of government service providers to allow for a more collaborative approach to risk in the community (Newberry, 2015). An evaluation of the connectivity table in the Waterloo Region found that individuals that were observed at a high risk of harm were successfully stabilized and experienced improvements to quality of life. Local hospitals experienced decreases of 14% and 69% in emergency department visits after interventions, and repeat police calls were reduced by 46% in a 90-day period recovering resources valued at approximately $100,000 (Newberry, 2017). Another evaluation conducted in the City of Brantford found that the Community Response Team significantly improved the identification of persons at risk in the community and the number of referrals to agencies able to support those persons. The initiative was also deemed to have significantly improved the partnership between existing agencies within the community (Babayan, 2015).

#### 1.1.6.3| Mental Health Courts in Canada

Mental health courts are a new form of problem-solving courts that are being created to intervene in situations where a criminal court may not be appropriate. The mental health courts are equipped with the expert means to identify and address mental health needs of the accused which a standard criminal court may fail to identify. The mental health courts of Canada are designed to divert persons with mental illness entering the criminal justice system and provide medical and community support, even in cases involving serious charges. The primary goal of the mental health courts is to reduce recidivism. Similar techniques have been applied in drug courts, domestic violence courts, and teen courts with a focus on addressing the root cause of an issue rather than the apparent cause (Reiksts, 2008).

To achieve these goals, mental health courts focus on how the law may be used to *help* the person, rather than how the person may be brought into conformity with the laws. As identified by Reiksts (2008) this important distinction means the courts can focus on rehabilitation rather than punishment.

The mental health courts operate on a set schedule with regular frequency. Eligibility criteria vary between individual courts, however most courts require that the individual be willing to participate in treatment if needed and most courts exclude individuals charged with class 3 offences (e.g., murder, sexual offences, etc.) (*Mental Health Courts in Ontario A Review of the Initiation and Operation of Mental Health Courts Across the Province*, 2017). The mental health courts often rely on close cooperation between the criminal justice and health care system to balance protection of the public with treatment designed to reduce the risk of recidivism through court-imposed treatment programs (Reiksts, 2008). As part of this process, the mental health court may also offer rewards to the accused, including certificates of completion, gift cards, or public praise from the judge and crown. In cases where the accused fails to comply with the treatment programs, sanctions may include the charges not being withdrawn or expulsion from the mental health court (return to standard criminal court) (*Mental Health Courts in Ontario A Review of the Initiation and Operation of Mental Health Courts Across the Province*, 2017).

Though studies on the results of the courts in Canada are fairly limited, early results suggest that the program has been successful at diverting large numbers of persons with mental illness from prison and into treatment programs and that the mental health courts are moderately effective for reducing recidivism (Sarteschi, 2011).

## 1.2| Machine Learning

Media coverage and public interest have brought much attention to the concept of machine learning, and much has been discussed about its potential uses for a variety of complex problems. Machine learning has been described as the study of learning algorithms that rely on statistical inference, rather than explicit instructions from the modeler, to perform pre-determined tasks (Witten, Frank, Hall, & Pal, 2017). Using computer systems, machine learning algorithms are commonly built (or ‘trained’) to perform a task on sample data and exploited on new data (Ayodele, 2010). Though many new techniques have emerged in recent years, machine learning is not considered a new technology. For example, the technique used in this thesis (Random Forests) has been around since 1995 (Ho, 1995). Machine learning may provide advantages over classical statistical modeling in some scenarios, but the benefit may be minor (Song, 2004).

### 1.2.1| Supervised Learning

The methods used in machine learning are organized based on the desired outcomes of the learning process. Although the field continues to evolve, and new methods are introduced, some of the most common learning algorithms (Ayodele, 2010) are known as ‘supervised learning’. Supervised learning produces statistical learning algorithms designed to map inputs to a desired output using example input-output pairs (or training examples/training data). This method maps the attributes and features of individual observations in a training data set to pre-identified outcomes. The resulting learning algorithm can then be applied to holdout data to perform the learned task. As was explored in this thesis, this method can be used to examine existing data (in this case, records of police interactions with persons with mental illness) for predicting outcomes in the future (likelihood of follow up crisis calls). The goal of the resulting learning algorithm is to exploit it with future data to predict the probability of those outcomes.

### 1.2.2| Random Forests

Classification and regression (‘decision’) trees is a predictive modelling approach that produces tree-like models to express the probability of a dependent variable based on a series of interacting independent variables or collection of rules that form nodes or splits in the tree (James, Witten, Hastie, & Tibshirani, 2017). The terminal node is defined by a set of visually interpretable decisions or nodes (James, Witten, Hastie, & Tibshirani, 2017). Random Forests extend these classification and regression trees by producing a learner algorithm that is the result of combining the results of multiple different decision trees trained on unique training samples and with access to different variables at each split in each tree node. This is made possible through a sampling method known as ‘bagging’ and the random selection of predictor variables at each tree node.

Bagging (‘bootstrap aggregating”) with replacement is the process of taking repeated random samples from a single training set (of equal size), and training a unique tree on each sample. These trees are then combined together to create a tree ensemble (single learning algorithm) that produces a single low error predictor. For a binary dependent variable (as is the case in this thesis) the final classification of the outcome is determined by the mode of the predictions (i.e., ‘*majority vote’* *–* the most commonly occurring class among the predictions).

To further improve prediction accuracy, random forests builds on bootstrap sampling by randomly restricting the number of independent variables that may be chosen at each split in each tree (known as ‘feature bagging’). A random selection of *m* variables (typically the square root of the total number of variables in the data set (Breiman & Cutler, n.d.) is taken at each split, thereby reducing the correlation between each tree produced by the method. In doing so random forests can reduce error in the learning algorithm more effectively than bagged trees that consider all variables at each split.

In this thesis, I will use the Random Forests algorithm to identify persons who are at acute risk of mental health crisis based on a limited sample of follow up crisis calls.

### 1.2.3| Machine Learning Applications in Policing

For policing, where there exist large volumes of complex data, machine learning techniques are thought to have much potential. As identified by Justice Iacobucci (2014), by intervening in mental health crisis before a critical incident occurs, there may be an opportunity to prevent situations that lead to death or injury. Using machine learning to predict these incidents is one such application which I will explore in this thesis.

Although little academic literature exists regarding the study of machine learning techniques in policing, there are numerous commercial solutions claiming to leverage the technology to enhance their products. Products like PredPol claim to be able to use machine learning techniques to predict break ins and small crimes, which are then overlaid onto maps to assist in patrol resource planning (PredPol, 2018). Another system called ShotSpotter claims to be able to accurately pinpoint the location of gunshots in a city using a network of sensors and machine learning (ShotSpotter, 2018).

Other companies such as Hikvision and Cortica claim to embed machine learning into large scale arrays of different types of sensors to identify suspicious behaviour, items, and provide facial recognition in real time (HikVision, 2018); (Cortica, 2018).

One notable company named ‘equivant’ has produced a system called ‘COMPAS Classification’, which claims to use machine learning techniques to manage inmates within the corrections system (equivant, 2018).

### 1.2.4| Machine Learning Applications in Healthcare

Unlike in policing, there has been a substantial amount of studies applying machine learning techniques to challenges in healthcare. These studies have primarily focused on predicting patient outcomes (Farran, 2013), identifying illnesses in electronic health record data (Chen, 2017) and using machine learning to boost the effectiveness of sensors used for monitoring patients (Hsu, 2014). Many studies report that machine learning methods perform as well or greater than other classical statistical techniques, with some outperforming expert scales and assessment systems (Desautels, 2016).

Though no examples currently exist of machine learning being applied to predict mental health crisis, there are a number of studies that have used machine learning techniques to make predictions about patients. Weiss (2012) used relational functional gradient boosting to predict myocardial infarctions (Area Under Curve (AUC)=.845). Zhu (2007) used support vector machine and k-nearest neighbour methods to predict rehabilitation potential in home care patients. Another study by Farran (2013) used k-nearest neighbour to predict risk of hypertension and type 2 diabetes.

Using machine learning techniques for the classification of electronic health record data has been another major focus of research in healthcare. There are numerous example of machine learning methods being applied to identify illness (Eerik¨ainen, 2015; Chen, 2017; Pogorelc, 2011) and interpret electronic health record data (Peissig, 2014; Pollettini, 2012).

Although there are many opportunities to apply machine learning to health care, much of the data collected in electronic health records is of an administrative nature. Data silos, privacy laws, and corrupt or incomplete data has been identified as challenges to future research (Johnson, 2015).

### 1.2.5| Predicting Mental Health Call Outcomes with Machine Learning

At the time of writing there are no examples in either commercial or academic publications of machine learning being applied to predict mental health crisis calls. One similar study found that Random Forests analysis could be used to predict general criminal recidivism amongst persons with mental illness with existing criminal records (Pflueger, 2015). Machine learning has also been applied to analysis of MRI data in a controlled setting to predict suicidal ideation (Just, 2017), but never as a predictor of subsequent mental health crisis following police mental health crisis intervention.

## 1.3| Rationale

As was identified by Justice Iacobucci (2014), proactive intervention *before* a mental health crisis occurs is the most effective means of preventing a critical incident from occurring. Though this concept is widely accepted, the means for detecting persons at risk of crisis are still quite limited. Mobile Crisis Teams are sometimes able to conduct proactive visits with individuals in the community, but often opportunities to do so are limited by call volume. In some communities Mobile Crisis Teams will also review mental health reports but evaluating the risk of each one and then following up is often impractical due to the call volume. Situation Tables and Hubs are also known to be effective at proactive intervention, but many meet only once per week. An algorithm capable of predicting mental health crisis recidivism with high risk of harm could be used to identify at-risk persons within existing police data and alert resources in the community able to proactively intervene.

Applying machine learning techniques within the intersection of law enforcement and public health would allow us to evaluate the effectiveness of machine learning techniques in this space for the first time. The study would also allow for the comparison between more commonly used logistic regression methods and machine learning methods within policing and mental health.

## 1.4| Objectives, Research Questions, and Hypotheses

The overall objective of the study was to prognosticate outcomes following police interactions with persons with mental illness, and specifically investigate the predictive validity and decision-making utility of basic machine learning techniques for police involved in mental health related calls. The specific research questions posed by this study were:

1. In the context of police mental health crisis response and assessment, does Random Forests outperform key informant based logistic regression and optimized logistic regression models to predict future police contact and related outcomes (high risk of harm to self, high risk of harm to others, high risk of failure to care for self) within 24 hours and 72 hours of baseline response and assessment?
   1. I hypothesized that Random Forests will outperform key informant and optimized logistic regression due to complexity of the data set and the limited incidence of target outcomes.
2. Is the predictive accuracy of a Random Forests classification (as an example of machine learning) in predicting future police contact and related outcomes (High risk of harm to self, high risk of harm to others, high risk of failure to care for self) sensitive to the Police Service data used to train the classification?
   1. I hypothesized that major differences exist between the regions included in the study. I suspected that this would have a negative effect on the predictive accuracy of the algorithm in some regions.

Specific outcomes for prediction related to the objectives of this study are:

* Repeat police contact within 24 hours, with a high risk of harm to others noted during repeat contact.
* Repeat police contact within 24 hours, with a high risk of harm to self noted during repeat contact.
* Repeat police contact within 24 hours, with a high risk of failure to care for self noted during repeat contact.
* Repeat police contact within 72 hours, with a high risk of harm to others noted during repeat contact.
* Repeat police contact within 72 hours, with a high risk of harm to self noted during repeat contact.
* Repeat police contact within 72 hours, with a high risk of failure to care for self noted during repeat contact.

# 2| Methods

## 2.1| Study Design

This study was a retrospective cohort study using police service population level police mental health call data. Standardized observations collected by police were analyzed to predict repeat contact with police within 24 and 72 hours. The study was approved by the Hamilton Integrated Research Ethics Board (5552-C).

## 2.2| Data Sources and Measurement

### 2.2.1| The interRAI Brief Mental Health Screener (BMHS)

The interRAI Brief Mental Health Screener (BMHS) was developed to promote effective and efficient delivery of services for persons in crisis presenting to health services with police (interRAI, 2019). The items contained within the BMHS were identified through analysis of the RAI-MH assessment. The RAI-MH was developed by interRAI in 2007 (interRAI, 2019) as a comprehensive mental health assessment that had been provincially mandated in Ontario. Anonymized RAI-MH data submitted quarterly to the Canadian Institute for Health Information (CIHI) was used for the analysis. In total 41,019 RAI-MH assessments were analyzed. The BMHS contains twenty-three (23) non-personally identifiable questions (sections B and C) related to risk screening, as well as additional identifiable questions related to administration of the calls (e.g., incident location). The questions are broken into six major sections: Section A: Identification (8 questions), Section B: Mental State Indicators (12 questions), Section C: Violence Indicators (11 questions), Section D: Disposition (7 questions), Section E: Notes (1 question), and Section F: Responder Details (2 questions) (Hoffman, 2013); (interRAI, 2018).

There are three validated scales (Severity of Self Harm, Risk of Harm to Others, and Self Care Index) embedded in the RAI-MH that were used as the target variable for prediction in the development of the BMHS risk scales. Multivariate analysis was conducted to identify the items in the RAI-MH most predictive of high risk (a score of 6 out of 6) in the embedded RAI-MH scales. These items were then used to produce three new scales in the BMHS: Risk of Harm to Others, Risk of Harm to Self, and Failure to Care for Self (interRAI, 2018) (Hoffman, 2013).

Table i: interRAI Brief Mental Health Screener (BMHS) Items by Section

|  |  |  |
| --- | --- | --- |
| **BMHS Code** | **Question** | **Response Levels** |
| **Section A: Identification** | | |
| A1 | Name( First Name, Middle Name, Last Name, Suffix) | Open field |
| A2 | Sex | Male, Female, Other |
| A3 | Birthdate (Year, Month, Day) | Open field |
| A4 | Primary Home Address (Street Name, Apartment / Unit, City, Province, Country, Postal Code) | Open field |
| A5 | Homeless | Yes, No |
| A6 | Date and time police arrival on scene (Year, Month, Day, 24hr Time) | Open field |
| A7 | Incident Number | Open field |
| A8 | Incident Location | Open field |
| **Section B: Mental State Indicators** | | |
| B1a | Irritability: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| B1b | Hallucinations: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| B1c | Command hallucinations: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| B1d | Delusions: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| B1e | Hyper-arousal: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| B1f | Pressured speech: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| B1g | Abnormal thought processes: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| B1h | Socially inappropriate behaviour: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| B1i | Verbal abuse: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| B1j | Intoxication: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| B2 | Degree of insight | Full, Limited, None |
| B3 | Daily Decision Making (CA) | Independent – Decision consistent reasonable safe, Modified independence or any impairment |
|  |  |  |
| **Section C: Violence Indicators** | | |
| C1 | Previous Police Contact | No contact, Any contact (no mental health apprehension), Any contact (mental health apprehension) |
| C2 | Carries Weapon | Yes, No |
| C3a | Violent ideation: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| C3b | Intimidation of others: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| C3c | Violence to others: 24 hrs | Not Present, Present but not exhibited within last 24 hours, Exhibited within last 24 hours |
| C4a | Self-injurious attempt last 7 days | Yes, No |
| C4b | Considered self injury last 30 days | Yes, No |
| C4c | Suicide Plan | Yes, No |
| C4d | Others concerned about self-injury | Yes, No |
| C5 | Squalid condition | Yes, No, Homeless or not visited |
| C6 | Refused Medication | Yes, No or no medications |
| **Section D: Disposition** | | |
| D1a | Disposition: Voluntary escort to hospital | Yes, No |
| D1b | Disposition: Involuntarily Apprehended | Yes, No |
| D1c | Disposition: Apprehended under existing order | Yes, No |
| D1d | Disposition: Referred to CMH | Yes, No |
| D1e | Disposition: Transferred to EMS/MCRRT | Yes, No |
| D1f | Disposition: Caseworker/Probation notified | Yes, No |
| **Section E: Notes** | | |
| E1 | Officer’s Notes | Open field |
| **Section F: Responder Details** | | |
| F1 | Signature of Person Coordinating / Completing the Assessment (Print Name, Signature, Badge Number or Agency, Police Service / Detachment / Division) | Open field |
| F2 | Date and Time (Year, Month, Day, 24hr Time) | Open field |

### 2.2.2| HealthIM

All BMHS reports used in the study were gathered using a digital tool called “HealthIM”. HealthIM provides Officers with the means to capture the BMHS on their duty issued phone or cruiser-mounted mobile workstation. The software provides the Officers with clinical feedback prior to the officer’s decision to apprehend, and then allows for the secure communication of a PDF summary of the BMHS to designated health care and community mental health partners in the community, along with the police service’s records management system. Aggregate anonymized data is presented back to police command staff to support service-level decision making. The software is also used to drive a case management system in some communities (HealthIM, 2016).

HealthIM has built in data quality checks. The system prevents Officers from incorrectly formatting the many open fields of the BMHS. It also requires Officers to complete each question in the assessment before submitting the report. Services using HealthIM mandate its use during all interactions with persons with mental illness. As a result, the data set used for this study is accurate and complete.

HealthIM is licensed by interRAI for use of the BMHS. As per interRAI’s license, HealthIM must remit de-identified data to interRAI on a semi-regular basis. The data used for this study was accessed through servers owned by interRAI and populated by BMHS data collected and remitted by HealthIM.

### 2.2.3| Measurement

While responding to calls for service, police Officers recorded their observations of mental health symptoms and other related behaviour using the interRAI Brief Mental Health Screener (BMHS) (interRAI, 2018). The BMHS was made available to all Officers, including those in specialist mental health teams (e.g., MCRRT, PACT, M-HEART) and those in other specialized units (e.g., canine unit). Officers completed the BMHS using a digital interface (HealthIM) that was accessible on the Officer’s mobile workstation and mobile phone. The digital interface allowed the officer to record their responses to the BMHS, review the embedded BMHS risk models, and communicate the results to local health care partners (E.g., hospitals, community mental health services). As an additional benefit, the digital tool has several features to maintain high data quality (e.g., format checking, completion checks, spell checks).

Officers completed the BMHS on all persons they suspected may be suffering from mental health issues regardless of demographic variables (e.g., age, sex). Standardized operating procedures require Officers to complete the BMHS while still on-scene with the individual, if they believed that mental health was a factor in the call. This includes calls explicitly coded in the Records Management System (RMS) as mental health crisis calls, but also includes other incidents (e.g., domestic violence, traffic stops, shop lifting) where police believed mental health was a factor. Reports were completed by Officers with the individual while still at the incident location whenever possible. In some extreme circumstances Officers were unable to complete the screener while on scene due to safety concerns. In these instances, Officers would complete the screener once it was safe to do so (typically in the ED of the receiving hospital facility).   
 Standard operating procedures for crisis response and the use of the BMHS tool by patrol Officers does not vary significantly between police services. However, use of support resources (such as mobile crisis teams) varies.

## 2.3| Setting

Reports were completed by Officers in thirteen (13) communities, including two (2) from Saskatchewan (Regina Police Service, Saskatoon Police Service) and eleven (11) from Ontario (Brantford Police Service, Brockville Police Service, Cobourg Police Service, Gananoque Police Service, Guelph Police Service, Kawartha Lakes Police Service, London Police Service, Niagara Regional Police Service, Orangeville Police Service, Ottawa Police Service, and Smiths Falls Police Service).

### 2.3.1| Brantford Police Service

The Brantford Police Service is responsible for the City of Brantford and serves a population of 100,791. Brantford Police Service employees 173 sworn Officers and 95 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). Resources unique to Brantford Police Service include the Brantford Police Service Mobile Crisis Rapid Response Team (MCRRT) and a partnership with St. Leonard’s Community Services (*Mobile Crisis Rapid Response Team (MCRRT)*, 2018). Mobile Crisis Rapid Response Team units are comprised of one uniformed police Officer and one mental health specialist. The team responds to calls involving persons in frequent mental health related contact with the police and conducts proactive outreach with vulnerable persons in the community. Mobile Crisis Rapid Response Teams may complete the BMHS at their discretion, including on proactive calls. St. Leonard’s Community Services provides evidence-based support programs (*Addictions & Mental Health*, 2018) for vulnerable persons in the community. Brantford Police Service Officers and Mobile Crisis Rapid Response Team may be generate referrals to St. Leonard’s Community Services (with consent) using the BMHS tool during incidents where the person is not at a high enough risk to warrant involuntary apprehension but does require additional support.

### 2.3.2| Brockville Police Service

The Brockville Police Service serves the City of Brockville and provides police services for a population of 22,470. Brockville Police Service employees 40 sworn Officers and 15 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). Resources unique to Brockville include a Police Community Outreach Team and the Lanark Leeds and Grenville Addictions and Mental Health service. The Police Community Outreach Team is comprised of a uniformed police Officer and a mental health specialist and provides proactive support for known vulnerable persons in the community (*Brockville Police*, 2018). Lanark Leeds and Grenville Addictions and Mental Health provides a variety of mental health services and support programs (*Lanark Leeds and Grenville Addictions and Mental Health Services*, 2018). Patrol Officers as well as the Community Outreach Team may elect to refer individual (with consent) to Lanark Leeds and Grenville Addictions and Mental Health using the BMHS tool in incidents where there is not enough risk to warrant involuntary apprehension but additional support in needed.

### 2.3.3| Cobourg Police Service

The Cobourg Police Service serves the Town of Cobourg and provides police services for a population of 19,880. Cobourg Police Service employees 35 sworn Officers and 46 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). Cobourg Police Service has also developed a Mental Health Engagement and Response Team (M-HEART) comprised of one mental health response Officer as well as a Social Worker or Mental Health Nurse from Northumberland Hills Hospital. Patrol Officers and Mental Health Engagement and Response Team may complete the BMHS at their discretion while responding to a mental health related call for service.

### 2.3.4| Gananoque Police Service

The Gananoque Police Service serves the Town of Gananoque and provides police services to a population of 5,312. Gananoque Police Service employees 14 sworn Officers and 12 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). Gananoque Police Service has also developed a partnership with Lanark Leeds and Grenville Addictions and Mental Health service. Patrol Officers may elect to refer individual to Lanark Leeds and Grenville Addictions and Mental Health (with consent) using the BMHS tool in incidents where there is not enough risk to warrant involuntary apprehension but additional support in needed.

### 2.3.5| Guelph Police Service

Guelph Police Service serves the City of Guelph and provides police services to a population of 132,350. Guelph Police Service employs 194 sworn Officers and 90 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). Guelph Police Service has also developed an Integrated Mobile Police and Crisis Team (IMPACT) to provide joint response to mental health and addiction issues. The Integrated Mobile Police and Crisis Team is comprised of two Canadian Mental Health Association Waterloo Wellington workers who are based in the Guelph Police Service headquarters (*IMPACT team earns nod from Guelph Police Service*, 2017). Patrol Officers may refer individuals to the Integrated Mobile Police and Crisis Team using the BMHS tool which will then trigger a follow up by the Integrated Mobile Police and Crisis Team.

### 2.3.6| Kawartha Lakes Police Service

The Kawartha Lakes Police Service serves the City of Kawartha Lakes and provides police services for a population of 26,790. Kawartha Lakes Police Service employs 42 sworn Officers and 20 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). Kawartha Lakes Police Service participates in the Kawartha Lakes Situation Table which can provided multi agency care for at risk individuals in the community. The situation table meets weekly to identify vulnerable persons in Kawartha Lakes and develop multi-agency care plans to support them. Officers at Kawartha Lakes Police Service may elect to flag individuals for the situation table using the BMHS. Individuals flagged by the BMHS are then reviewed by a dedicated liaison Officer. The liaison Officer may then elect to highlight the individual at the next situation table meeting.

### 2.3.7| London Police Service

The London Police Service services the City of London and provides police services for a population of 397,493. London Police Service employs 605 sworn Officers and 224 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). London Police Service has also partnered with the CMHA Middlesex Crisis Centre. When responding to calls involving mental health, Officers will screen the individual with the BMHS. If the officer deems that the individual does not require apprehension, the officer may elect to transport the individual (with consent) to the Middlesex Crisis Centre. The Middlesex Crisis Centre offers same-day support services for individuals in crisis (*Crisis Services*, 2016).

### 2.3.8| Niagara Regional Police Service

The Niagara Regional Police Service serves the Niagara Region and provides police services to a population of 397,493. Niagara Regional Police Service employs 605 sworn Officers and 224 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). Resources unique to Niagara Regional Police Service include the Mobile Crisis Rapid Response Team (MCRRT) and the Crisis Outreach and Support Team (COAST). The Mobile Crisis Rapid Response Team is comprised of one uniformed Niagara Regional Police Service officer and one Mental Health worker from CMHA Niagara. The Mobile Crisis Rapid Response Team responds to emergency calls known to be mental health related and provides on scene risk assessment (*Mobile Crisis Rapid Response Team*, 2017). The Crisis Outreach and Support Team is comprised of uniformed Officers and health professionals and provides follow up outreach and support for individuals who have experienced mental health crisis in the community (*Niagara Regional Police Service*, 2015). Uniformed Officers and the Mobile Crisis Rapid Response Team may elect to refer individuals to the Crisis Outreach and Support Team using the BMHS tool (with consent).

### 2.3.9| Orangeville Police Service

The Orangeville Police Service serves the Town of Orangeville and provides police services to a population of 31,496. Orangeville Police Service employs 39 sworn Officers and 29 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). Orangeville Police Service also participates in the Dufferin Situation Table. Officers may use the BMHS to flag individuals they believe to be candidates for the situation table. A designated liaison Officer will then review the report and determine if it is appropriate to be reviewed by the situation table.

### 2.3.10| Ottawa Police Service

The Ottawa Police Service serves the City of Ottawa and provides police services to a population of 973,481. Ottawa Police Service employs 1,242 sworn Officers and 599 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). Ottawa Police Service also operates a police Mental Health Unit (MHU). Mental Health Unit Officers provide follow up support, primarily as liaisons with other mental health services in the community (*Mental Health Unit*, 2018). Officers may use the BMHS tool to flag individuals that require support from the Mental Health Unit. The Mental Health Unit will then review the file, identify the appropriate mental health resource in the community, and connect that individual with the appropriate services.

### 2.3.11| Regina Police Service

The Regina Police Service serves the City of Regina and provides police services to a population of 223,637. Regina Police Service employs 397 sworn Officers and 178 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). Regina Police Service also provides specialized mental health services with the Police and Crisis Team (PACT) (Regina Police Service, 2018). The Police and Crisis Team is comprised of a uniformed Officer and a Regina Qu’Appelle Health Region Registered Social Worker and responds to active crisis situations. The Police and Crisis Team may also review BMHS report and conduct follow up as needed. Any BMHS reports completed by patrol Officers are flagged for review by the Police and Crisis Team.

### 2.3.12| Saskatoon Police Service

The Saskatoon Police Service serves the City of Saskatoon and provides police services to a population of 266,064. Saskatoon Police Service employs 460 sworn Officers and 221 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). Resources unique to Saskatoon Police Service include the Police and Crisis Team, the Saskatoon Crisis Intervention Service, and HUB. The Police and Crisis Team is comprised of Saskatoon Police Service Officers and health care professionals from Saskatoon Crisis Intervention Service and responds to active crisis situations in the community (*Police and Crisis Team (PACT)*, 2018). Saskatoon Crisis Intervention Service also provides counselling and support services to members of the community (*Saskatoon Crisis Intervention Service*, 2018). Patrol Officers and the Police and Crisis Team may elect to refer individuals to Saskatoon Crisis Intervention Service (with consent) using the BMHS tool. HUB provides services similar to a situation table (multi-agency support and care planning for identified vulnerable individuals) (*Police and Crisis Team (PACT)*, 2018). Patrol Officers and the Police and Crisis Team may flag individuals they believe should be reviewed at the HUB using the BMHS tool. A liaison Officer will then review the report and determine if it is appropriate for the HUB.

### 2.3.13| Smiths Falls Police Service

The Smiths Falls Police Service serves the Town of Smiths Falls and provides police services to a population of 9,394. Smiths Falls Police Service employs 23 sworn Officers and 9 civilian staff (*Police personnel and selected crime statistics, municipal police services*, 2018). Resources unique to Smiths Falls Police Service include Open Doors for Lanark Children and Youth, Lanark County Mental Health, and a Community Service Officer. The Community Service Officer acts as a liaison between Smiths Falls Police Service and resources in the community (*Community Service Officer*, 2008). Patrol Officers may elect to flag individuals for the Community Service Officer to review using the BMHS tool. Patrol Officers and the Community Service Officer may provide referrals (with consent) to Opens Doors and Lanark County Mental Health using the BMHS tool. Lanark County Mental Health provides support services for persons aged 17 and up in Smiths Falls (*Lanark County Mental Health*, 2018). Open Doors provide counselling, programs and crisis stabilization for children and youth (*Quick Response*, 2016).

### 2.3.14 | Mental Health Strategy Summary

The unique combination of police and healthcare resources available in each community can lead to significantly different outcomes for persons in crisis. Table 2 provides a summary of each community’s response strategy.

Table ii, Police Mental Health Crisis Response Strategy by Region

|  |  |  |  |
| --- | --- | --- | --- |
| **Region** | **Mobile Crisis Resources** | **Community Mental Health Resources** | **Response Type** |
| Brantford | Yes, MCRRT | Yes, St. Leonard’s | Proactive and Reactive |
| Brockville | Yes, Police Community Outreach Team | Yes, LLGAMH | Proactive and Reactive |
| Cobourg | Yes, M-HEART | No | Proactive and Reactive |
| Gananoque | Yes, Police Community Outreach Team | Yes, LLGAMH | Proactive and Reactive |
| Guelph | Yes, IMPACT | Yes, CMHA WW | Proactive and Reactive |
| Kawartha Lakes | No | Yes, Community Resource Officer | Proactive and Reactive |
| London | No | Yes, CMHA Middlesex Crisis Centre | Reactive |
| Niagara | Yes, MCRRT, COAST | Yes, CMHA Niagara | Proactive and Reactive |
| Orangeville | No | No | Reactive |
| Ottawa | No | Yes, Police Mental Health Unit | Proactive and Reactive |
| Regina | Yes, PACT | No | Reactive |
| Saskatoon | Yes, PACT | Yes, Saskatoon Crisis Intervention Service | Reactive |
| Smiths Falls | No | Yes, Community Resource Officer, LCMH, ODLCMH | Reactive |

## 2.4| Variables

### 2.4.1| interRAI BMHS Risk Scale Items

In addition to the BMHS questions, interRAI has produced three (3) additional variables related to the person’s risk of harm to self, harm to others, and risk of failure to care for self. The risk scores are generated based on clinical decision tree models produced by interRAI, and produce a score on a scale of 1 to 10, 1 being the lowest possible risk and 10 being the highest possible risk (Hirdes, 2018). See Appendices 9, 10, and 11 for diagrams of the full decision trees.

### 2.4.2| Dependent / Target Variables

Six (6) outcomes (described below) were created as target variables for the logistic regression and Random Forests analyses. A score from 1-6 was considered low or medium risk (coded as “0”), and a score of 7 – 10 was considered high risk (coded as “1”). The cut points for the risk categories are per interRAI guidelines for use and interpretation of the BMHS scales (Hirdes, Re: interRAI Recommendations for BMHS Scale Cut Points, 2018). My goal was to predict only the high risk follow up encounters; low and medium risk scores were merged into a single category. Individual calls were linked together with a meaningless but unique identifier, and new variables were created to indicate when an individual had been seen twice within 24 and 72 hours and with a high risk (7 to 10 on a risk scale) on the follow up call.

The target variables were identified by expert opinion, which suggested that a key success metric for police was to avoid re-contact with an individual in an elevated state of crisis within 24 hours, and for situation tables / HUB avoiding re-contact with police in an elevated state of crisis within 72 hours (Savage, 2018). The different types of risk (harm to self, harm to others, and failure to care for self) were broken out into separate variables for application purposes (being able to predict different types of risk would allow police to take more appropriate action). These target variables also align well with the reasons for involuntary apprehension (Harm to Self, Harm to Others, Failure to Care for Self) described in the Mental Health Acts of each province.

### 2.4.3| Target Variables

**Hihocat24h** = Recontact by police within 24 hours of previous contact, with a high risk of harm to others (Risk of Harm to Others ≥ 7) in the second presentation.

**Hishcat24h** = Recontact by police within 24 hours of previous contact,, with a high risk of harm to self (Risk of Harm to Self ≥ 7) in the second presentation.

**Hisccat24h** = Recontact by police within 24 hours of previous contact,, with a high risk of failure to care for self (Risk of Failure to Care for Self ≥ 7) in the second presentation.

**Hihocat72h** = Recontact by police within 72 hours of previous contact,, with a high risk of harm to others Risk of (Harm to Others ≥ 7) in the second presentation.

**Hishcat72h** = Recontact by police within 72 hours of previous contact,, with a high risk of harm to self (Risk of Harm to Self ≥ 7) in the second presentation.

**Hisccat72h** = Recontact by police within 72 hours of previous contact,, with a high risk of failure to care for self (Risk of Failure to Care for Self ≥ 7) in the second presentation.

### 2.4.4| Independent Variables for Expert Informed Logistic Regression

Expert informed logistic regression analyses was conducted to estimate the predictive validity of current police decision-making on these outcomes. A logistic model was used given its assumed likeness to police decision-making heuristics (e.g., additivity) and ease of implementation. I surveyed the Brantford Police Service Mobile Crisis Rapid Response team to determine which BMHS items they intuitively use to risk assess these outcomes and which they felt were predictive. No restrictions or constraints were placed on the mobile crisis rapid response Officers (e.g., number of variables) except that the variables must be selected from the BMHS. Expert opinion identified “Refused to take some or all medication in last 3 days” and “Homeless” as the most influential and important variables (Savage, 2018). The team indicated that these items were associated with frequent police contact due to the de-stabilizing effects they had on the person’s baseline behaviour.

### 2.4.5| Independent Variables for Best Subset Logistic Regression

Best subset logistic regression was conducted using forty (39) BMHS items. To support best-subset logistic regression, the harm to self, harm to others, and failure to care for self scales were converted into binary variables (Low Harm Others Risk, Low Harm Self Risk, Low Self Care Risk, Medium Harm Others Risk, Medium Self Harm Risk, Medium Self Care Risk) binned by risk category (1 - 3 = low risk, 4 – 6 medium risk). Through the best subset model selection process each model was tuned to use the most effective subset of variables for each target outcome.

### 2.4.6| Independent Variables for Random Forests

The Random Forests analysis was conducted using thirty-six (36) items including the three interRAI risk scales in their unmodified state (see Appendices 9, 10, 11).

## 2.5| Data Preparation

Before analysis could begin the “ApparentAgeOccurrence” (describing the age of the individual at the time of the incident) variable required error correction and recoding. Although errors were limited due to the embedded data quality checks in the digital version of the BMHS, the “ApparentAgeOccurence” had 30 entries removed as likely errors. Specifically, persons indicated as aged 5 and under and persons aged 96 and older were cut based on the extremely small amount of entries and unlikely age.

Once errors were removed, the “ApparentAgeOccurrence” variable was grouped into five categories (based on interRAI’s standard age grouping (Hirdes, Re: interRAI Recommendations for BMHS Scale Cut Points, 2018): Ages 6 to 17, 18 to 29, 30 to 49, 50 to 64, and 65+.

Five new variables were created to assist with the analysis process. “f24h” and “f72h” were created to measure the maximum time window in which the next report (with the same unique ID) could occur where the reports would be paired together. “hoscale”, “scscale” and “shscale” were created based on the interRAI BMHS harm scales (Harm to Others, Harm to Self, Failure to Care for Self) to create categorical variables for each risk type. Creation of the categorical variables was necessary to evaluate if a follow up report (within 24 hours or 72 hours) was also a high-risk call.

Following the creation of the new variables, reports with the same meaningless but unique identifier were paired together (in chronological order). If the time of occurrence for the second report fell within the “f24h” or “f72h” of the first report, the reports would be paired using the left join process in SAS (see Figure 1). Reports paired with the next most immediate follow up report, meaning a single report would not be paired with multiple follow up reports.

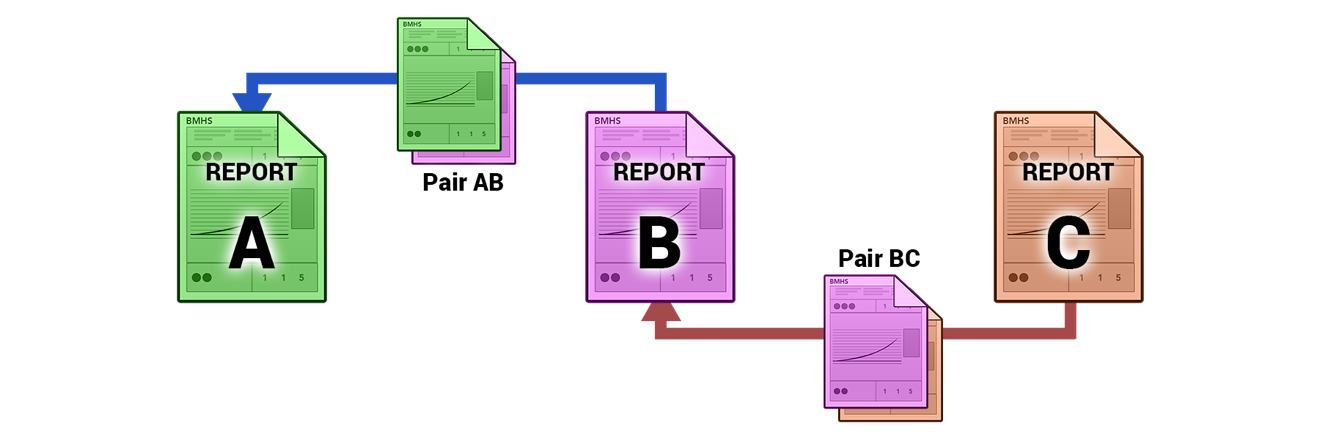


Figure i: Visual Guide, Report Pairing Process for Identifying High Risk Follow Up Reports within 24 Hours and 72 Hours

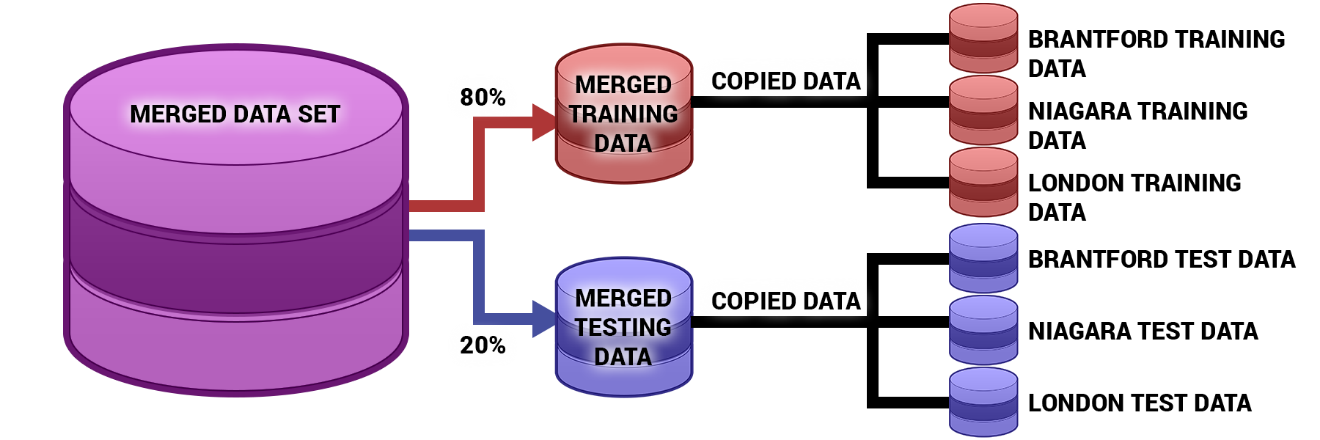
Once reports were paired, a stratified survey select (stratifying by region) with a fixed seed (2112) was applied to create separate training and holdout data sets. The training and holdout sets featured data from all 13 police service communities. Three region-specific holdout and training sets were extracted from the merged holdout set and merged training set. The three community-specific sets included Brantford, London and Niagara (see Figure 2). These communities were selected for two reasons. 1) There was sufficient holdout data to evaluate the Random Forests learning algorithm in each community and 2) the three communities each represented different response models (Brantford: specialized teams, proactive strategy, Niagara: Specialized teams, reactive strategy, London: no specialized teams, reactive strategy).

Figure ii: Data Architecture, Holdout and Training Sets

## 2.6| Statistical Methods

Analysis was conducted using three methods: expert informed logistic regression, best subset logistic regression and Random Forests.

### 2.6.1| Expert Informed Logistic Regression

Logistic Regression analysis was conducted using SAS V9.4 for Windows. The purpose of the analysis was to evaluate the performance of indicators identified by police as predictive of future crisis for comparison with random forests. The variables used to conduct the logistic regression included “Homelessness” and “Refused Some or All Medication in Last 3 Days”. These variables were identified as significant predictors by the Brantford Police Service Mobile Crisis Rapid Response Team (Savage, 2018). The Logistic Regression procedure (proc logistic) was applied to the entire merged data set.

### 2.6.2| Best Subset Logistic Regression

Best Subset Logistic Regression analysis was conducted using SAS V9.4 for Windows. Variables were selected for use in each model using the best subset method. Using the merged (all communities) training data set, I applied the best subset method with best=2 to each target outcome (harm to self 24 hours, harm to others 24 hours, failure to care for self 24 hours, harm to self 72 hours, harm to others 72 hours, failure to care for self 72 hours) to determine the point at which adding additional variables in a multivariable model resulted in diminishing return (measured by the log-likelihood chi-square score) (See Appendix 8). After identifying the point of diminishing returns, the best subset methods was a applied a second time with best=3 and start / stop configured to span the most optimal models within plus or minus 2 additional or less variables from the diminishing returns point (see Appendix 9). Finally I compared the AIC, Chi-Square Score, and AUC scores of each of the 3 models at the chosen number of variables to determine the best model (See Appendix 10). Following identification of the most effective model for harm to self 24 hours, harm to others 24 hours, failure to care for self 24 hours, harm to self 72 hours, harm to others 72 hours, failure to care for self 72 hours, I applied the selected models to the merged (all communities) holdout set, Brantford holdout set, London holdout set, and Niagara holdout set. Model fit and accuracy was determined using the adjusted odds ratio (AOR) (with confidence intervals) and the area under the receiver operator curve (AUC) (with confidence intervals).

### 2.6.3| Random Forests

Thirty-six (36) variables were used in the Random Forests analysis (see Appendix 4 for full list) using the MLR package for R (version 3.4.3). Each learner algorithm was tuned with the parameters mtry=3,6,9,12 and ntree=1,100,200,300,400,500,1000,2500,5000 in keeping with Breiman’s recommendations (Breiman, Manual - Setting Up, Using, And Understanding Random Forests V4.0, 2004). Cross validation was conducted using the MLR makeResampleDesc with the parameters iters=5L. The results of cross validation were evaluated and charted using mmce during the learner algorithm selection process. Prediction type was configured to ‘prob’ (probability) with importance=T. The Gini index was used for the split criterion. Mtry and ntree were selected for each learner algorithm first by cross validation of the mean misclassification error (MMCE) and then by identifying the learner algorithm with the highest observed AUC within that group. In total, 6 learner algorithms were trained on the merged training set (one for each outcome) as well as 6 learner algorithms on each identified regional training set (Brantford, London and Niagara). These three regions were identified as appropriate for individual evaluation because a) collectively they make up more than 50% of the data set and b) each has enough observations within the holdout dataset to support a reasonable evaluation of the Random Forests learning algorithm. These learner algorithms were then applied to the holdout data sets to predict the outcomes identified in Section 2.3.3. Predictive accuracy measures included AUC (area under curve), ACC (accuracy), sensitivity and specificity.

# 3| Results

## 3.1| Participants

The total data set included 13,058 BMHS reports, related to 9,334 unique individuals screened by police. The majority of the data set had individuals screened in London (31.84%), Brantford (23.46%) and Niagara Region (21.89%). Guelph Police Service contributed another lager portion of the data set (8.08%) with the remainder being made up of police services contributing 4% or less. Though Kawartha Lakes (0.84%), Smiths Falls (0.47%), Orangeville (0.46%), and Gananoque (0.37%) had relatively small contributions to the total data set, I chose to include them due to their potential benefit to the training process of the Random Forests algorithm. Differences in the number of unique persons observed in each community are likely due to differences in size of the populations served and the duration of time which each community’s police service had been using the BMHS.

Figure iii: Number of Reports Submitted by Region, All Reports, All Regions (N=13,058)

## 3.2| Descriptive Data

### 3.2.1| Unique Persons

7731 (82.83%) of the unique individuals observed by police were only screened once during the study period. Another 966 (10.35%) were screened twice, while the remainder of persons were screened 3 (3.06%), 4 (1.31%), or 5 or more (2.45%) times. Alias checking and automatic merging of reports was included in the BMHS software, reducing the likelihood that unique individuals were double counted. Though most police interactions involved individuals who had not been screened previously, there were notable cases in which a single individual had been screened multiple times. 2.9% of the total data set can be attributed to 11 individuals, with the most reports attributed to a single person being 66 (0.5% of the total data set).

Table iii: Number of Reports Completed per Unique Person by Region, Unique Persons, All Communities (n=9,334)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Region** | **Number of BMHS Reports by Unique Person** | | | | |
| **1 Report** | **2 Report** | **3 Report** | **4 Report** | **5+ Reports** |
| Brantford | 1643 (75.02%) | 275 (12.56%) | 109 (4.98%) | 52 (2.37%) | 111 (5.07%) |
| Brockville | 154 (84.15%) | 21 (11.48%) | 5 (2.73%) | 1 (0.55%) | 2 (1.09%) |
| Cobourg | 146 (82.49%) | 20 (11.30%) | 8 (4.52%) | 2 (1.13%) | 1 (0.56%) |
| Gananoque | 34 (97.14%) | 1 (2.86%) | 0(0%) | 0 (0%) | 0 (0%) |
| Guelph | 630 (83.55%) | 74 (9.81%) | 22 (2.92%) | 9 (1.19%) | 19 (2.52%) |
| Kawartha Lakes | 67 (85.90%) | 9 (11.54%) | 0 (0%) | 2 (2.56%) | 0 (0%) |
| London | 2450 (82.44%) | 338 (11.37%) | 84 (2.83%) | 38 (1.28%) | 62 (2.09%) |
| Niagara | 1767 (86.49%) | 182 (8.91%) | 47 (2.3%) | 15 (0.73%) | 32 (1.57%) |
| Orangeville | 40 (93.02%) | 1 (2.33%) | 0 (0%) | 1 (2.33%) | 1 (2.33%) |
| Ottawa | 326 (96.17%) | 9 (2.65%) | 4 (1.18%) | 0 (0%) | 0 (0%) |
| Regina | 252 (90.65%) | 19 (6.83%) | 4 (1.44%) | 2 (0.72%) | 1 (0.36%) |
| Saskatoon | 18 3(92.42%) | 14 (7.07%) | 1 (0.51%) | 0 (0%) | 0 (0%) |
| Smiths Falls | 39 (88.64%) | 3 (6.82%) | 2 (4.55%) | 0 (0%) | 0 (0%) |
| **Total** | **7731 (82.83%)** | **966 (10.35%)** | **286(3.06%)** | **122(1.31%)** | **229(2.45%)** |

### 3.2.2| Demographics

Of unique persons, 4,293 were female (46%) and 914 were homeless (10%). 3,221 (35%) presented with intoxication at the time of screening, and 1,815 (19%) were refusing to take prescribed medications. Most common risks observed (score of over 5 on the interRAI harm scales) were: risk of harm to self (59%), then risk of failure to care for self (55%), then risk of harm to others (45%). In terms of dangerousness, 3,394 (36%) had previous police contact (of any kind), 1,496 (16%) were known to carry weapons, 1,694 (18%) had committed acts of violence to others, and 2,986 (32%) had a suicide plan within 30 days of screening. For a full description of demographics for all reports and unique persons, see Appendices 5 and 6.

Table iv: Descriptive Statistics, by BMHS Indicators, Unique Persons, All Regions (n=9,334)

|  |  |  |
| --- | --- | --- |
| **Variable** | **All Regions** | |
| (N=9334) | |
| **Identification** | | |
| Gender is Female | 4293 | (46%) |
| Homeless | 914 | (10%) |
| **Mental State Indicators** | | |
| \*Irritability | 5082 | (54%) |
| \*Hallucinations | 1572 | (17%) |
| \*Command hallucinations | 844 | (9%) |
| \*Delusions | 2080 | (22%) |
| \*Hyper-arousal | 2877 | (31%) |
| \*Pressured speech | 3121 | (33%) |
| \*Abnormal thought processes | 4789 | (51%) |
| \*Socially inappropriate behaviour | 3887 | (42%) |
| \*Verbal abuse | 2862 | (31%) |
| \*Intoxication | 3221 | (35%) |
| \*Poor insight into mental health | 6257 | (67%) |
| \*Daily Decision Making | 3502 | (38%) |
| **Violence Indicators** | | |
| \*Previous Police Contact | 3394 | (36%) |
| Carries Weapon | 1496 | (16%) |
| \*Violent ideation | 2255 | (24%) |
| \*Intimidation of others | 2232 | (24%) |
| \*Violence to others | 1694 | (18%) |
| Self-injurious attempt last 7 days | 3037 | (33%) |
| Considered self-injury last 30 days | 4708 | (50%) |
| Suicide Plan in Last 30 Days | 2986 | (32%) |
| Others concerned about self-injury | 5388 | (58%) |
| \*\*Squalid condition | 2654 | (28%) |
| Refused Medication | 1815 | (19%) |
| **interRAI Risk Scales** | | |
| \*\*\*Risk of Harm to Other (Score of 6 – 10) | 4156 | (45%) |
| \*\*\*Risk of Self Care Score (Score of 6 – 10) | 5106 | (55%) |
| \*\*\*Risk of Self Harm Score (Score of 6 – 10) | 5493 | (59%) |

**Legend**  
\*Collapsed to none or present within last week.  
\*\*Yes to squalid home environment  
\*\*\*Risk scores at time of first encounter

### 3.2.3| Call Outcomes

Of all reports, 3,800 (41%) ended in an involuntary apprehension under the authority of a peace officer’s power with another 730 (8%) ending in apprehension under the authority of a judge’s warrant or physician’s order. An additional 1,884 (20%) accepted a voluntary escort to hospital. For a full description of outcomes for each community, see appendices 5.

Table v: Call Outcomes, All Reports, All Communities (N=13,058)

|  |  |  |
| --- | --- | --- |
| **Variable** | **All Regions** | |
| (N=13,058) | |
| Voluntary escort to hospital | 1884 | (20%) |
| Involuntarily Apprehended | 3800 | (41%) |
| Apprehended under existing order | 730 | (8%) |
| Referred to Community Mental Health Services | 2654 | (28%) |
| Transferred to EMS/MCRRT | 1993 | (21%) |
| Caseworker/Probation notified | 779 | (8%) |

## 3.3| Outcome data

Despite the large sample size, the target variables for analysis were rare. An average of 0.99% of reports had a follow up report with high risk within 24 hours, and an average of 244 (1.86%) reports had a follow up report with high risk within 72 hours. The most common type of high risk repeat contact within both 24 hours and 72 hours was risk of harm to self (1.34%, 2.5%).

Table vi: Incidence of Dependent Variable by Region, All Reports, All Communities (N=13,058)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Region** | **Follow Up Report** | | | | | |
| High Risk of Harm to Others, within 24 hours | High Risk of Harm to Self, within 24 hours | High Risk of Failure to care for self, within 24 hours | High Risk of Harm to Others, within 72 hours | High Risk of Harm to self, within 72 hours | High Risk of Failure to care for self, within 72 hours |
| Brantford | 32 (0.84%) | 48 (1.28%) | 39 (1.03%) | 75 (1.97%) | 87 (2.29%) | 76 (2%) |
| Brockville | 0 (0%) | 0 (0%) | 2 (0.87%) | 2 (0.87%) | 3 (1.31%) | 4 (1.75%) |
| Cobourg | 0 (0%) | 0 (0%) | 1 (0.46%) | 0 (0%) | 0 (0%) | 1 (0.46%) |
| Gananoque | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) | 0 (0%) |
| Guelph | 12 (1.19%) | 20 (1.98%) | 7 (0.69%) | 18 (1.79%) | 29 (2.88%) | 15 (1.49%) |
| Kawartha Lakes | 2 (2.15%) | 0 (0%) | 1 (1.08%) | 2 (2.15%) | 0 (0%) | 2 (2.15%) |
| London | 29 (0.71%) | 68 (1.67%) | 37 (0.91%) | 56 (1.37%) | 132 (3.24%) | 61 (1.5%) |
| Niagara | 17 (0.65%) | 27 (1.04%) | 21 (0.81%) | 31 (1.19%) | 56 (2.15%) | 36 (1.38%) |
| Orangeville | 2 (3.92%) | 3 (5.88%) | 2 (3.92%) | 2 (3.92%) | 3 (5.88%) | 2 (3.92%) |
| Ottawa | 1 (0.28%) | 0 (0%) | 1 (0.28%) | 3 (0.84%) | 1 (0.28%) | 4 (1.12%) |
| Regina | 2 (0.63%) | 6 (1.90%) | 3 (0.95%) | 3 (0.95%) | 10 (3.17%) | 6 (1.9%) |
| Saskatoon | 0 (0%) | 0 (0%) | 1 (0.47%) | 1 (0.47%) | 2 (0.93%) | 2 (0.93%) |
| Smiths Falls | 2 (3.85%) | 3 (5.77%) | 2 (3.85%) | 2 (3.85%) | 3 (5.77%) | 2 (3.85%) |
| **Total** | **99 (0.76%)** | **175 (1.34%)** | **117 (0.90%)** | **195 (1.49%)** | **326 (2.5%)** | **211 (1.62%)** |

## 3.4| Main Results

### 3.4.1| Logistic Regression Results

#### 3.4.1.1| Expert Informed Logistic Regression

For most (4 of 6) target outcomes in the Merged Data set, the predictive accuracy of the logistic regression was significantly different than chance (with the exception of two outcomes which contained AUC=.5 in the confidence interval). Overall, homelessness proved to be a stronger predictor (mean AOR =1.706 in the merged data) than refusing medication (mean Adjusted Odds Ration (AOR)=1.2942 in the merged data). For example, the odds of homeless persons having police recontact within 24 hours with high risk of harm to others was 2.1 times greater than those who were not homeless. The odds of persons who refused medications having police recontact within 24 hours with high risk of harm to others was unchanged (P≥.05). With exception to police recontacts with high risk of failure to self-care in some communities, the odds of police recontact for those who refused to take medication was the same as those who did not refuse to take medication. The odds of homeless persons experiencing the outcomes was frequently 2 times greater than those who were not homeless, though often it was much lower or not significant. When compared against the region specific data, the expert informed logistic regression performed worst against the London data (5 out 6 models no better than chance) and best against the Niagara data (1 out of 6 predictions no better than chance). Overall, the expert informed logistic regression model poorly classified the outcomes, and only homelessness showed some association with the outcomes.

Table vii: Expert Informed Logistic Regression Results for Each Holdout Set, by Dependent Variable (N=13,058)

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Data Set** | **Risk Type** | **Time Period** | **Covariates** | **AOR** | **AOR 95% CI** | | **AUC** | **AUC 95% CI** | |
| Merged Data | Harm to Others | 24 Hour | Refusing Medication | 1.267 | 0.798 | 2.013 | 0.5737 | 0.5226 | 0.6428 |
| Homeless | 2.131 | 1.311 | 3.464 |
| 72 Hour | Refusing Medication | 1.35 | 0.973 | 1.872 | 0.5591 | 0.5235 | 0.5947 |
| Homeless | 1.728 | 1.193 | 2.503 |
| Harm to Self | 24 Hour | Refusing Medication | 0.986 | 0.676 | 1.438 | 0.5070 | 0.4730 | 0.5410 |
| Homeless | 1.089 | 0.688 | 1.725 |
| 72 Hour | Refusing Medication | 1.014 | 0.77 | 1.336 | 0.5111 | 0.4853 | 0.5370 |
| Homeless | 1.217 | 0.878 | 1.685 |
| Failure to Care for Self | 24 Hour | Refusing Medication | 1.629 | 1.089 | 2.436 | 0.5853 | 0.5379 | 0.6328 |
| Homeless | 2.115 | 1.353 | 3.306 |
| 72 Hour | Refusing Medication | 1.519 | 1.118 | 2.063 | 0.5749 | 0.5400 | 0.6099 |
| Homeless | 1.956 | 1.387 | 2.756 |
| Brantford Data | Harm to Others | 24 Hour | Refusing Medication | 0.880 | 0.307 | 2.529 | 0.6192 | 0.5229 | 0.7154 |
| Homeless | 4.653 | 2.226 | 9.728 |
| 72 Hour | Refusing Medication | 0.968 | 0.494 | 1.899 | 0.5559 | 0.4966 | 0.6152 |
| Homeless | 2.612 | 1.505 | 4.532 |
| Harm to Self | 24 Hour | Refusing Medication | 0.915 | 0.387 | 2.163 | 0.5161 | 0.4550 | 0.5772 |
| Homeless | 1.244 | 0.525 | 2.946 |
| 72 Hour | Refusing Medication | 0.829 | 0.426 | 1.613 | 0.5224 | 0.4783 | 0.5666 |
| Homeless | 1.267 | 0.667 | 2.405 |
| Failure to Care for Self | 24 Hour | Refusing Medication | 0.916 | 0.356 | 2.359 | 0.5877 | 0.5034 | 0.6721 |
| Homeless | 3.480 | 1.719 | 7.048 |
| 72 Hour | Refusing Medication | 0.843 | 0.417 | 1.704 | 0.5613 | 0.5042 | 0.6184 |
| Homeless | 2.573 | 1.485 | 4.461 |
| London Data | Harm to Others | 24 Hour | Refusing Medication | 1.344 | 0.571 | 3.163 | 0.5151 | 0.4196 | 0.6106 |
| Homeless | 0.981 | 0.295 | 3.262 |
| 72 Hour | Refusing Medication | 1.422 | 0.772 | 2.620 | 0.5307 | 0.4662 | 0.5953 |
| Homeless | 0.827 | 0.328 | 2.088 |
| Harm to Self | 24 Hour | Refusing Medication | 0.921 | 0.491 | 1.728 | 0.5277 | 0.4786 | 0.5767 |
| Homeless | 0.544 | 0.197 | 1.502 |
| 72 Hour | Refusing Medication | 0.939 | 0.599 | 1.473 | 0.5101 | 0.4721 | 0.5480 |
| Homeless | 0.872 | 0.477 | 1.593 |
| Failure to Care for Self | 24 Hour | Refusing Medication | 1.960 | 0.978 | 3.930 | 0.5800 | 0.4940 | 0.6660 |
| Homeless | 1.930 | 0.839 | 4.437 |
| 72 Hour | Refusing Medication | 2.012 | 1.169 | 3.461 | 0.5818 | 0.5153 | 0.6483 |
| Homeless | 1.823 | 0.939 | 3.541 |
| Niagara Data | Harm to Others | 24 Hour | Refusing Medication | 1.035 | 0.363 | 2.954 | 0.5721 | 0.4328 | 0.7114 |
| Homeless | 2.610 | 0.913 | 7.459 |
| 72 Hour | Refusing Medication | 1.814 | 0.883 | 3.726 | 0.6206 | 0.5227 | 0.7185 |
| Homeless | 2.525 | 1.152 | 5.536 |
| Harm to Self | 24 Hour | Refusing Medication | 1.060 | 0.462 | 2.435 | 0.5458 | 0.4419 | 0.6497 |
| Homeless | 1.786 | 0.716 | 4.458 |
| 72 Hour | Refusing Medication | 1.299 | 0.741 | 2.275 | 0.5723 | 0.5009 | 0.6437 |
| Homeless | 1.894 | 1.008 | 3.561 |
| Failure to Care for Self | 24 Hour | Refusing Medication | 1.880 | 0.788 | 4.487 | 0.6337 | 0.5180 | 0.7439 |
| Homeless | 2.451 | 0.944 | 6.368 |
| 72 Hour | Refusing Medication | 2.012 | 1.035 | 3.911 | 0.6476 | 0.5600 | 0.7352 |
|  | Homeless | 2.719 | 1.324 | 5.582 |

#### 3.4.1.2| Best Subset Logistic Regression

The best-subset variable selection method used on the Harm to Others, 24 hours, merged training set (all police services) revealed that the log-likelihood Chi-Square Score showed diminishing returns between 5 to 8 variables (See Appendix 8). The Chi-Square Score was 85.318 for the best 8 variable model compared to 76.4606 for the best 5 variable model (See Appendix 9). A comparison of the ‘best’ (highest Chi-Square Score) 8 variable model AUC= 0.763, AIC= 872.178) to the ‘best’ 5 variable model (AUC= 0.7543, AIC= 896.755) revealed only marginal improvement in classification (AUC) and information quality (AIC). Closer inspection of the 6, 7 and 8 variable models revealed that some variables included in the models were not statistically significant at the P<.05 cut off. Models with insignificant variables were removed from the possible models for selection. The ‘best’ 3 logistic models with 5 variables were compared for their classification accuracy (AUC), goodness of fit (Hosmer), and the magnitude of their odds ratios. A final model was selected that included: Hyperarousal, Abnormal Thought Process, Involuntarily Apprehended, Previous Police Contact in Last 30 Days and Intimidation of Others or Threatened Violence.

The selected model’s adjusted odds ratios and classification accuracy in the merged training set (all police services) is shown in Table 8. For example, all other parameter being equal, the odds of police recontact within 24 hours initial police contact with high risk of harm to others was 1.67 times higher (95% CI 1.29 – 2.15) for those with hyperarousal relative to those without hyperarousal at time of initial police contact. Those who were involuntary apprehended during initial police contact were, overall, 50% less likely (95% CI 0.31-0.82) to experience police recontact within 24 hours with high risk of harm to others. The model’s odds ratio parameters and classification accuracy in the holdout set(s) is/are shown in Table 7. Although the adjust odds ratios were similar to those in the merged training set, they were not significant / precise at the 95% confidence level. The classification accuracy of the 5 variable model was higher in the merged training than in the merged holdout data (AUC training=0.7543, AUC holdout =0.728), which demonstrated overfitting / high variance in the model. As demonstrated by the insignificant adjusted odds ratios and highly variable AUCs, the model did not fit the region specific holdout sets. Most of the predictors could not be estimated given the very low prevalence of the outcomes in the region specific holdout sets.

Table viii: Best Subset Logistic Regression Results for training and holdout sets for harm to others, 24 hours (N=13,058)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Data set** | **Variable** | **AOR** | **CI (Low)** | **CI (High)** | **P** | **AUC** | **CI (Low)** | **CI (High)** |
| Merged Training | Hyperarousal | 1.665 | 1.292 | 2.147 | <.0001 | 0.7543 | 0.7039 | 0.8047 |
| Abnormal Thought Process | 2.479 | 1.465 | 4.193 | 0.0007 |
| Involuntarily Apprehended | 0.502 | 0.307 | 0.821 | 0.0061 |
| Previous Police Contact in Last 30 Days | 1.442 | 1.087 | 1.912 | 0.0111 |
| Intimidation of Others or Threatened Violence | 1.554 | 1.196 | 2.018 | 0.001 |
| Merged Holdout | Hyperarousal | 1.586 | 0.936 | 2.687 | 0.0863 | 0.728 | 0.6231 | 0.8328 |
| Abnormal Thought Process | 1.487 | 0.422 | 5.245 | 0.5369 |
| Involuntarily Apprehended | 0.555 | 0.196 | 1.571 | 0.2673 |
| Previous Police Contact in Last 30 Days | 1.447 | 0.795 | 2.633 | 0.2265 |
| Intimidation of Others or Threatened Violence | 1.422 | 0.815 | 2.48 | 0.2153 |
| Brantford Holdout | Hyperarousal | 1.35 | 0.546 | 3.338 | 0.5158 | 0.8396 | 0.7446 | 0.9347 |
| Abnormal Thought Process | 2.468 | 0.434 | 14.027 | 0.3081 |
| Involuntarily Apprehended | <0.001 | <0.001 | >999.999 | 0.9625 |
| Previous Police Contact in Last 30 Days | 1.294 | 0.394 | 4.25 | 0.6706 |
| Intimidation of Others or Threatened Violence | 1.841 | 0.731 | 4.637 | 0.1953 |
| London Holdout | Hyperarousal | 0.834 | 0.273 | 2.548 | 0.7505 | 0.9113 | 0.8178 | 1 |
| Abnormal Thought Process | <0.001 | <0.001 | >999.999 | 0.9774 |
| Involuntarily Apprehended | 2.085 | 0.165 | 26.382 | 0.5706 |
| Previous Police Contact in Last 30 Days | 2.179 | 0.593 | 8.002 | 0.2408 |
| Intimidation of Others or Threatened Violence | 3.75 | 0.96 | 14.658 | 0.0574 |
| Niagara Holdout | Hyperarousal | 220.543 | <0.001 | >999.999 | 0.9448 | 0.997 | 0.9939 | 1 |
| Abnormal Thought Process | 0.933 | <0.001 | >999.999 | 0.9999 |
| Involuntarily Apprehended | <0.001 | <0.001 | >999.999 | 0.9152 |
| Previous Police Contact in Last 30 Days | <0.001 | <0.001 | >999.999 | 0.94 |
| Intimidation of Others or Threatened Violence | 346.519 | <0.001 | >999.999 | 0.9398 |

The selected model’s adjusted odds ratios and classification accuracy in the merged training set (all police services) is shown in Table 9. For example, all other parameter being equal, the odds of police recontact within 24 hours initial police contact with high risk of harm to self were 2.4 times higher (95% CI 1.58 – 3.72) for those with abnormal thought processes relative to those without abnormal thought processes at time of initial police contact. Those who were apprehended under an existing order during initial police contact were, overall, 90% less likely (95% CI 0.02 – 0.76) to experience police recontact within 24 hours with high risk of harm to self. The model’s odds ratio parameters and classification accuracy in the holdout set(s) is/are shown in Table 8. The adjusted odds ratios varied from those in the merged training set, and most were not significant / precise at the 95% confidence level (with the exception of Previous Police Contact in Last 30 Days and Low Self Harm Risk). The classification accuracy of the 7 variable model was higher in the merged training than in the merged holdout data (AUC training= 0.75, AUC holdout = 0.71), which demonstrated overfitting / high variance in the model. As demonstrated by the insignificant adjusted odds ratios and highly variable AUCs, the model did not fit the region specific holdout sets. Most of the predictors could not be estimated given the very low prevalence of the outcomes in the region specific holdout sets.

Table ix: Best Subset Logistic Regression Results for training and holdout sets for harm to self, 24 hours (N=13,058)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Data set** | **Variable** | **AOR** | **CI (Low)** | **CI (High)** | **P** | **AUC** | **CI (Low)** | **CI (High)** |
| Merged Training | Transferred to EMS/Mobile Crisis Team | 0.443 | 0.276 | 0.712 | 0.0008 | 0.7507 | 0.7088 | 0.7925 |
| Abnormal Thought Process | 2.422 | 1.576 | 3.722 | <.0001 |
| Apprehended Under Existing Order | 0.105 | 0.015 | 0.759 | 0.0255 |
| Involuntarily Apprehended | 0.454 | 0.31 | 0.664 | <.0001 |
| Previous Police Contact in Last 30 Days | 1.818 | 1.473 | 2.243 | <.0001 |
| Low Self Harm Risk | 0.19 | 0.113 | 0.319 | <.0001 |
| Medium Self Harm Risk | 0.321 | 0.182 | 0.566 | <.0001 |
| Merged Holdout | Transferred to EMS/Mobile Crisis Team | 1.221 | 0.575 | 2.594 | 0.6032 | 0.7119 | 0.6303 | 0.7935 |
| Abnormal Thought Process | 0.682 | 0.206 | 2.255 | 0.5306 |
| Apprehended Under Existing Order | 0.278 | 0.037 | 2.085 | 0.2131 |
| Involuntarily Apprehended | 0.993 | 0.51 | 1.935 | 0.9838 |
| Previous Police Contact in Last 30 Days | 2.137 | 1.44 | 3.17 | 0.0002 |
| Low Self Harm Risk | 0.253 | 0.086 | 0.749 | 0.013 |
| Medium Self Harm Risk | 0.887 | 0.391 | 2.013 | 0.7751 |
| Brantford Holdout | Transferred to EMS/Mobile Crisis Team | 0.547 | 0.067 | 4.495 | 0.5747 | 0.7688 | 0.627 | 0.9105 |
| Abnormal Thought Process | 0.638 | 0.079 | 5.148 | 0.6728 |
| Apprehended Under Existing Order | <0.001 | <0.001 | >999.999 | 0.9823 |
| Involuntarily Apprehended | 1.283 | 0.329 | 5.006 | 0.7194 |
| Previous Police Contact in Last 30 Days | 2.456 | 1.079 | 5.59 | 0.0323 |
| Low Self Harm Risk | 0.209 | 0.037 | 1.165 | 0.0741 |
| Medium Self Harm Risk | 1.028 | 0.226 | 4.683 | 0.9714 |
| London Holdout | Transferred to EMS/Mobile Crisis Team | 1.273 | 0.365 | 4.444 | 0.7053 | 0.7664 | 0.6577 | 0.875 |
| Abnormal Thought Process | <0.001 | <0.001 | >999.999 | 0.9729 |
| Apprehended Under Existing Order | <0.001 | <0.001 | >999.999 | 0.9658 |
| Involuntarily Apprehended | 1 | 0.271 | 3.686 | 0.9998 |
| Previous Police Contact in Last 30 Days | 2.199 | 1.104 | 4.378 | 0.0249 |
| Low Self Harm Risk | 0.387 | 0.047 | 3.178 | 0.3767 |
| Medium Self Harm Risk | 1.716 | 0.491 | 5.993 | 0.3976 |
| Niagara Holdout | Transferred to EMS/Mobile Crisis Team | 1.15 | 0.21 | 6.292 | 0.8721 | 0.7842 | 0.649 | 0.9194 |
| Abnormal Thought Process | 1.09 | 0.114 | 10.427 | 0.9405 |
| Apprehended Under Existing Order | 2.003 | 0.229 | 17.536 | 0.5302 |
| Involuntarily Apprehended | 0.695 | 0.134 | 3.604 | 0.6646 |
| Previous Police Contact in Last 30 Days | 2.059 | 0.887 | 4.78 | 0.0929 |
| Low Self Harm Risk | <0.001 | <0.001 | >999.999 | 0.9576 |
| Medium Self Harm Risk | <0.001 | <0.001 | >999.999 | 0.952 |

The selected model’s adjusted odds ratios and classification accuracy in the merged training set (all police services) is shown in Table 10. For example, all other parameter being equal, the odds of police recontact within 24 hours initial police contact with high risk of failure to care for self was 1.5 times higher (95% CI 1.18 – 1.89) for those with pressured speech or racing thoughts relative to those without pressured speech or racing thoughts at time of initial police contact. Those who had low self care risk during initial police contact were, overall, 69% less likely (95% CI 0.17 – 0.61) to experience police recontact within 24 hours with high risk of failure to care for self. The model’s odds ratio parameters and classification accuracy in the holdout set(s) is/are shown in Table 9. Although the adjust odds ratios were similar to those in the merged training set, they were not significant / precise at the 95% confidence level (with the exception of pressured speech or racing thoughts). The classification accuracy of the 4 variable model was higher in the merged training than in the merged holdout data (AUC training= 0.709, AUC holdout = 0.707), which demonstrated overfitting / high variance in the model. As demonstrated by the insignificant adjusted odds ratios and highly variable AUCs, the model did not fit the region specific holdout sets. Most of the predictors could not be estimated given the very low prevalence of the outcomes in the region specific holdout sets.

Table x: Best Subset Logistic Regression Results for training and holdout sets for failure to care for self, 24 hours (N=13,058)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Data set** | **Variable** | **AOR** | **CI (Low)** | **CI (High)** | **P** | **AUC** | **CI (Low)** | **CI (High)** |
| Merged Training | Pressured Speech or Racing Thought | 1.491 | 1.179 | 1.885 | 0.0008 | 0.70907 | 0.6546 | 0.7648 |
| Involuntarily Apprehended | 0.43 | 0.267 | 0.693 | 0.0005 |
| Previous Police Contact in Last 30 Days | 1.497 | 1.138 | 1.97 | 0.004 |
| Low Self Care Risk | 0.319 | 0.168 | 0.607 | 0.0005 |
| Merged Holdout | Pressured Speech or Racing Thought | 1.514 | 1.024 | 2.239 | 0.0376 | 0.7069 | 0.6111 | 0.8027 |
| Involuntarily Apprehended | 0.495 | 0.228 | 1.074 | 0.0752 |
| Previous Police Contact in Last 30 Days | 1.546 | 0.981 | 2.435 | 0.0602 |
| Low Self Care Risk | 0.38 | 0.137 | 1.052 | 0.0625 |
| Brantford Holdout | Pressured Speech or Racing Thought | 1.693 | 0.882 | 3.251 | 0.1136 | 0.6714 | 0.4923 | 0.8506 |
| Involuntarily Apprehended | 0.248 | 0.031 | 2.008 | 0.1914 |
| Previous Police Contact in Last 30 Days | 1.186 | 0.504 | 2.792 | 0.6958 |
| Low Self Care Risk | 0.665 | 0.179 | 2.467 | 0.5417 |
| London Holdout | Pressured Speech or Racing Thought | 1.653 | 0.783 | 3.488 | 0.1873 | 0.8501 | 0.7682 | 0.9319 |
| Involuntarily Apprehended | 0.648 | 0.163 | 2.574 | 0.5376 |
| Previous Police Contact in Last 30 Days | 2.147 | 0.939 | 4.91 | 0.0701 |
| Low Self Care Risk | <0.001 | <0.001 | >999.999 | 0.9483 |
| Niagara Holdout | Pressured Speech or Racing Thought | 1.378 | 0.522 | 3.639 | 0.5175 | 0.6549 | 0.3285 | 0.9814 |
| Involuntarily Apprehended | 0.299 | 0.047 | 1.891 | 0.1993 |
| Previous Police Contact in Last 30 Days | 1.352 | 0.445 | 4.105 | 0.5943 |
| Low Self Care Risk | 1.069 | 0.104 | 11.022 | 0.9555 |

The selected model’s adjusted odds ratios and classification accuracy in the merged training set (all police services) is shown in Table 11. For example, all other parameter being equal, the odds of police recontact within 24 hours initial police contact with high harm to others was 1.8 times higher (95% CI 1.15 – 2.71) for those with abnormal thought processes relative to those without abnormal thought processes at time of initial police contact. Those who were apprehended under an existing order during initial police contact were, overall, 70% less likely (95% CI 0.11 – 0.82) to experience police recontact within 24 hours with high risk of harm to others. The model’s odds ratio parameters and classification accuracy in the holdout set(s) is/are shown in Table 10. Although the adjust odds ratios were similar to those in the merged training set, they were not significant / precise at the 95% confidence level (with the exception of sex and previous police contact in last 30 days). The classification accuracy of the 8 variable model was equal in the merged training and merged holdout data (AUC training = 0.727, AUC holdout = 0.727. As demonstrated by the insignificant adjusted odds ratios, the model did not fit the region specific holdout sets. Most of the predictors could not be estimated given the very low prevalence of the outcomes in the region specific holdout sets.

Table xi: Best Subset Logistic Regression Results for training and holdout sets for harm to others, 72 hours (N=13,058)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Data set** | **Variable** | **AOR** | **CI (Low)** | **CI (High)** | **P** | **AUC** | **CI (Low)** | **CI (High)** |
| Merged Training | Sex | 0.642 | 0.464 | 0.89 | 0.0077 | 0.7272 | 0.6902 | 0.7643 |
| Socially Inappropriate or Disruptive Behaviour | 1.418 | 1.178 | 1.707 | 0.0002 |
| Pressured Speech or Racing Thought | 1.337 | 1.118 | 1.598 | 0.0015 |
| Transferred to EMS/Mobile Crisis Team | 0.573 | 0.358 | 0.916 | 0.0199 |
| Abnormal Thought Process | 1.768 | 1.153 | 2.712 | 0.009 |
| Apprehended Under Existing Order | 0.303 | 0.111 | 0.822 | 0.0191 |
| Involuntarily Apprehended | 0.504 | 0.352 | 0.72 | 0.0002 |
| Previous Police Contact in Last 30 Days | 1.751 | 1.428 | 2.146 | <.0001 |
| Merged Holdout | Sex | 0.362 | 0.163 | 0.801 | 0.0122 | 0.7271 | 0.6582 | 0.7961 |
| Socially Inappropriate or Disruptive Behaviour | 1.187 | 0.812 | 1.737 | 0.3765 |
| Pressured Speech or Racing Thought | 1.391 | 0.958 | 2.019 | 0.0826 |
| Transferred to EMS/Mobile Crisis Team | 0.586 | 0.203 | 1.688 | 0.3218 |
| Abnormal Thought Process | 0.828 | 0.249 | 2.753 | 0.7578 |
| Apprehended Under Existing Order | 0.302 | 0.041 | 2.244 | 0.2418 |
| Involuntarily Apprehended | 0.55 | 0.254 | 1.192 | 0.1299 |
| Previous Police Contact in Last 30 Days | 1.598 | 1.035 | 2.467 | 0.0344 |
| Brantford Holdout | Sex | 0.348 | 0.073 | 1.656 | 0.1848 | 0.8185 | 0.7063 | 0.9306 |
| Socially Inappropriate or Disruptive Behaviour | 1.277 | 0.661 | 2.464 | 0.4665 |
| Pressured Speech or Racing Thought | 2.607 | 1.36 | 5.001 | 0.0039 |
| Transferred to EMS/Mobile Crisis Team | <0.001 | <0.001 | >999.999 | 0.9604 |
| Abnormal Thought Process | 1.244 | 0.255 | 6.073 | 0.7873 |
| Apprehended Under Existing Order | 2.377 | 0.248 | 22.768 | 0.4527 |
| Involuntarily Apprehended | 0.376 | 0.074 | 1.916 | 0.2391 |
| Previous Police Contact in Last 30 Days | 1.256 | 0.557 | 2.833 | 0.5832 |
| London Holdout | Sex | 0.57 | 0.156 | 2.083 | 0.3953 | 0.7841 | 0.638 | 0.9301 |
| Socially Inappropriate or Disruptive Behaviour | 1.072 | 0.501 | 2.296 | 0.8575 |
| Pressured Speech or Racing Thought | 0.83 | 0.378 | 1.826 | 0.6436 |
| Transferred to EMS/Mobile Crisis Team | 1.078 | 0.237 | 4.911 | 0.9228 |
| Abnormal Thought Process | <0.001 | <0.001 | >999.999 | 0.9753 |
| Apprehended Under Existing Order | <0.001 | <0.001 | >999.999 | 0.9682 |
| Involuntarily Apprehended | 1.302 | 0.279 | 6.069 | 0.7365 |
| Previous Police Contact in Last 30 Days | 2.734 | 1.213 | 6.167 | 0.0153 |
| Niagara Holdout | Sex | 0.567 | 0.051 | 6.359 | 0.6458 | 0.7987 | 0.6692 | 0.9281 |
| Socially Inappropriate or Disruptive Behaviour | 1.215 | 0.33 | 4.473 | 0.7696 |
| Pressured Speech or Racing Thought | 1.012 | 0.298 | 3.434 | 0.9844 |
| Transferred to EMS/Mobile Crisis Team | <0.001 | <0.001 | >999.999 | 0.9688 |
| Abnormal Thought Process | <0.001 | <0.001 | >999.999 | 0.9775 |
| Apprehended Under Existing Order | <0.001 | <0.001 | >999.999 | 0.9746 |
| Involuntarily Apprehended | 0.4 | 0.032 | 5.047 | 0.4785 |
| Previous Police Contact in Last 30 Days | 1.145 | 0.251 | 5.218 | 0.8612 |

The selected model’s adjusted odds ratios and classification accuracy in the merged training set (all police services) is shown in Table 12. For example, all other parameter being equal, the odds of police recontact within 24 hours initial police contact with high risk of harm to self was 2 times higher (95% CI 1.69 – 2.31) for those with previous police contact in last 30 days relative to those without previous police contact in last 30 days at time of initial police contact. Those who were apprehended under an existing order during initial police contact were, overall, 82% less likely (95% CI 0.06 – 0.57) to experience police recontact within 24 hours with high risk of harm to self. The model’s odds ratio parameters and classification accuracy in the holdout set(s) is/are shown in Table 11. The adjust odds ratios varied between the merged training set and merged holdout set. Most variables in the merged holdout set were not significant / precise at the 95% confidence level (with the exception of involuntarily apprehended, previous police contact in last 30 days and low self harm risk. The classification accuracy of the 8 variable model was higher in the merged holdout than in the merged training data (AUC training= 0.74, AUC holdout = 0.77), However, as demonstrated by the insignificant adjusted odds ratios, the model did not fit the region specific holdout sets. Most of the predictors could not be estimated given the very low prevalence of the outcomes in the region specific holdout sets.

Table xii: Best Subset Logistic Regression Results for training and holdout sets for harm to self, 72 hours (N=13,058)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Data set** | **Variable** | **AOR** | **CI (Low)** | **CI (High)** | **P** | **AUC** | **CI (Low)** | **CI (High)** |
| Merged Training | Transferred to EMS/Mobile Crisis Team | 0.657 | 0.475 | 0.907 | 0.0108 | 0.7416 | 0.7116 | 0.7717 |
| Referred to Community Mental Health Agency | 1.364 | 1.032 | 1.803 | 0.0292 |
| Abnormal Thought Process | 1.92 | 1.358 | 2.714 | 0.0002 |
| Apprehended Under Existing Order | 0.182 | 0.058 | 0.572 | 0.0036 |
| Involuntarily Apprehended | 0.61 | 0.46 | 0.81 | 0.0006 |
| Previous Police Contact in Last 30 Days | 1.976 | 1.689 | 2.312 | <.0001 |
| Low Self Harm Risk | 0.234 | 0.161 | 0.34 | <.0001 |
| Medium Self Harm Risk | 0.344 | 0.225 | 0.524 | <.0001 |
| Merged Holdout | Transferred to EMS/Mobile Crisis Team | 1.463 | 0.869 | 2.462 | 0.1519 | 0.7652 | 0.711 | 0.8194 |
| Referred to Community Mental Health Agency | 1.149 | 0.69 | 1.914 | 0.5922 |
| Abnormal Thought Process | 0.651 | 0.271 | 1.566 | 0.3379 |
| Apprehended Under Existing Order | 0.161 | 0.022 | 1.189 | 0.0734 |
| Involuntarily Apprehended | 0.548 | 0.327 | 0.918 | 0.0222 |
| Previous Police Contact in Last 30 Days | 2.472 | 1.846 | 3.31 | <.0001 |
| Low Self Harm Risk | 0.166 | 0.069 | 0.396 | <.0001 |
| Medium Self Harm Risk | 0.825 | 0.457 | 1.491 | 0.5249 |
| Brantford Holdout | Transferred to EMS/Mobile Crisis Team | 1.338 | 0.42 | 4.26 | 0.6219 | 0.7981 | 0.7 | 0.8962 |
| Referred to Community Mental Health Agency | 0.609 | 0.248 | 1.493 | 0.2783 |
| Abnormal Thought Process | 0.995 | 0.276 | 3.584 | 0.9942 |
| Apprehended Under Existing Order | <0.001 | <0.001 | >999.999 | 0.9839 |
| Involuntarily Apprehended | 0.621 | 0.216 | 1.785 | 0.3763 |
| Previous Police Contact in Last 30 Days | 2.655 | 1.453 | 4.852 | 0.0015 |
| Low Self Harm Risk | 0.146 | 0.043 | 0.496 | 0.002 |
| Medium Self Harm Risk | 0.618 | 0.2 | 1.905 | 0.4019 |
| London Holdout | Transferred to EMS/Mobile Crisis Team | 1.421 | 0.638 | 3.163 | 0.3901 | 0.798 | 0.7277 | 0.8684 |
| Referred to Community Mental Health Agency | 1.38 | 0.571 | 3.338 | 0.4742 |
| Abnormal Thought Process | <0.001 | <0.001 | >999.999 | 0.9697 |
| Apprehended Under Existing Order | <0.001 | <0.001 | >999.999 | 0.9641 |
| Involuntarily Apprehended | 0.659 | 0.253 | 1.714 | 0.3925 |
| Previous Police Contact in Last 30 Days | 2.602 | 1.647 | 4.11 | <.0001 |
| Low Self Harm Risk | 0.142 | 0.019 | 1.075 | 0.0587 |
| Medium Self Harm Risk | 1.343 | 0.578 | 3.125 | 0.4931 |
| Niagara Holdout | Transferred to EMS/Mobile Crisis Team | 0.719 | 0.128 | 4.028 | 0.7071 | 0.729 | 0.5855 | 0.8725 |
| Referred to Community Mental Health Agency | 1.254 | 0.188 | 8.371 | 0.8152 |
| Abnormal Thought Process | 0.806 | 0.073 | 8.895 | 0.8599 |
| Apprehended Under Existing Order | 1.337 | 0.16 | 11.192 | 0.7887 |
| Involuntarily Apprehended | 0.61 | 0.154 | 2.414 | 0.4816 |
| Previous Police Contact in Last 30 Days | 1.761 | 0.863 | 3.595 | 0.1202 |
| Low Self Harm Risk | <0.001 | <0.001 | >999.999 | 0.9686 |
| Medium Self Harm Risk | <0.001 | <0.001 | >999.999 | 0.9645 |

The selected model’s adjusted odds ratios and classification accuracy in the merged training set (all police services) is shown in Table 13. For example, all other parameter being equal, the odds of police recontact within 24 hours initial police contact with high risk of failure to care for self was 1.8 times higher (95% CI 1.26 – 2.46) for those with low self harm risk relative to those without low self harm risk at time of initial police contact. Those who were involuntarily apprehended during initial police contact were, overall, 49% less likely (95% CI 0.36 – 0.74) to experience police recontact within 24 hours with high risk of failure to care for self. The model’s odds ratio parameters and classification accuracy in the holdout set(s) is/are shown in Table 12. Although the adjust odds ratios were similar to those in the merged training set, most were not significant / precise at the 95% confidence level (with the exception of delusions, involuntarily apprehended, and previous police contact in last 30 days). The classification accuracy of the 6 variable model was higher in the merged holdout than in the merged training data (AUC training= 0.729, AUC holdout = 0.748). As demonstrated by the insignificant adjusted odds ratios, the model did not fit the region specific holdout sets. Most of the predictors could not be estimated given the very low prevalence of the outcomes in the region specific holdout sets.

Table xiii: Best Subset Logistic Regression Results for training and holdout sets for failure to care for self, 72 hours (N=13,058)

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Data set** | **Variable** | **AOR** | **CI (Low)** | **CI (High)** | **P** | **AUC** | **CI (Low)** | **CI (High)** |
| Merged Training | Sex | 0.685 | 0.498 | 0.942 | 0.0198 | 0.729 | 0.6912 | 0.7669 |
| Abnormal Thought Process | 1.563 | 1.288 | 1.897 | <.0001 |
| Delusions | 1.351 | 1.128 | 1.618 | 0.0011 |
| Involuntarily Apprehended | 0.514 | 0.359 | 0.737 | 0.0003 |
| Previous Police Contact in Last 30 Days | 1.633 | 1.333 | 2.001 | <.0001 |
| Low Self Harm Risk | 1.761 | 1.263 | 2.455 | 0.0009 |
| Merged Holdout | Sex | 0.567 | 0.306 | 1.049 | 0.0709 | 0.748 | 0.6741 | 0.8219 |
| Abnormal Thought Process | 1.308 | 0.915 | 1.869 | 0.1408 |
| Delusions | 1.712 | 1.209 | 2.423 | 0.0024 |
| Involuntarily Apprehended | 0.471 | 0.242 | 0.917 | 0.0268 |
| Previous Police Contact in Last 30 Days | 1.785 | 1.225 | 2.601 | 0.0026 |
| Low Self Harm Risk | 1.145 | 0.608 | 2.154 | 0.6751 |
| Brantford Holdout | Sex | 0.407 | 0.131 | 1.262 | 0.1194 | 0.7549 | 0.6215 | 0.8882 |
| Abnormal Thought Process | 1.834 | 1.053 | 3.193 | 0.032 |
| Delusions | 1.364 | 0.782 | 2.379 | 0.2742 |
| Involuntarily Apprehended | 0.335 | 0.07 | 1.608 | 0.1719 |
| Previous Police Contact in Last 30 Days | 1.517 | 0.779 | 2.953 | 0.2199 |
| Low Self Harm Risk | 2.112 | 0.636 | 7.018 | 0.2222 |
| London Holdout | Sex | 0.957 | 0.325 | 2.816 | 0.9364 | 0.783 | 0.6778 | 0.8877 |
| Abnormal Thought Process | 1.172 | 0.61 | 2.252 | 0.6332 |
| Delusions | 2.05 | 1.071 | 3.923 | 0.0301 |
| Involuntarily Apprehended | 0.43 | 0.124 | 1.49 | 0.1833 |
| Previous Police Contact in Last 30 Days | 2.242 | 1.143 | 4.395 | 0.0188 |
| Low Self Harm Risk | 0.362 | 0.073 | 1.784 | 0.2116 |
| Niagara Holdout | Sex | 0.829 | 0.183 | 3.757 | 0.8078 | 0.7344 | 0.6131 | 0.8557 |
| Abnormal Thought Process | 0.536 | 0.216 | 1.328 | 0.1779 |
| Delusions | 2.008 | 0.804 | 5.014 | 0.1352 |
| Involuntarily Apprehended | 0.509 | 0.093 | 2.793 | 0.4372 |
| Previous Police Contact in Last 30 Days | 1.4 | 0.541 | 3.624 | 0.4886 |
| Low Self Harm Risk | 0.806 | 0.087 | 7.447 | 0.8492 |

### 

### 3.4.2| Random Forests Results

The grid search (cross-validation) of the Random Forests learner algorithms for each outcome (6 outcomes) in each training set (4 training sets) demonstrated that learner algorithm prediction accuracy was not particularly sensitive to different vales of mtry/feature bagging, but rather was more sensitive to the ntree/number of trees hyperparameter (see Appendix 11).

Use of the Random Forests method yielded modest to good predictive accuracy (AUC≥0.7) for 24 of 42 total test outcomes (6 outcomes in each of 7 data set combinations), with higher accuracy clustered around the city of Brantford. The predictive accuracy of Random Forests trained on the merged training set and applied to Brantford test set had relatively higher accuracy well in all 6 outcomes with AUC≥0.7. Notably the predictive accuracy for harm to others, 72 hour follow up (AUC=0.754) and harm to self, 24 hour follow up (AUC=0.764) was greater in the Brantford holdout dataset compared to the merged dataset (AUC=0.687, AUC=0.68)

In London, Random Forests trained on the merged data set struggled to provide accurate predictions for harm to self in both 24 hour (AUC=0.574) and 72 hour (AUC=0.656) follow up periods. Performance on other outcomes were also modest (AUC≥0.6) with the exception of failure to care for self, 72 hours (AUC=0.770). The performance of the Random Forests trained on the merged data set and applied to Niagara was mixed, with half of outcomes (Harm to Others, 24 Hour, Harm to Self, 24 Hour, Failure to Care for Self, 24 hour) displaying good predictive performance (AUC≥0.7) and the other half of outcomes (Harm to Others, 72 Hour, Harm to Self, 72 Hour, Failure to Care for Self, 72 hour) displaying modest performance (AUC≥0.6). The performance of the Random Forests trained on the Niagara training data set was very poor, with most (4/6) Random Forests models displaying predictive performance of AUC<0.6. Notably the Merged Training Brantford Holdout and Brantford Training Brantford Holdout results performed much better than the other two communities, and in some cases (e.g., harm to others 72 hours, harm to self 24 hours) even performed better than the merged training merged holdout sets. High variability in the AUCs is likely due to the rarity of the target variable.

Variable importance data and plots are shown in Appendices 13 and 14. For the outcome repeat contact within 24 hours with high risk of harm to others, the variables age, risk scales, and region showed the greatest mean decrease in Gini. Beyond that, most variables had similar importance in the Random Forests model. Except for previous police contact, the variable importance plot was not similar to the best subset logistic regression model, and none of the variables selected by the police services had substantial variable importance. The variable importance plot for all other outcomes was also dissimilar from the best subset logistic regression models, and none of the variables selected by the police services demonstrated substantial variable importance.

Table xiv Random Forests Results, by Dependent Variable, All Reports, All Communities (ntrain=10,441; ntest=2,617)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Data Sets** | **Risk Type** | **Time Period** | **AUC** | **TPR** | **TNR** |
| Merged Training Merged Holdout | Harm to Others | 24 Hour | 0.7185777 | 0.5000000 | 0.6883417 |
| 72 Hour | 0.6869038 | 0.8285714 | 0.4442293 |
| Harm to Self | 24 Hour | 0.6797955 | 0.7179487 | 0.5581846 |
| 72 Hour | 0.7243082 | 0.8947368 | 0.3656041 |
| Failure to Care for Self | 24 Hour | 0.7104072 | 0.6451613 | 0.6337974 |
| 72 Hour | 0.7656760 | 0.8723404 | 0.5108949 |
| Merged Training  Brantford Holdout | Harm to Others | 24 Hour | 0.7896773 | 0.5000000 | 0.6962865 |
| 72 Hour | 0.75373217 | 0.91666667 | 0.42245989 |
| Harm to Self | 24 Hour | 0.7638063 | 0.7272727 | 0.6101469 |
| 72 Hour | 0.82132299 | 0.95454545 | 0.45392954 |
| Failure to Care for Self | 24 Hour | 0.7542177 | 0.6363636 | 0.6769025 |
| 72 Hour | 0.8327718 | 0.8888889 | 0.5309973 |
| Merged  Training  London  Holdout | Harm to Others | 24 Hour | 0.6032943 | 0.5000000 | 0.7278325 |
| 72 Hour | 0.6638958 | 0.8000000 | 0.4925558 |
| Harm to Self | 24 Hour | 0.5741929 | 0.5384615 | 0.5541719 |
| 72 Hour | 0.6562101 | 0.8125000 | 0.3354592 |
| Failure to Care for Self | 24 Hour | 0.6970949 | 0.5555556 | 0.6307311 |
| 72 Hour | 0.7700392 | 0.8571429 | 0.5423940 |
| Merged  Training  Niagara  Holdout | Harm to Others | 24 Hour | 0.8790787 | 1.0000000 | 0.6717850 |
| 72 Hour | 0.6217084 | 0.6666667 | 0.4508671 |
| Harm to Self | 24 Hour | 0.7414883 | 0.8750000 | 0.5797665 |
| 72 Hour | 0.68768902 | 0.90909091 | 0.36594912 |
| Failure to Care for Self | 24 Hour | 0.7835590 | 0.8000000 | 0.6615087 |
| 72 Hour | 0.6945908 | 0.8571429 | 0.5339806 |
| Brantford Training  Brantford Holdout | Harm to Others | 24 Hour | 0.8153183 | 0.8333333 | 0.6843501 |
| 72 Hour | 0.77055481 | 0.91666667 | 0.51470588 |
| Harm to Self | 24 Hour | 0.7260590 | 0.8181818 | 0.6275033 |
| 72 Hour | 0.82230845 | 0.95454545 | 0.50677507 |
| Failure to Care for Self | 24 Hour | 0.7655055 | 0.6363636 | 0.7690254 |
| 72 Hour | 0.7821204 | 0.8333333 | 0.5619946 |
| London  Training  London  Holdout | Harm to Others | 24 Hour | 0.6547106 | 0.5000000 | 0.7290640 |
| 72 Hour | 0.7086228 | 0.8000000 | 0.4925558 |
| Harm to Self | 24 Hour | 0.6043203 | 0.6923077 | 0.4458281 |
| 72 Hour | 0.6608339 | 0.8437500 | 0.3073980 |
| Failure to Care for Self | 24 Hour | 0.7735784 | 0.7777778 | 0.6406444 |
| 72 Hour | 0.7690595 | 0.7857143 | 0.5448878 |
| Niagara  Training  Niagara  Holdout | Harm to Others | 24 Hour | 0.9616123 | 1.0000000 | 0.7274472 |
| 72 Hour | 0.5510597 | 0.3333333 | 0.5973025 |
| Harm to Self | 24 Hour | 0.5007296 | 0.1250000 | 0.7120623 |
| 72 Hour | 0.6666963 | 1.0000000 | 0.4637965 |
| Failure to Care for Self | 24 Hour | 0.4402321 | 0.2000000 | 0.7098646 |
| 72 Hour | 0.5754508 | 0.7142857 | 0.5300971 |

Pre-test probabilities (i.e., prevalence) for all outcomes in all data sets were very low (0.19% - 3.92%). The most common outcome within the merged data set was Harm to Self, 72 hours (2.9%).

The highest positive likelihood ratio observed in the Merged Training Merged Holdout data set was Failure to Care for Self, 72 hours (1.784). The highest positive likelihood ratio observed among region specific sets was found in the Niagara Training Niagara Holdout set, Harm to Others, 24 hours (3.669). The lowest negative likelihood ratio observed in the Merged Training Merged Holdout data set was Failure to Care for Self, 72 hours (0.25). The lowest negative likelihood ratio observed among region specific sets was found in Niagara, Harm to Others, 24 hours and Harm to Self, 24 hours (0).

The algorithm with the best ability to rule in the outcome within the Merged Training Merged Holdout data set was harm to self, 72 hours (4.05%). The algorithm with the best ability to rule in within the region specific sets was found in the Brantford Training Brantford Holdout set, harm to self, 72 hours (5.45%). The algorithm with the best ability to rule out within the Merged Training Merged Holdout data set was failure to care for self, 72 hours (0.5%). The algorithm with the best ability to rule out within the region specific sets was found in the Niagara Training Niagara Holdout set, harm to others, 24 hours (0%).

For a full table including false positive rate, false negative rate, true positives, false positives, true negatives, false negative, sensitivity, specificity, accuracy, positive predictive value and negative predictive value please see Appendix 12.

Table xv Random Forests Likelihood Ratios and Conditional Probabilities, by Dependent Variable (ntrain=10,441; ntest=2,617)

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Data Sets** | **Risk Type** | **Time Period** | **Pre-test Probability** | **Likelihood Ratio** | | **Post-test Probability** | |
| **Positive** | **Negative** | **Positive** | **Negative** |
| Merged  Training  Merged  Holdout | Harm to Others | 24 Hour | 1% | 1.604 | 0.726 | 1% | 1% |
| 72 Hour | 1% | 1.491 | 0.386 | 2% | 1% |
| Harm to Self | 24 Hour | 1% | 1.625 | 0.505 | 2% | 1% |
| 72 Hour | 3% | 1.410 | 0.288 | 4% | 1% |
| Failure to Care for Self | 24 Hour | 1% | 1.762 | 0.560 | 2% | 1% |
| 72 Hour | 2% | 1.784 | 0.250 | 3% | 0% |
| Merged  Training  Brantford  Holdout | Harm to Others | 24 Hour | 1% | 1.646 | 0.718 | 1% | 1% |
| 72 Hour | 2% | 1.587 | 0.197 | 2% | 0% |
| Harm to Self | 24 Hour | 1% | 1.866 | 0.447 | 3% | 1% |
| 72 Hour | 3% | 1.748 | 0.100 | 5% | 0% |
| Failure to Care for Self | 24 Hour | 1% | 1.970 | 0.537 | 3% | 1% |
| 72 Hour | 2% | 1.895 | 0.209 | 4% | 1% |
| Merged  Training  London  Holdout | Harm to Others | 24 Hour | 0% | 1.837 | 0.687 | 1% | 0% |
| 72 Hour | 1% | 1.577 | 0.406 | 2% | 1% |
| Harm to Self | 24 Hour | 2% | 1.208 | 0.833 | 2% | 1% |
| 72 Hour | 4% | 1.223 | 0.559 | 5% | 2% |
| Failure to Care for Self | 24 Hour | 1% | 1.504 | 0.705 | 2% | 1% |
| 72 Hour | 2% | 1.873 | 0.263 | 3% | 0% |
| Merged  Training  Niagara  Holdout | Harm to Others | 24 Hour | 0% | 3.047 | 0.000 | 1% | 0% |
| 72 Hour | 1% | 1.214 | 0.739 | 1% | 0% |
| Harm to Self | 24 Hour | 2% | 2.082 | 0.216 | 3% | 0% |
| 72 Hour | 2% | 1.434 | 0.248 | 3% | 1% |
| Failure to Care for Self | 24 Hour | 1% | 2.363 | 0.302 | 2% | 0% |
| 72 Hour | 1% | 1.839 | 0.268 | 2% | 0% |
| Brantford  Training  Brantford  Holdout | Harm to Others | 24 Hour | 1% | 2.640 | 0.244 | 2% | 0% |
| 72 Hour | 2% | 1.889 | 0.162 | 3% | 0% |
| Harm to Self | 24 Hour | 1% | 2.196 | 0.290 | 3% | 0% |
| 72 Hour | 3% | 1.935 | 0.090 | 5% | 0% |
| Failure to Care for Self | 24 Hour | 1% | 2.755 | 0.473 | 4% | 1% |
| 72 Hour | 2% | 1.903 | 0.297 | 4% | 1% |
| London  Training  London  Holdout | Harm to Others | 24 Hour | 0% | 1.845 | 0.686 | 1% | 0% |
| 72 Hour | 1% | 1.577 | 0.406 | 2% | 1% |
| Harm to Self | 24 Hour | 2% | 1.249 | 0.690 | 2% | 1% |
| 72 Hour | 4% | 1.218 | 0.508 | 5% | 2% |
| Failure to Care for Self | 24 Hour | 1% | 2.164 | 0.347 | 2% | 0% |
| 72 Hour | 2% | 1.726 | 0.393 | 3% | 1% |
| Niagara  Training  Niagara  Holdout | Harm to Others | 24 Hour | 0% | 3.669 | 0.000 | 1% | 0% |
| 72 Hour | 1% | 0.828 | 1.116 | 0% | 1% |
| Harm to Self | 24 Hour | 2% | 0.434 | 1.229 | 1% | 2% |
| 72 Hour | 2% | 1.865 | 0.000 | 4% | 0% |
| Failure to Care for Self | 24 Hour | 1% | 0.689 | 1.127 | 1% | 1% |
| 72 Hour | 1% | 1.520 | 0.539 | 2% | 1% |

# 4| Discussion

## 4.1| Major findings

Overall, the ability to predict the target outcomes of police service calls was fairly limited across each methods compared. The rareness of the target outcomes and the poor specificity (53%) meant that any additional risk inferred by any classification algorithm was marginal when conditional probabilities were calculated.   
 The use of Random Forests learning algorithms resulted in a predictive accuracy between AUC= 0.7 and AUC= 0.8 on 4 of the 6 target outcomes and between AUC= 0.6 and AUC= 0.69 on the remaining two. The two outcomes the Random Forests learning algorithms struggled to predict were acute risk of harm to others within 72 hours (AUC=0.687) and acute risk of harm to self within a 24 hour window (AUC=0.68). These were amongst the most rare outcomes in the data.

When compared to the outcomes of the best-subsets logistic regression analyses, the Random Forests analysis had greater predictive accuracy overall and less predictive variability within police services communities. This was likely due to the relative methodological utility of sample bagging and feature bagging to limit learning algorithm variance/overfitting. Evidence of this can be found in the grid search, where a greater number of trees in the Random Forests ensemble often translated into better overall prediction. In contrast, the best-subsets logistic regression models were overfitted to the small number of outcomes in the merged training set, which created a poor fit on the merged holdout set and community specific holdout sets. In all 6 outcomes for the random forest learner, age was the most important (type 2) variable, and apprehension under existing order was the least important. For best subset logistic regression, apprehension under existing order was included in 3 models, but in all three cases was the weakest variable. Age was not included in any of the best subset logistic regression models because it is a nominal variable. The most important variable in the best subset logistic regression model was abnormal thought process (3 models) and previous police contact (2 models).

The expert informed logistic regression resulted in predictions that were only slightly greater than chance for most outcomes in the entire merged dataset. The predictive accuracy of the Random Forests analysis exceeded that of the expert informed logistic regression by a healthy margin for all 6 outcomes in the merged data set.

When applied to individual communities, the Random Forests learning algorithms performed with mixed results. Brantford Police Service had the best results, with an average AUC = 0.7693 in the 24 hour time frame and an average AUC = 0.803 in the 72 hour time frame. London Police Service had the worst results, with an average AUC = 0.625 in the 24 hour time frame and an average AUC = 0.697 in the 72 hour time frame. Overall, the Random Forests learning algorithms trained in specific communities did not perform better in those communities compared to the Random Forests learning algorithms trained on the entire merged training set. This suggests that there is likely no benefit in implementing Random Forests learning algorithm that are specific to each police service community. However, this is a provisional conclusion given the small sample size for each community and rareness of the outcomes included.

## 4.2| Explanations of reasons for key findings

Predictive ability of the Random Forests learning algorithms was the most accurate of the explored statistical methods. Low specificity and mixed (0.6 - 0.9) sensitivity will limit the clinical significance of the findings. This is likely due in part to the stochastic nature of mental health crisis. Major life events, such as an eviction or loss of job may occur between police interactions and would not reasonably be predicted by officer using a mental health screening form. The rareness of the target outcomes also means even small differences in each observation may have a large effect on the predictive accuracy of the algorithm. I do not have reason to believe the BMHS questions were the limiting factor in the analysis. Since the BMHS was the result of analyzing and condensing the RAI-MH to determine the items most predictive of risk of harm, additional questions are not likely to capture any additional risk factors that are not already captured by the BMHS.

Predictive accuracy of the Random Forests learning algorithms varied by community. One possible explanation for this phenomenon is that the differences in mental health resources between communities limited the performance of a “one size fits all” algorithm. For example, the Brantford Police Service conducts proactive intervention with vulnerable persons in their community using the MCRRT, while the London Police Service does not. While London Police Service completes BMHS forms on every interaction with persons with mental illness, Niagara Regional Police Service Officers tend to only complete BMHS forms when transporting a person with mental illness to the hospital. Although the ‘Region’ variable was included in the Random Forests, patterns in one Region may not be reproducible in the other regions.

Although it was suspected that the variances between each community would make the merged training set algorithm less effective when compared against community specific holdout data, the results were mixed. For some outcomes the merged training algorithm performed better, while for others the community specific algorithm performed better. Using the AUC as the measure, the merged training algorithm performed better than community specific algorithm in 8 (44%) of tests. The mixed results could be due to the rareness of the outcomes. It is possible that we do not currently have the power to accurately compare between communities.

Another example of these mixed results through a lens of clinical significance is differences between the false negatives. The merged training learning algorithms failed to identify the target outcomes a total of 51 times (false negatives summed for all 6 outcomes). In comparison, the community specific learning algorithms failed to identify the target outcomes 45 times (false negatives summed for all 6 outcomes in all 3 community specific tests). While this may suggest marginally better performance for the merged training learning algorithms, when examined at the community level the differences are more dramatic. Brantford had almost no difference - the community specific algorithm failed to identify 12 outcomes, while the merged algorithm failed to identify 14. In London, the merged algorithm failed to identify 22 outcomes while the community specific algorithm only failed to identify 18. In contrast to London, the Niagara community specific algorithm failed to identify 15 outcomes, while the merged algorithm only failed to identify 5.

One possible explanation for these mixed results is that in communities where the BMHS is completed only during mental health apprehensions, there is insufficient data to build a strong predictive learning algorithm (e.g., Niagara). In these cases, the community would benefit from the inclusion of non-apprehension data from other communities. However if the community has sufficient training examples for both apprehension and non-apprehension reports, the nuanced differences within that community will provide greater predictive accuracy when the algorithm is trained on only that community.

## 4.3| Comparison to existing research

Though there are numerous studies that examine the use of machine learning to predict health outcomes in a healthcare setting, to the best of my knowledge this is the first study examining the use of machine learning to predict health outcomes in a law enforcement setting.

Other research has noted that machine learning may only slightly outperform classical statistical techniques (Song, 2004) however in these results I found that optimized logistic regression performed slightly greater than the machine learning example (random forests). Despite these findings, it is important to note that ‘classical statistical techniques’ and ‘machine learning’ are very broad categories, and the choice of techniques to compare between each category will significantly affect the difference in performance between the two categories.

## 4.4| Implications for government /policy makers

Many reports suggest that most mental health calls involve repeat contact with the same person in crisis (Iacobucci, 2014), however the data suggests that only 17% of all calls involve persons who have been screened by police in the past. The number of unique individuals seen multiple times would likely increase given more time to collect data, however it is reasonable to assume with these outcomes that less than half of police mental health calls involve persons who have had previous mental health crisis interactions. Many inquests have stressed the need for police services to make existing mental health information available to patrol Officer’s during mental health calls (Office of the Chief Coroner, Ontario, 2012), but my findings suggest that this information will rarely be available through police service records. Though not currently supported by privacy laws in Canada, allowing 2-way sharing of mental health information between law enforcement and healthcare services could improve Officer’s awareness of mental health risks prior to interacting with persons in crisis.

Another major challenge faced by law enforcement and healthcare services is response to individuals in an intoxicated state. The data suggests that 34% of all calls involve a person who is or has recently been intoxicated. Intoxication by drugs or alcohol can often make individuals appear to be in a state of mental health crisis, and it can be very difficult for Officers to screen drug induced behavior from mental health related behavior (Herrington, 2014). If Officers and healthcare staff were able to access learning algorithms that could predict the risk of follow up crisis *despite* intoxication, it may allow for new protocols to assist in transfer of care of persons who are currently intoxicated. It remains to be seen how the recent legalization of marijuana in Canada will affect mental health crisis calls.

Though persons who are homeless have been found to be in contact with police a disproportionality high amount of time (*Mental Health and Contact with Police in Canada*, 2015) my findings suggest that calls involving persons who are homeless make up only a small proportion of the total mental health call volume (11%). However, persons who are homeless are 12% more likely to be intoxicated (45%) than the housed population (33%) (see Appendix 18). Officer’s sometimes struggle to identify persons who are homeless, which (along with the increased rate of intoxication) makes it more difficult for officer’s to understand the extent of mental health problems with the individual. I did not differentiate outcomes with intoxication during the initial report from those that did not have intoxication in the initial report. It is possible that creating separate learning algorithms for intoxicated versus non-intoxicated persons could lead to greater predictive accuracy.

### 4.4.1| Implications for Law Enforcement

For police, managing mental health crisis calls is about striking a balance between risk incurred and resources used. One extreme would be for police to avoid all apprehensions possible, saving significant patrol resources but incurring substantial risk in the process. The other extreme would be to apprehend virtually everyone presenting with mental health symptoms, and this is closest to the reality of most police mental health strategies in Canada. My study found modest predictive sensitivity (an average of 74%) at the expense of poor specificity (52%), averaged from the 6 merged training learning algorithms. Using a learning algorithm like this to justify an apprehension in a system where few are apprehended would be a serious concern, due to the probability of inappropriately apprehending a large proportion of the population. However, in the current police culture of apprehending the vast majority of calls, these scores are unlikely to alter the officer on-scene decision making, and instead could be used to identify individuals that may benefit from additional support after the call is ended. The benefits of identifying those persons who are at higher risk could be realized without incurring the negative consequences of poor specificity. This could be useful for specialized mental health resources in the community, which could use the learning algorithms as one of several pieces of evidence to identify candidates for extra support or interventions.

Per the recommendations of many inquests (Iacobucci, 2014), early identification of persons at an acute risk of crisis within 24 – 72 hours could also be used to strengthen connections with community mental health partners. By identifying vulnerable individuals prior to a mental health crisis, Officer’s would have an opportunity to refer the person with mental illness to community mental health services proactively. As identified by Justice Iacobucci, 2014, the priority must be on preventing mental health crisis from happening rather than reacting to crisis where escalation presents real risk to both the person in crisis and the responding Officers.

In addition to the potential benefits of a predictive learning algorithm, my findings also suggest that as of today, Officers are taking appropriate action when responding to mental health crisis calls. Only 1.87% (average of the three risk category outcomes within 72 hours, merged training set) of all calls observed in this study resulted in a high risk follow up within 72 hours. For most calls, the person in crisis does not present in a crisis state again shortly after police contact.

#### 4.4.1.1| Implications for Mobile Crisis Teams

Much attention has been given to the benefits of using mobile crisis teams for proactive intervention with known vulnerable persons. One common challenge faced by mobile crisis teams is reviewing the large volume of mental health crisis calls to identify the best candidates for proactive intervention. Though post-test probability only a modest improvement (ranging from 2.32% to 3.28%), the analysis did correctly identify 138 persons of 158 who experienced a repeat mental health crisis within 72 hours. As a retrospective cohort study, it is reasonable to assume that most or all target outcomes were missed at the time of screening. The merged training learning algorithms are not a perfect solution to identify who should have extra support and who should not, but within the 72 hour outcome set they could be used as one piece of evidence in a strategy to prioritize outreach services. Using the Random Forests learning algorithms, those 138 repeat crisis could theoretically have been identified. However, this would require immediate action by the police and their community which may not always be feasible. The Random Forests failed to identify 20 persons who experienced repeat crisis, however these 20 persons were missed with existing police practices and so, if used to augment those practices (not replace), the use of the learning algorithms would be a net positive (I.e., the Random Forests learning algorithms would be a decision support tool, not a replacement for the professional judgement of the Mobile Crisis Team). Mobile crisis team Officers could be given to a prioritized list that updates in real time as Officers complete BMHS reports. This list could then be used to help filter down the number of reports that need to be scrutinized further.

Another challenge often faced by police services operating mobile crisis teams is securing funding for the operation of the team. Though the benefits of mobile crisis teams are well documented (Kisely, 2010), finding metrics to prove value for money can be challenging. Tracking how many individuals are flagged, visited by the mobile crisis team and diverted from future crisis could provide clear evidence of the financial benefits of the specialized team.

#### 4.4.1.2| Implications for Situation Tables / Hubs

Much like the suggested prioritization for mobile crisis teams, police liaisons to the situations tables / HUBs could make use of a predictive algorithm to narrow the list of potential candidates. By design, the learning algorithms predict persons who are a) presenting with mental health needs and b) at an acute risk of harm. This automatically meets the criteria for situation tables / HUBs in which the risk may not be resolved by a single agency (police cannot provide mental health treatment) and the risk is found to be acute. Though the predictive accuracy is not sufficient to be a replacement for the professional judgement of the liaison officer, a positive result from the algorithm could be used as evidence to justify the person’s fit with the situation table / HUB. As part of the situation table / HUB model, liaison’s must give evidence as to why the person they have identified meets the criteria of high risk. The algorithm results could be one such piece of evidence.

#### 4.4.1.3| Implications for Mental Health Courts

Mental health courts focus on providing treatment, not punishment to address the needs of persons with mental illness. To be admitted to a mental health court, there needs to be evidence proving that mental health was a major factor in the crime committed. Unfortunately, the performance of the algorithm in this context is not sufficient to provide additional evidence beyond what is already available to the courts.

### 4.4.2| Implications for Hospitals

Although a warning flag could support an officer in articulating his/her reasonable grounds for apprehension to hospital staff, it would not be suitable for use by the hospital staff in evaluating the individual. The algorithm does not have sufficient predictive accuracy to use as a clinical tool. Interpreting a positive result from the algorithm as a piece of evidence to justify admission would likely result in many unnecessary involuntary admissions.

### 4.4.3| Implications for Community Mental Health

Community mental health organizations may benefit from the use a predictive algorithm to drive referrals. If Officer’s are made aware of an acute risk of repeat crisis contact, the Officer’s may be more likely to conduct a referral to community mental health services. However, in consideration of the privacy laws in Canada, the individual would still need to consent to follow up with the mental health service. This may present challenging situations where the individual is at an acute risk of follow up crisis but does not wish to receive support. Despite this challenge, identifying risk earlier on would potentially give community mental health services an opportunity to intervene in cases where the person would have otherwise gone into crisis.

Aside from the benefits to the individual (more timely and appropriate care, reduced risk of escalation with police) the clear care pathway could strengthen ties with police and provide valuable metrics to prove value for money in the community.

## 4.5| Implications for interRAI

Results from my study found that Officers are currently using the BMHS and other resources in their community to make effective decisions when responding to mental health. A very small proportion of calls result in repeat contact within 24 – 72 hours. My study did not examine the proportion of report pairs where the first report resulted in transport to hospital. It is possible that after controlling for cases where the Officer did transport to hospital, the rate of Officer’s risk evaluation producing false negatives would decrease below 1-2%. Though there are many factors likely contributing to the success of crisis response in the surveyed communities, the use the BMHS as a medium of communication and risk evaluation is likely an important factor.

interRAI has produced several instruments which are used in a variety of setting (home care, community mental health, hospitals, etc).. As part of these instruments, clinical assessment protocols are typically produced to assist in transforming the results of an assessment into action (*Clinical Assessment Protocols (CAPs)*, 2019). As an interRAI instrument, the BMHS is already coded in the same way that the follow up assessments conducted at the hospital (RAI-ESP, RAI-MH) would be coded. There may be opportunities to integrate the results of the risk assessment into existing care planning protocols in other interRAI instruments to further support collaboration between law enforcement and health care services.

## 4.6| Implications for Future Research

Though increasing the specificity of the predictions remains a challenge, the use of Random Forests analysis holds promise for a number of other applications. For example, the same technique could be applied to more common outcomes for prediction (e.g., any contact with police within the next 7 days). There are several other intersections between law enforcement and public health (e.g., domestic violence, addictions, check for wellness, etc). where the prediction of negative outcomes could drive proactive intervention at an early stage.

The exceedingly rare occurrence rate of the target outcomes will present a challenge to any future research. Even small changes in the demographics of the training and holdout data sets could alter the results significantly. The continued use of the BMHS, as well as the development of centralized data warehouses (e.g., Canadian Institute for Health Information) will ensure that more robust data is available for future analysis.

## 4.7| Strengths of the Study

Although overall performance of the merged training set was modest, the learner algorithms were able to integrate multiple regions with substantial variance in culture, resources, and mental health strategy. The study was conducted using a fairly comprehensive data set with a large sample size (despite the small amount of observations with the target outcome) and multiple communities / regions. The analysis was also possible using easily accessible tools and technology, meaning follow up analysis by others interested in the topic will be possible. At a high level, this study demonstrates that there is potential for the use of machine learning techniques at the intersection between law enforcement and public health.

## 4.8| Limitations of the Study

Though in some cases I was able to predict outcomes with good accuracy, other cases still struggled to provide accurate predictions. This was most apparent when working with individual community data. A larger dataset spanning a great period of time may be needed. Smaller communities were particularly difficult to assess. This study fails to evaluate the performance of the machine learning algorithm on smaller communities (e.g., Gananoque) due to the extremely limited amount of data. In addition to the limited amounts of data, the training and holdout sets were stratified by region during the first split of the data set. Data was not stratified by outcome prior to the training / holdout data sets split, and therefore some communities may have had a smaller or greater proportion of target variables in the holdout set compared to others. It is also possible that some communities would have no target outcomes in the holdout set.

Another consideration is that most of the study participants were screened in Ontario, and no first nations communities were included in the dataset. It is unclear how much local culture and resources will affect the performance of the learning algorithms. More analysis is needed to determine if the algorithm will perform well in other areas of Canada or internationally.

Finally, the extent of my comparison between classical statistical techniques and machine learning techniques was extremely limited. The use of logistic regression versus Random Forests is hardly a scoping comparison of all techniques in both categories. It is quite likely that the difference in performance would be significantly different had I selected different methodologies from each category. Furthermore the selection of variables for use in the logistic regression was limited to feedback from one expert group. It is possible that with a more robust feedback process, more or different variables would be selected that could boost the performance of the logistic regression.

# APPENDICES



Appendix i National Use of Force Framework, (2000)



Appendix ii RCMP Incident Management Intervention Model (IMIM), (2017)



Appendix iii Crisis Intervention and De-Escalation (CID) model (Dube, 2016)

Appendix iv Items Used for Random Forests Analysis (Inputs)

|  |  |  |
| --- | --- | --- |
| **interRAI iCode** | **BMHS Code** | **Name** |
| **Section A: Identification** | | |
| iA2 | A2 | Gender |
| iA43 | A5 | Homeless |
| **Section B: Mental State Indicators** | | |
| iE11q | B1a | Irritability: 24 hrs |
| iE11x | B1b | Hallucinations: 24 hrs |
| iE11y | B1c | Command hallucinations: 24 hrs |
| iE11z | B1d | Delusions: 24 hrs |
| iE11p | B1e | Hyper-arousal: 24 hrs |
| iE11s | B1f | Pressured speech: 24 hrs |
| iE11aa | B1g | Abnormal thought processes: 24 hrs |
| iE11gg | B1h | Socially inappropriate: 24 hrs |
| iE11hh | B1i | Verbal abuse: 24 hrs |
| iE11ii | B1j | Intoxication: 24 hrs |
| iE7 | B2 | Degree of insight |
| iC1b | B3 | Daily Decision Making (CA) |
| **Section C: Violence Indicators** | | |
| iX19 | C1 | Previous Police Contact |
| iX12d | C2 | Carries Weapon |
| iX20a | C3a | Violent ideation: 24 hrs |
| iX20b | C3b | Intimidation of others: 24 hrs |
| iX20c | C3c | Violence to others: 24 hrs |
| iX1h | C4a | Self injurious attempt last 7 days |
| iX1i | C4b | Considered self injury last 30 days |
| iX1e | C4c | Suicide Plan |
| iX1d | C4d | Others concerned about self-injury |
| iQ5b | C5 | Squalid condition |
| iM4 | C6 | Refused Medication |
| **Section D: Disposition** | | |
| iT11a | D1a | Disposition: Voluntary escort to hospital |
| iT11i | D1b | Disposition: Involuntarily Apprehended |
| iT11h | D1c | Disposition: Apprehended under existing order |
| iT11d | D1d | Disposition: Referred to CMH |
| iT11b | D1e | Disposition: Transferred to EMS/MCRRT |
| iT11g | D1f | Disposition: Caseworker/Probation notified |
| **Other** | | |
| N/A | N/A | Harm to Others Scale |
| N/A | N/A | Self Harm Scale |
| N/A | N/A | Self Care Scale |
| N/A | N/A | Region |
| N/A | N/A | Age |

Appendix v Demographics, BMHS Reports, All Communities (N=13,058)

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **All Regions** | | **Brantford** | | **Brockville** | | **Cobourg** | | **Gananoque** | | **Guelph** | | **KawarthaLake** | | **London** | | **Niagara** | | **Orangeville** | | **Ottawa** | | **Regina** | | **Saskatoon** | | **Smiths Falls** | |
| **(N=13058)** | | **(n = 3800)** | | **(n=229)** | | **(n=219)** | | **(n=36)** | | **(n=1008)** | | **(n=93)** | | **(n=4079)** | | **(n=2606)** | | **(n=51)** | | **(n=356)** | | **(n=315)** | | **(n=214)** | | **(n=52)** | |
| Gender is Female | 6096 | 47% | 1676 | 44% | 111 | 48% | 100 | 46% | 14 | 39% | 508 | 51% | 36 | 39% | 1993 | 49% | 1220 | 47% | 21 | 42% | 143 | 41% | 153 | 49% | 107 | 50% | 14 | 27% |
| Homeless | 1456 | 11% | 393 | 10% | 13 | 6% | 30 | 14% | 7 | 19% | 109 | 11% | 15 | 16% | 420 | 10% | 361 | 14% | 13 | 25% | 44 | 12% | 26 | 8% | 20 | 9% | 5 | 10% |
| Irritability | 7056 | 54% | 1723 | 45% | 133 | 58% | 117 | 53% | 25 | 69% | 551 | 55% | 58 | 62% | 2077 | 51% | 1796 | 69% | 38 | 75% | 202 | 57% | 188 | 60% | 113 | 53% | 35 | 67% |
| Hallucinations | 2378 | 18% | 524 | 14% | 29 | 13% | 49 | 22% | 7 | 19% | 179 | 18% | 23 | 25% | 756 | 19% | 633 | 24% | 11 | 22% | 56 | 16% | 60 | 19% | 41 | 19% | 10 | 19% |
| Command hallucinations | 1266 | 10% | 125 | 3% | 11 | 5% | 21 | 10% | 5 | 14% | 100 | 10% | 8 | 9% | 439 | 11% | 453 | 17% | 19 | 37% | 31 | 9% | 30 | 10% | 17 | 8% | 7 | 13% |
| Delusions | 3166 | 24% | 895 | 24% | 51 | 22% | 69 | 32% | 13 | 36% | 233 | 23% | 23 | 25% | 891 | 22% | 741 | 28% | 20 | 39% | 93 | 26% | 72 | 23% | 53 | 25% | 12 | 23% |
| Hyper-arousal | 4058 | 31% | 866 | 23% | 76 | 33% | 64 | 29% | 18 | 50% | 331 | 33% | 36 | 39% | 1209 | 30% | 1196 | 46% | 20 | 39% | 77 | 22% | 97 | 31% | 50 | 23% | 18 | 35% |
| Pressured speech | 4483 | 34% | 930 | 24% | 85 | 37% | 74 | 34% | 16 | 44% | 350 | 35% | 40 | 43% | 1285 | 32% | 1380 | 53% | 23 | 45% | 109 | 31% | 110 | 35% | 61 | 29% | 20 | 38% |
| Abnormal thought processes | 6684 | 51% | 1227 | 32% | 124 | 54% | 113 | 52% | 20 | 56% | 571 | 57% | 41 | 44% | 2068 | 51% | 2000 | 77% | 41 | 80% | 149 | 42% | 194 | 62% | 112 | 52% | 24 | 46% |
| Socially inappropriate | 5500 | 42% | 1235 | 33% | 99 | 43% | 80 | 37% | 19 | 53% | 473 | 47% | 34 | 37% | 1507 | 37% | 1611 | 62% | 39 | 76% | 160 | 45% | 127 | 40% | 96 | 45% | 20 | 38% |
| Verbal abuse | 3996 | 31% | 1015 | 27% | 65 | 28% | 71 | 32% | 20 | 56% | 320 | 32% | 35 | 38% | 1066 | 26% | 1114 | 43% | 28 | 55% | 110 | 31% | 89 | 28% | 47 | 22% | 16 | 31% |
| Intoxication | 4461 | 34% | 1186 | 31% | 57 | 25% | 86 | 39% | 18 | 50% | 349 | 35% | 30 | 32% | 1403 | 34% | 929 | 36% | 26 | 51% | 108 | 30% | 161 | 51% | 94 | 44% | 14 | 27% |
| Degree of insight | 8745 | 67% | 2616 | 69% | 182 | 79% | 171 | 78% | 24 | 67% | 670 | 66% | 58 | 62% | 2444 | 60% | 1956 | 75% | 30 | 59% | 225 | 63% | 197 | 63% | 143 | 67% | 29 | 56% |
| Daily Decision Making | 4948 | 38% | 866 | 23% | 91 | 40% | 95 | 43% | 22 | 61% | 394 | 39% | 42 | 45% | 1590 | 39% | 1386 | 53% | 22 | 43% | 151 | 42% | 156 | 50% | 110 | 51% | 23 | 44% |
| Previous Police Contact | 6224 | 48% | 1989 | 52% | 95 | 41% | 111 | 51% | 16 | 44% | 460 | 46% | 41 | 44% | 1838 | 45% | 1284 | 49% | 31 | 61% | 129 | 36% | 126 | 40% | 79 | 37% | 25 | 48% |
| Carries Weapon | 2415 | 19% | 708 | 19% | 37 | 16% | 31 | 14% | 8 | 22% | 129 | 13% | 14 | 15% | 751 | 18% | 574 | 22% | 24 | 47% | 52 | 15% | 46 | 15% | 30 | 14% | 11 | 21% |
| Violent ideation | 3146 | 24% | 562 | 15% | 44 | 19% | 57 | 26% | 12 | 33% | 215 | 21% | 20 | 22% | 954 | 23% | 1014 | 39% | 21 | 41% | 107 | 30% | 70 | 22% | 55 | 26% | 15 | 29% |
| Intimidation of others | 3155 | 24% | 684 | 18% | 45 | 20% | 59 | 27% | 12 | 33% | 233 | 23% | 27 | 29% | 791 | 19% | 1015 | 39% | 31 | 61% | 107 | 30% | 85 | 27% | 51 | 24% | 15 | 29% |
| Violence to others | 2387 | 18% | 514 | 14% | 26 | 11% | 44 | 20% | 12 | 33% | 172 | 17% | 19 | 20% | 633 | 16% | 748 | 29% | 25 | 49% | 93 | 26% | 61 | 19% | 29 | 14% | 11 | 21% |
| Self injurious attempt last 7 days | 4084 | 31% | 544 | 14% | 62 | 27% | 65 | 30% | 8 | 22% | 286 | 28% | 27 | 29% | 1484 | 36% | 1274 | 49% | 31 | 61% | 86 | 24% | 101 | 32% | 96 | 45% | 20 | 38% |
| Considered self injury last 30 days | 6429 | 49% | 1078 | 28% | 92 | 40% | 98 | 45% | 21 | 58% | 431 | 43% | 41 | 44% | 2400 | 59% | 1749 | 67% | 37 | 73% | 155 | 44% | 181 | 57% | 115 | 54% | 31 | 57% |
| Suicide Plan in Last 30 Days | 4093 | 31% | 585 | 15% | 53 | 23% | 74 | 34% | 7 | 19% | 224 | 22% | 23 | 25% | 1463 | 36% | 1327 | 51% | 22 | 43% | 98 | 28% | 108 | 34% | 86 | 40% | 23 | 44% |
| Others concerned about self-injury | 7056 | 54% | 1391 | 37% | 108 | 47% | 121 | 55% | 23 | 64% | 488 | 48% | 51 | 55% | 2430 | 60% | 1917 | 74% | 29 | 57% | 170 | 48% | 179 | 57% | 122 | 57% | 27 | 52% |
| Squalid condition | 3885 | 30% | 1115 | 29% | 91 | 40% | 56 | 26% | 18 | 50% | 335 | 33% | 30 | 32% | 1090 | 27% | 862 | 33% | 25 | 49% | 94 | 26% | 90 | 29% | 54 | 25% | 25 | 48% |
| Refused Medication | 2558 | 20% | 511 | 13% | 38 | 17% | 24 | 11% | 14 | 39% | 179 | 18% | 30 | 32% | 783 | 19% | 733 | 28% | 18 | 35% | 92 | 26% | 75 | 24% | 48 | 22% | 13 | 25% |
| Voluntary escort to hospital | 2513 | 19% | 319 | 8% | 47 | 21% | 72 | 33% | 4 | 11% | 203 | 20% | 22 | 24% | 940 | 23% | 634 | 24% | 4 | 8% | 64 | 18% | 128 | 41% | 65 | 30% | 11 | 21% |
| Involuntarily Apprehended | 5113 | 39% | 823 | 22% | 76 | 33% | 94 | 43% | 22 | 61% | 227 | 23% | 37 | 40% | 1417 | 35% | 2043 | 78% | 28 | 55% | 151 | 42% | 82 | 26% | 94 | 44% | 19 | 37% |
| Apprehended under existing order | 966 | 7% | 124 | 3% | 20 | 9% | 10 | 5% | 3 | 8% | 34 | 3% | 5 | 5% | 405 | 10% | 268 | 10% | 1 | 2% | 47 | 13% | 21 | 7% | 28 | 13% | 0 | 0% |
| Referred to CMH | 3869 | 30% | 1896 | 50% | 78 | 34% | 53 | 24% | 17 | 47% | 333 | 33% | 18 | 19% | 836 | 21% | 440 | 17% | 7 | 14% | 32 | 9% | 108 | 34% | 18 | 8% | 33 | 63% |
| Transferred to EMS/MCRRT | 2643 | 20% | 378 | 10% | 22 | 10% | 51 | 23% | 4 | 11% | 137 | 14% | 11 | 12% | 1395 | 34% | 518 | 20% | 13 | 25% | 48 | 13% | 26 | 8% | 34 | 16% | 6 | 12% |
| Caseworker/Probation notified | 1249 | 10% | 503 | 13% | 29 | 13% | 22 | 10% | 1 | 3% | 87 | 9% | 6 | 6% | 285 | 7% | 247 | 9% | 3 | 6% | 14 | 4% | 38 | 12% | 7 | 3% | 7 | 13% |
| Transported to Hospital | 7391 | 57% | 1020 | 27% | 84 | 37% | 110 | 50% | 20 | 56% | 323 | 32% | 48 | 52% | 2703 | 66% | 2461 | 94% | 41 | 80% | 232 | 65% | 160 | 51% | 158 | 74% | 31 | 60% |
| High Risk of Harm to Other Score | 4585 | 35% | 1033 | 27% | 71 | 31% | 81 | 37% | 18 | 50% | 339 | 34% | 38 | 41% | 1262 | 31% | 1351 | 52% | 39 | 76% | 140 | 39% | 121 | 38% | 72 | 34% | 20 | 38% |
| High Risk of Self Care Score | 5841 | 45% | 1133 | 30% | 100 | 44% | 104 | 47% | 23 | 64% | 471 | 47% | 47 | 51% | 1727 | 42% | 1718 | 66% | 33 | 65% | 176 | 49% | 169 | 54% | 119 | 56% | 21 | 40% |
| High Risk of Self Harm Score | 6924 | 53% | 1173 | 31% | 103 | 45% | 109 | 50% | 22 | 61% | 472 | 47% | 44 | 47% | 2555 | 63% | 1868 | 72% | 43 | 84% | 166 | 47% | 199 | 63% | 137 | 64% | 33 | 63% |

Appendix vi Demographics, Unique Persons, All Communities (n=9,334)

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **All Regions** | | **Brantford** | | **Brockville** | | **Cobourg** | | **Gananoque** | | **Guelph** | | **KawarthaLake** | | **London** | | **Niagara** | | **Orangeville** | | **Ottawa** | | **Regina** | | **Saskatoon** | | **Smiths Falls** | |
| **(N=9334)** | | **(n = 2190)** | | **(n=183)** | | **(n=177)** | | **(n=35)** | | **(n=754)** | | **(n=78)** | | **(n=2972)** | | **(n=2043)** | | **(n=43)** | | **(n=339)** | | **(n=278)** | | **(n=198)** | | **(n=44)** | |
| Gender is Female | 4293 | 46% | 984 | 45% | 88 | 48% | 84 | 47% | 13 | 37% | 369 | 50% | 34 | 44% | 1413 | 48% | 910 | 45% | 16 | 38% | 136 | 40% | 135 | 49% | 98 | 50% | 13 | 30% |
| Homeless | 914 | 10% | 170 | 8% | 10 | 5% | 24 | 14% | 7 | 20% | 78 | 10% | 13 | 17% | 281 | 9% | 235 | 12% | 13 | 30% | 38 | 11% | 21 | 8% | 19 | 10% | 5 | 11% |
| Irritability | 5082 | 54% | 972 | 44% | 104 | 57% | 93 | 53% | 24 | 69% | 405 | 54% | 48 | 62% | 1521 | 51% | 1392 | 68% | 31 | 72% | 187 | 55% | 167 | 60% | 109 | 55% | 29 | 66% |
| Hallucinations | 1572 | 17% | 257 | 12% | 21 | 11% | 37 | 21% | 6 | 17% | 119 | 16% | 19 | 24% | 502 | 17% | 456 | 22% | 7 | 16% | 53 | 16% | 48 | 17% | 38 | 19% | 9 | 20% |
| Command hallucinations | 844 | 9% | 65 | 3% | 8 | 4% | 18 | 10% | 5 | 14% | 64 | 8% | 8 | 10% | 275 | 9% | 315 | 15% | 15 | 35% | 29 | 9% | 22 | 8% | 14 | 7% | 6 | 14% |
| Delusions | 2080 | 22% | 418 | 19% | 39 | 21% | 53 | 30% | 12 | 34% | 158 | 21% | 19 | 24% | 621 | 21% | 543 | 27% | 16 | 37% | 85 | 25% | 58 | 21% | 48 | 24% | 10 | 23% |
| Hyper-arousal | 2877 | 31% | 450 | 21% | 60 | 33% | 48 | 27% | 17 | 49% | 241 | 32% | 30 | 38% | 888 | 30% | 910 | 45% | 16 | 37% | 70 | 21% | 85 | 31% | 48 | 24% | 14 | 32% |
| Pressured speech | 3121 | 33% | 465 | 21% | 67 | 37% | 58 | 33% | 15 | 43% | 240 | 32% | 33 | 42% | 910 | 31% | 1050 | 51% | 18 | 42% | 100 | 30% | 92 | 33% | 57 | 29% | 16 | 36% |
| Abnormal thought processes | 4789 | 51% | 657 | 30% | 93 | 51% | 88 | 50% | 19 | 54% | 417 | 55% | 33 | 42% | 1472 | 50% | 1549 | 76% | 33 | 77% | 140 | 41% | 165 | 59% | 104 | 53% | 19 | 43% |
| Socially inappropriate | 3887 | 42% | 644 | 29% | 78 | 43% | 64 | 36% | 19 | 54% | 346 | 46% | 25 | 32% | 1090 | 37% | 1225 | 60% | 33 | 77% | 146 | 43% | 109 | 39% | 92 | 46% | 16 | 36% |
| Verbal abuse | 2862 | 31% | 572 | 26% | 54 | 30% | 51 | 29% | 20 | 57% | 228 | 30% | 28 | 36% | 778 | 26% | 868 | 42% | 25 | 58% | 104 | 31% | 76 | 27% | 45 | 23% | 13 | 30% |
| Intoxication | 3221 | 35% | 634 | 29% | 44 | 24% | 65 | 37% | 18 | 51% | 270 | 36% | 23 | 29% | 1046 | 35% | 753 | 37% | 20 | 47% | 105 | 31% | 144 | 52% | 86 | 43% | 13 | 30% |
| Degree of insight | 6257 | 67% | 1483 | 68% | 149 | 81% | 135 | 76% | 23 | 66% | 492 | 65% | 47 | 60% | 1802 | 61% | 1553 | 76% | 26 | 60% | 210 | 62% | 178 | 64% | 135 | 68% | 24 | 55% |
| Daily Decision Making | 3502 | 38% | 475 | 22% | 65 | 36% | 73 | 41% | 21 | 60% | 277 | 37% | 32 | 41% | 1094 | 37% | 1053 | 52% | 18 | 42% | 141 | 42% | 135 | 49% | 101 | 51% | 17 | 39% |
| Previous Police Contact | 3394 | 36% | 747 | 34% | 60 | 33% | 86 | 49% | 15 | 43% | 267 | 35% | 28 | 36% | 1035 | 35% | 810 | 41% | 24 | 56% | 114 | 34% | 94 | 34% | 66 | 33% | 18 | 41% |
| Carries Weapon | 1496 | 16% | 333 | 15% | 24 | 13% | 25 | 14% | 7 | 20% | 94 | 12% | 11 | 14% | 437 | 15% | 420 | 21% | 20 | 47% | 51 | 15% | 40 | 14% | 27 | 14% | 7 | 16% |
| Violent ideation | 2255 | 24% | 310 | 14% | 33 | 18% | 44 | 25% | 12 | 34% | 156 | 21% | 18 | 23% | 665 | 22% | 775 | 38% | 17 | 40% | 102 | 30% | 60 | 22% | 52 | 26% | 11 | 25% |
| Intimidation of others | 2232 | 24% | 372 | 17% | 36 | 20% | 45 | 25% | 12 | 34% | 167 | 22% | 23 | 29% | 557 | 19% | 761 | 37% | 25 | 58% | 102 | 30% | 71 | 26% | 48 | 24% | 13 | 30% |
| Violence to others | 1694 | 18% | 283 | 13% | 23 | 13% | 30 | 17% | 12 | 34% | 122 | 16% | 17 | 22% | 451 | 15% | 555 | 27% | 22 | 51% | 90 | 27% | 53 | 19% | 28 | 14% | 8 | 18% |
| Self injurious attempt last 7 days | 3037 | 33% | 348 | 16% | 50 | 27% | 54 | 31% | 8 | 23% | 212 | 28% | 23 | 29% | 1056 | 36% | 982 | 48% | 24 | 56% | 81 | 24% | 95 | 34% | 88 | 44% | 16 | 36% |
| Considered self injury last 30 days | 4708 | 50% | 651 | 30% | 75 | 41% | 78 | 44% | 21 | 60% | 320 | 42% | 37 | 47% | 1686 | 57% | 1371 | 67% | 31 | 72% | 145 | 43% | 162 | 58% | 105 | 53% | 26 | 59% |
| Suicide Plan in Last 30 Days | 2986 | 32% | 364 | 17% | 41 | 22% | 58 | 33% | 7 | 20% | 154 | 20% | 23 | 29% | 1008 | 34% | 1032 | 51% | 18 | 42% | 91 | 27% | 94 | 34% | 77 | 39% | 19 | 43% |
| Others concerned about self-injury | 5388 | 58% | 915 | 42% | 89 | 49% | 96 | 54% | 23 | 66% | 384 | 51% | 45 | 58% | 1812 | 61% | 1535 | 75% | 25 | 58% | 164 | 48% | 164 | 59% | 114 | 58% | 22 | 50% |
| Squalid condition | 2654 | 28% | 601 | 27% | 73 | 40% | 45 | 25% | 17 | 49% | 244 | 32% | 23 | 29% | 754 | 25% | 637 | 31% | 22 | 51% | 89 | 26% | 78 | 28% | 51 | 26% | 20 | 45% |
| Refused Medication | 1815 | 19% | 281 | 13% | 29 | 16% | 20 | 11% | 13 | 37% | 130 | 17% | 26 | 33% | 558 | 19% | 543 | 27% | 16 | 37% | 84 | 25% | 61 | 22% | 43 | 22% | 11 | 25% |
| Voluntary escort to hospital | 1884 | 20% | 184 | 8% | 35 | 19% | 62 | 35% | 4 | 11% | 145 | 19% | 20 | 26% | 670 | 23% | 518 | 25% | 3 | 7% | 63 | 19% | 112 | 40% | 58 | 29% | 10 | 23% |
| Involuntarily Apprehended | 3800 | 41% | 498 | 23% | 59 | 32% | 70 | 40% | 21 | 60% | 174 | 23% | 31 | 40% | 1024 | 34% | 1582 | 77% | 23 | 53% | 140 | 41% | 75 | 27% | 87 | 44% | 16 | 36% |
| Apprehended under existing order | 730 | 8% | 70 | 3% | 14 | 8% | 8 | 5% | 3 | 9% | 26 | 3% | 5 | 6% | 298 | 10% | 219 | 11% | 0 | 0% | 44 | 13% | 18 | 6% | 25 | 13% | 0 | 0% |
| Referred to CMH | 2654 | 28% | 1134 | 52% | 63 | 34% | 40 | 23% | 17 | 49% | 264 | 35% | 15 | 19% | 611 | 21% | 335 | 16% | 6 | 14% | 30 | 9% | 96 | 35% | 14 | 7% | 29 | 66% |
| Transferred to EMS/MCRRT | 1993 | 21% | 245 | 11% | 17 | 9% | 41 | 23% | 4 | 11% | 104 | 14% | 10 | 13% | 1036 | 35% | 415 | 20% | 10 | 23% | 48 | 14% | 25 | 9% | 33 | 17% | 5 | 11% |
| Caseworker/Probation notified | 779 | 8% | 248 | 11% | 23 | 13% | 19 | 11% | 1 | 3% | 59 | 8% | 3 | 4% | 183 | 6% | 181 | 9% | 3 | 7% | 12 | 4% | 34 | 12% | 7 | 4% | 6 | 14% |
| Transported to Hospital | 5493 | 59% | 611 | 28% | 68 | 37% | 93 | 53% | 19 | 54% | 239 | 32% | 40 | 51% | 1935 | 65% | 1919 | 94% | 33 | 77% | 220 | 65% | 146 | 53% | 145 | 73% | 25 | 57% |
| High Risk of Harm to Other Score | 3262 | 35% | 565 | 26% | 56 | 31% | 62 | 35% | 18 | 51% | 245 | 32% | 30 | 38% | 894 | 30% | 1041 | 51% | 33 | 77% | 132 | 39% | 102 | 37% | 69 | 35% | 15 | 34% |
| High Risk of Self Care Score | 4156 | 45% | 611 | 28% | 74 | 40% | 80 | 45% | 22 | 63% | 331 | 44% | 37 | 47% | 1211 | 41% | 1320 | 65% | 29 | 67% | 164 | 48% | 149 | 54% | 110 | 56% | 18 | 41% |
| High Risk of Self Harm Score | 5106 | 55% | 720 | 33% | 84 | 46% | 86 | 49% | 22 | 63% | 351 | 47% | 39 | 50% | 1814 | 61% | 1465 | 72% | 36 | 84% | 156 | 46% | 178 | 64% | 127 | 64% | 28 | 64% |

Appendix vii Target Variable Prevalence, All Reports, All Communities (N=13,058)

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Variable** | **All Regions** | | **Brantford** | | **Brockville** | | **Cobourg** | | **Gananoque** | | **Guelph** | | **KawarthaLake** | | **London** | | **Niagara** | | **Orangeville** | | **Ottawa** | | **Regina** | | **Saskatoon** | | **Smiths Falls** | |
| **(N=13058)** | | **(n = 3800)** | | **(n=229)** | | **(n=219)** | | **(n=36)** | | **(n=1008)** | | **(n=93)** | | **(n=4079)** | | **(n=2606)** | | **(n=51)** | | **(n=356)** | | **(n=315)** | | **(n=214)** | | **(n=52)** | |
| hihocat (24hrs) | 99 | 0.76% | 32 | 0.84% | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% | 12 | 1.19% | 2 | 2.15% | 29 | 0.71% | 17 | 0.65% | 2 | 3.92% | 1 | 0.28% | 2 | 0.63% | 0 | 0.00% | 2 | 3.85% |
| hihocat (72hrs) | 195 | 1.49% | 75 | 1.97% | 2 | 0.87% | 0 | 0.00% | 0 | 0.00% | 18 | 1.79% | 2 | 2.15% | 56 | 1.37% | 31 | 1.19% | 2 | 3.92% | 3 | 0.84% | 3 | 0.95% | 1 | 0.47% | 2 | 3.85% |
| hishcat (24hrs) | 175 | 1.34% | 48 | 1.26% | 0 | 0.00% | 0 | 0.00% | 0 | 0.00% | 20 | 1.98% | 0 | 0.00% | 68 | 1.67% | 27 | 1.04% | 3 | 5.88% | 0 | 0.00% | 6 | 1.90% | 0 | 0.00% | 3 | 5.77% |
| hishcat (72hrs) | 326 | 2.50% | 87 | 2.29% | 3 | 1.31% | 0 | 0.00% | 0 | 0.00% | 29 | 2.88% | 0 | 0.00% | 132 | 3.24% | 56 | 2.15% | 3 | 5.88% | 1 | 0.28% | 10 | 3.17% | 2 | 0.93% | 3 | 5.77% |
| hisccat (24hrs) | 117 | 0.90% | 39 | 1.03% | 2 | 0.87% | 1 | 0.46% | 0 | 0.00% | 7 | 0.69% | 1 | 1.08% | 37 | 0.91% | 21 | 0.81% | 2 | 3.92% | 1 | 0.28% | 3 | 0.95% | 1 | 0.47% | 2 | 3.85% |
| hisccat  (72 hrs) | 211 | 1.62% | 76 | 2.00% | 4 | 1.75% | 1 | 0.46% | 0 | 0.00% | 15 | 1.49% | 2 | 2.15% | 61 | 1.50% | 36 | 1.38% | 2 | 3.92% | 4 | 1.12% | 6 | 1.90% | 2 | 0.93% | 2 | 3.85% |

Appendix viii Example Output Best Subset Logistic Regression, Chi-Square Score by Number of Variables (n=10,441)

Appendix ix Example Output Best Subset Logistic Regression (Narrowed Results) (n=10,441)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **ho24** | **Number of Variables** | **AIC** | **Chi-Square** | **AUC** |
| 5 | 896.755 | 76.4606 | 0.754 |
| 6 | 875.213 | 79.2621 | 0.748 |
| 7 | 871.855 | 82.5959 | 0.755 |
| 8 | 872.178 | 85.318 | 0.763 |

Appendix x Learning algorithm Selection from Random Forests Tuning Process (n=10,441)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | ho24\_all | | | |
|  | mtry=3 | mtry=6 | mtry=9 | mtry=12 |
| ntree=1 | 0.0153243 | 0.0177188 | 0.0157075 | 0.021454 |
| ntree=100 | 0.0077578 | 0.0077578 | 0.0077578 | 0.0077578 |
| ntree=200 | 0.0077578 | 0.0077578 | 0.0077578 | 0.0077578 |
| ntree=300 | 0.0077578 | 0.0077578 | 0.0077578 | 0.0077578 |
| ntree=400 | 0.0077578 | 0.0077578 | 0.0077578 | 0.0078536 |
| ntree=500 | 0.0077578 | 0.0077578 | 0.0077578 | 0.0077578 |
| ntree=1000 | 0.0077578 | 0.0077578 | 0.0077578 | 0.0077578 |
| ntree=2500 | 0.0077578 | 0.0077578 | 0.0077578 | 0.0077578 |
| ntree=5000 | 0.0077578 | 0.0077578 | 0.0077578 | 0.0077578 |
|  | MIN: | 0.0078 | MAX: | 0.0215 |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | ho24\_all | | | |
|  | mtry=3 | mtry=6 | mtry=9 | mtry=12 |
| ntree=1 | 0.493789 | 0.5029265 | 0.5080272 | 0.5096213 |
| ntree=100 | 0.5950423 | 0.6008258 | 0.5774303 | 0.6023153 |
| ntree=200 | 0.5924847 | 0.6168299 | 0.6242114 | 0.6157237 |
| ntree=300 | 0.6203533 | 0.6251671 | 0.6143216 | 0.6221693 |
| ntree=400 | 0.6164537 | 0.6250242 | 0.618157 | 0.6231628 |
| ntree=500 | 0.6037988 | 0.6251531 | 0.6207429 | 0.6224438 |
| ntree=1000 | 0.6706953 | 0.6756965 | 0.6708393 | 0.6670775 |
| ntree=2500 | 0.6973524 | 0.6847556 | 0.6764309 | 0.6647854 |
| ntree=5000 | 0.6940956 | 0.6781684 | 0.6726347 | 0.6745352 |
|  | MIN: | 0.4938 | MAX: | 0.6974 |

Appendix xi Random Forest Tuning Results, all target variables, mmce and auc (n=10,441)

Appendix xii Random Forests Output by Dependent Variable, All Data sets (N=13,058)

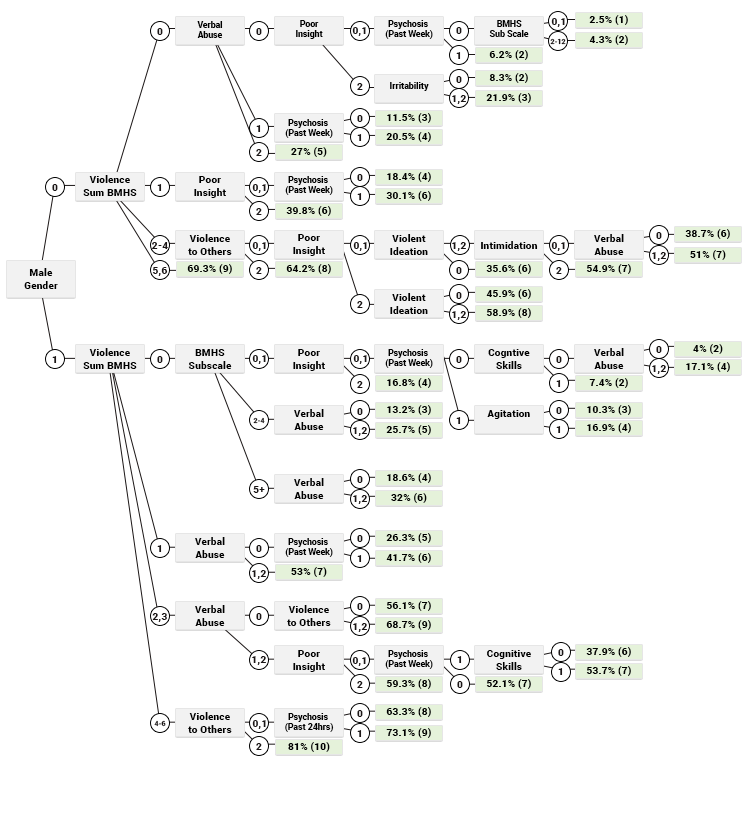
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Data Sets** | **Risk Type** | **Time Period** | **AUC** | **TPR** | **FPR** | **TNR** | **FNR** | **TP** | **FP** | **TN** | **FN** | **Sensitivity** | **Specificity** | **PPV** | **NPV** | **ACC** | **LRP** | **LRN** |
| Merged Training Merged Holdout | Harm to Others | 24 Hour | 0.719 | 0.500 | 0.312 | 0.688 | 0.500 | 9 | 810 | 1789 | 9 | 0.500 | 0.688 | 0.989 | 0.995 | 0.687 | 1.604 | 0.726 |
| 72 Hour | 0.687 | 0.829 | 0.556 | 0.444 | 0.171 | 29 | 1435 | 1147 | 6 | 0.829 | 0.444 | 0.980 | 0.995 | 0.449 | 1.491 | 0.386 |
| Harm to Self | 24 Hour | 0.680 | 0.718 | 0.442 | 0.558 | 0.282 | 28 | 1139 | 1439 | 11 | 0.718 | 0.558 | 0.976 | 0.992 | 0.561 | 1.625 | 0.505 |
| 72 Hour | 0.724 | 0.895 | 0.634 | 0.366 | 0.105 | 68 | 1612 | 929 | 8 | 0.895 | 0.366 | 0.960 | 0.991 | 0.381 | 1.410 | 0.288 |
| Failure to Care for Self | 24 Hour | 0.710 | 0.645 | 0.366 | 0.634 | 0.355 | 20 | 947 | 1639 | 11 | 0.645 | 0.634 | 0.979 | 0.993 | 0.634 | 1.762 | 0.560 |
| 72 Hour | 0.766 | 0.872 | 0.489 | 0.511 | 0.128 | 41 | 1257 | 1313 | 6 | 0.872 | 0.511 | 0.968 | 0.995 | 0.517 | 1.784 | 0.250 |
| Merged Training  Brantford Holdout | Harm to Others | 24 Hour | 0.790 | 0.500 | 0.304 | 0.696 | 0.500 | 3 | 229 | 525 | 3 | 0.500 | 0.696 | 0.987 | 0.994 | 0.695 | 1.646 | 0.718 |
| 72 Hour | 0.754 | 0.917 | 0.578 | 0.422 | 0.083 | 11 | 432 | 316 | 1 | 0.917 | 0.422 | 0.975 | 0.997 | 0.430 | 1.587 | 0.197 |
| Harm to Self | 24 Hour | 0.764 | 0.727 | 0.390 | 0.610 | 0.273 | 8 | 292 | 457 | 3 | 0.727 | 0.610 | 0.973 | 0.993 | 0.612 | 1.866 | 0.447 |
| 72 Hour | 0.821 | 0.955 | 0.546 | 0.454 | 0.045 | 21 | 403 | 335 | 1 | 0.955 | 0.454 | 0.950 | 0.997 | 0.468 | 1.748 | 0.100 |
| Failure to Care for Self | 24 Hour | 0.754 | 0.636 | 0.323 | 0.677 | 0.364 | 7 | 242 | 507 | 4 | 0.636 | 0.677 | 0.972 | 0.992 | 0.676 | 1.970 | 0.537 |
| 72 Hour | 0.833 | 0.889 | 0.469 | 0.531 | 0.111 | 16 | 348 | 394 | 2 | 0.889 | 0.531 | 0.956 | 0.995 | 0.539 | 1.895 | 0.209 |
| Merged  Training  London  Holdout | Harm to Others | 24 Hour | 0.603 | 0.500 | 0.272 | 0.728 | 0.500 | 2 | 221 | 591 | 2 | 0.500 | 0.728 | 0.991 | 0.997 | 0.727 | 1.837 | 0.687 |
| 72 Hour | 0.664 | 0.800 | 0.507 | 0.493 | 0.200 | 8 | 409 | 397 | 2 | 0.800 | 0.493 | 0.981 | 0.995 | 0.496 | 1.577 | 0.406 |
| Harm to Self | 24 Hour | 0.574 | 0.538 | 0.446 | 0.554 | 0.462 | 7 | 358 | 445 | 6 | 0.538 | 0.554 | 0.981 | 0.987 | 0.554 | 1.208 | 0.833 |
| 72 Hour | 0.656 | 0.813 | 0.665 | 0.335 | 0.188 | 26 | 521 | 263 | 6 | 0.813 | 0.335 | 0.952 | 0.978 | 0.354 | 1.223 | 0.559 |
| Failure to Care for Self | 24 Hour | 0.697 | 0.556 | 0.369 | 0.631 | 0.444 | 5 | 298 | 509 | 4 | 0.556 | 0.631 | 0.983 | 0.992 | 0.630 | 1.504 | 0.705 |
| 72 Hour | 0.770 | 0.857 | 0.458 | 0.542 | 0.143 | 12 | 367 | 435 | 2 | 0.857 | 0.542 | 0.968 | 0.995 | 0.548 | 1.873 | 0.263 |
| Merged  Training  Niagara  Holdout | Harm to Others | 24 Hour | 0.879 | 1.000 | 0.328 | 0.672 | 0.000 | 1 | 171 | 350 | 0 | 1.000 | 0.672 | 0.994 | 1.000 | 0.672 | 3.047 | 0.000 |
| 72 Hour | 0.622 | 0.667 | 0.549 | 0.451 | 0.333 | 2 | 285 | 234 | 1 | 0.667 | 0.451 | 0.993 | 0.996 | 0.452 | 1.214 | 0.739 |
| Harm to Self | 24 Hour | 0.741 | 0.875 | 0.420 | 0.580 | 0.125 | 7 | 216 | 298 | 1 | 0.875 | 0.580 | 0.969 | 0.997 | 0.584 | 2.082 | 0.216 |
| 72 Hour | 0.688 | 0.909 | 0.634 | 0.366 | 0.091 | 10 | 324 | 187 | 1 | 0.909 | 0.366 | 0.970 | 0.995 | 0.377 | 1.434 | 0.248 |
| Failure to Care for Self | 24 Hour | 0.784 | 0.800 | 0.338 | 0.662 | 0.200 | 4 | 175 | 342 | 1 | 0.800 | 0.662 | 0.978 | 0.997 | 0.663 | 2.363 | 0.302 |
| 72 Hour | 0.695 | 0.857 | 0.466 | 0.534 | 0.143 | 6 | 240 | 275 | 1 | 0.857 | 0.534 | 0.976 | 0.996 | 0.538 | 1.839 | 0.268 |
| Brantford Training  Brantford Holdout | Harm to Others | 24 Hour | 0.815 | 0.833 | 0.316 | 0.684 | 0.167 | 5 | 238 | 516 | 1 | 0.833 | 0.684 | 0.979 | 0.998 | 0.686 | 2.640 | 0.244 |
| 72 Hour | 0.771 | 0.917 | 0.485 | 0.515 | 0.083 | 11 | 363 | 385 | 1 | 0.917 | 0.515 | 0.971 | 0.997 | 0.521 | 1.889 | 0.162 |
| Harm to Self | 24 Hour | 0.726 | 0.818 | 0.372 | 0.628 | 0.182 | 9 | 279 | 470 | 2 | 0.818 | 0.628 | 0.969 | 0.996 | 0.630 | 2.196 | 0.290 |
| 72 Hour | 0.822 | 0.955 | 0.493 | 0.507 | 0.045 | 21 | 364 | 374 | 1 | 0.955 | 0.507 | 0.945 | 0.997 | 0.520 | 1.935 | 0.090 |
| Failure to Care for Self | 24 Hour | 0.766 | 0.636 | 0.231 | 0.769 | 0.364 | 7 | 173 | 576 | 4 | 0.636 | 0.769 | 0.961 | 0.993 | 0.767 | 2.755 | 0.473 |
| 72 Hour | 0.782 | 0.833 | 0.438 | 0.562 | 0.167 | 15 | 325 | 417 | 3 | 0.833 | 0.562 | 0.956 | 0.993 | 0.568 | 1.903 | 0.297 |
| London  Training  London  Holdout | Harm to Others | 24 Hour | 0.655 | 0.500 | 0.271 | 0.729 | 0.500 | 2 | 220 | 592 | 2 | 0.500 | 0.729 | 0.991 | 0.997 | 0.728 | 1.845 | 0.686 |
| 72 Hour | 0.709 | 0.800 | 0.507 | 0.493 | 0.200 | 8 | 409 | 397 | 2 | 0.800 | 0.493 | 0.981 | 0.995 | 0.496 | 1.577 | 0.406 |
| Harm to Self | 24 Hour | 0.604 | 0.692 | 0.554 | 0.446 | 0.308 | 9 | 445 | 358 | 4 | 0.692 | 0.446 | 0.980 | 0.989 | 0.450 | 1.249 | 0.690 |
| 72 Hour | 0.661 | 0.844 | 0.693 | 0.307 | 0.156 | 27 | 543 | 241 | 5 | 0.844 | 0.307 | 0.953 | 0.980 | 0.328 | 1.218 | 0.508 |
| Failure to Care for Self | 24 Hour | 0.774 | 0.778 | 0.359 | 0.641 | 0.222 | 7 | 290 | 517 | 2 | 0.778 | 0.641 | 0.976 | 0.996 | 0.642 | 2.164 | 0.347 |
| 72 Hour | 0.769 | 0.786 | 0.455 | 0.545 | 0.214 | 11 | 365 | 437 | 3 | 0.786 | 0.545 | 0.971 | 0.993 | 0.549 | 1.726 | 0.393 |
| Niagara  Training  Niagara  Holdout | Harm to Others | 24 Hour | 0.962 | 1.000 | 0.273 | 0.727 | 0.000 | 1 | 142 | 379 | 0 | 1.000 | 0.727 | 0.993 | 1.000 | 0.728 | 3.669 | 0.000 |
| 72 Hour | 0.551 | 0.333 | 0.403 | 0.597 | 0.667 | 1 | 209 | 310 | 2 | 0.333 | 0.597 | 0.995 | 0.994 | 0.596 | 0.828 | 1.116 |
| Harm to Self | 24 Hour | 0.501 | 0.125 | 0.288 | 0.712 | 0.875 | 1 | 148 | 366 | 7 | 0.125 | 0.712 | 0.993 | 0.981 | 0.703 | 0.434 | 1.229 |
| 72 Hour | 0.667 | 1.000 | 0.536 | 0.464 | 0.000 | 11 | 274 | 237 | 0 | 1.000 | 0.464 | 0.961 | 1.000 | 0.475 | 1.865 | 0.000 |
| Failure to Care for Self | 24 Hour | 0.440 | 0.200 | 0.290 | 0.710 | 0.800 | 1 | 150 | 367 | 4 | 0.200 | 0.710 | 0.993 | 0.989 | 0.705 | 0.689 | 1.127 |
| 72 Hour | 0.575 | 0.714 | 0.470 | 0.530 | 0.286 | 5 | 242 | 273 | 2 | 0.714 | 0.530 | 0.980 | 0.993 | 0.533 | 1.520 | 0.539 |

Appendix xiii Variable Importance Type 1 (mean decrease in accuracy)

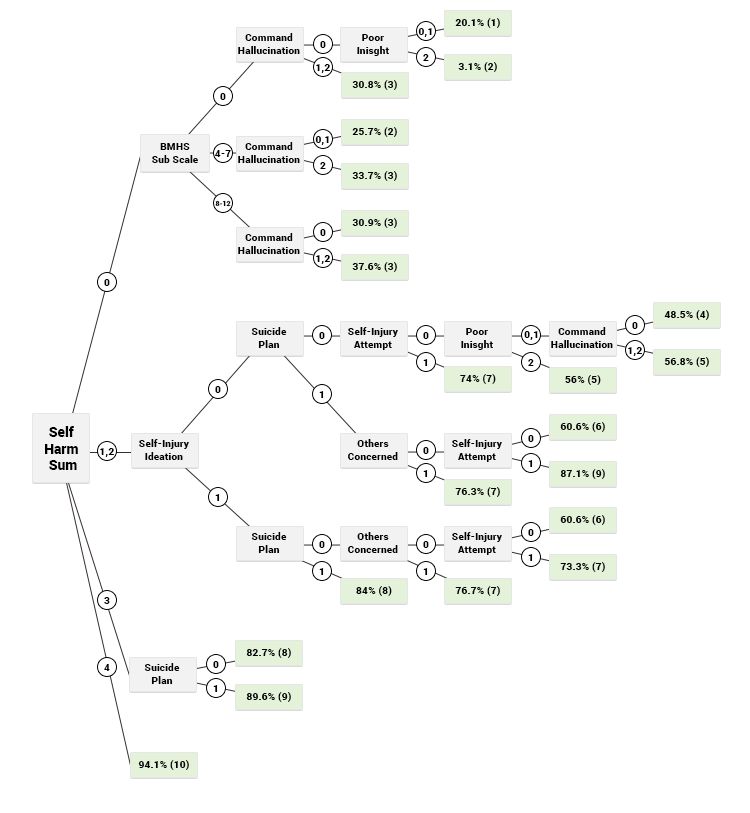
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **MERGED TRAINING** | | | | | | **BRANTFORD TRAINING** | | | | | | **LONDON TRAINING** | | | | | | **NIAGARA TRAINING** | | | | | |
| **HO24** | **SH24** | **SC24** | **HO72** | **SH72** | **SC72** | **HO24** | **SH24** | **SC24** | **HO72** | **SH72** | **SC72** | **HO24** | **SH24** | **SC24** | **HO72** | **SH72** | **SC72** | **HO24** | **SH24** | **SC24** | **HO72** | **SH72** | **SC72** |
| Region | 11.611 | 18.219 | 12.284 | 9.264 | 36.476 | 12.895 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Homeless | 3.477 | 10.059 | 5.760 | 5.705 | 21.451 | 10.982 | -0.940 | 6.596 | 0.568 | -4.909 | 15.829 | -0.303 | 0.267 | 14.696 | 3.891 | 5.020 | 16.333 | 2.406 | 8.078 | 3.870 | 3.087 | 4.241 | 4.196 | 13.696 |
| Gender | 0.740 | 1.354 | 0.953 | 2.677 | 1.332 | -4.400 | 1.197 | -0.305 | -1.905 | -4.556 | -1.178 | -1.292 | 1.885 | 2.754 | 0.534 | 3.795 | 3.505 | -3.023 | -5.650 | -0.876 | -1.865 | -3.077 | 0.366 | -1.436 |
| Irritability: 24 hrs | 11.713 | 8.920 | 20.199 | 13.931 | 26.277 | 29.806 | 0.278 | 2.211 | 5.988 | 8.469 | 2.274 | 4.370 | 6.017 | 18.276 | 26.269 | 14.396 | 13.285 | 14.126 | 12.846 | 4.934 | 2.144 | 2.536 | 9.018 | 8.217 |
| Hallucinations: 24 hrs | 13.611 | 14.645 | 17.565 | 19.661 | 37.131 | 26.882 | 3.153 | 11.901 | 10.757 | 22.110 | 16.089 | 4.715 | 1.226 | 13.006 | 0.903 | 13.390 | 24.438 | 2.890 | 17.692 | 4.904 | 6.761 | 6.059 | 7.363 | 18.364 |
| Command hallucinations: 24 hrs | 7.679 | 10.543 | 6.718 | 10.066 | 25.245 | 15.760 | -0.994 | 0.806 | -6.794 | -7.310 | -3.113 | -0.971 | 2.734 | 14.371 | 6.258 | 11.083 | 25.927 | 8.809 | 8.709 | 3.786 | 4.215 | 4.710 | 7.480 | 10.725 |
| Delusions: 24 hrs | 13.215 | 4.720 | 6.895 | 18.581 | 26.480 | 16.017 | 9.215 | 2.277 | 2.893 | 20.927 | 10.365 | 2.540 | -3.099 | 10.459 | -5.818 | 12.469 | 21.401 | 2.723 | 6.835 | 5.109 | 3.278 | 5.822 | 8.005 | 13.949 |
| Hyper-arousal: 24 hrs | -2.881 | 3.052 | 0.383 | 19.729 | 25.789 | 16.433 | 7.484 | 9.035 | 6.487 | 34.846 | 15.508 | 8.167 | -10.363 | -1.354 | -6.700 | 2.594 | 13.480 | 1.691 | 1.489 | 1.707 | -0.688 | 3.601 | 10.389 | 1.736 |
| Pressured speech: 24 hrs | 16.695 | 10.150 | 14.573 | 19.448 | 31.830 | 24.710 | 3.864 | 6.031 | -0.209 | 16.939 | 18.763 | 4.472 | -1.479 | 16.124 | -10.598 | 3.311 | 21.627 | 1.870 | 16.242 | 6.064 | 8.298 | 4.752 | 9.870 | 19.777 |
| Abnormal thought processes: 24 hrs | 25.716 | 10.803 | 23.677 | 24.958 | 28.832 | 27.568 | 8.059 | 6.938 | 14.543 | 20.255 | 19.011 | 5.129 | 7.248 | -2.013 | 20.717 | 18.258 | 15.116 | 6.718 | 8.054 | 0.527 | 4.886 | 2.286 | 5.354 | 7.474 |
| Socially inappropriate: 24 hrs | 24.926 | 6.912 | 10.085 | 26.021 | 20.620 | 9.509 | 9.615 | 4.848 | 5.284 | 17.163 | 4.355 | 0.989 | -1.102 | 15.171 | 4.314 | 10.955 | 14.374 | 1.912 | 4.940 | 1.177 | -1.206 | 1.625 | 9.084 | 1.606 |
| Verbal abuse: 24 hrs | 13.806 | 4.625 | 11.481 | 18.808 | 28.367 | 19.770 | 1.174 | -0.303 | 0.824 | -1.135 | -1.215 | 2.576 | 2.497 | 11.764 | 12.291 | 9.415 | 11.451 | 6.343 | 11.097 | 3.324 | 7.583 | 6.667 | 10.609 | 22.031 |
| Intoxication: 24 hrs | 5.107 | -1.672 | 6.542 | 11.844 | 9.729 | 12.386 | 2.582 | 2.924 | 5.826 | 12.031 | 4.849 | 3.098 | 0.194 | -4.013 | -2.806 | 2.450 | 6.048 | -0.988 | 1.146 | 2.541 | 3.202 | 0.451 | 0.566 | 5.883 |
| Degree of insight | 12.673 | 4.950 | 8.631 | 10.346 | 11.368 | 8.936 | 6.705 | 9.161 | 5.265 | 12.570 | 3.653 | 3.267 | 5.225 | 10.199 | 8.654 | 9.153 | 10.226 | 5.898 | -4.423 | -3.862 | -2.811 | -0.333 | 3.176 | 1.404 |
| Daily Decision Making (CA) | 7.580 | 2.882 | 8.165 | 11.789 | 19.505 | 4.228 | 1.352 | 1.980 | 7.862 | 6.097 | 4.225 | 0.039 | 2.819 | 14.089 | 8.693 | 6.490 | 23.188 | -2.022 | 4.237 | 2.005 | -1.130 | 1.034 | 1.795 | 3.811 |
| Previous Police Contact | -2.191 | 2.850 | -5.317 | -0.236 | 15.068 | -0.160 | -6.239 | 2.126 | -11.633 | -2.453 | -0.728 | -1.729 | -0.032 | 13.285 | 1.056 | 1.812 | 16.633 | 1.887 | -1.946 | 1.464 | -0.833 | -2.275 | 0.453 | -3.747 |
| Carries Weapon | -2.832 | 7.824 | 1.737 | 0.567 | 16.392 | 4.554 | -1.514 | -0.033 | -0.704 | -0.136 | 7.748 | -0.082 | 1.618 | 12.995 | 7.251 | 2.930 | 12.167 | 5.791 | -10.189 | -1.279 | -1.958 | -2.553 | -0.754 | -7.683 |
| Violent ideation: 24 hrs | 9.353 | 7.875 | 2.055 | 17.359 | 25.655 | 12.930 | 3.852 | 8.094 | -1.698 | 26.630 | 26.030 | 2.547 | 0.689 | 8.790 | 5.727 | 5.721 | 14.916 | 3.044 | 17.229 | 6.503 | 1.634 | 5.319 | 9.983 | 11.864 |
| Intimidation of others: 24 hrs | 11.864 | 10.026 | -3.804 | 17.842 | 31.003 | 5.955 | 2.230 | 8.893 | 5.758 | 19.436 | 25.366 | 0.296 | 7.939 | 18.370 | 5.130 | 13.279 | 17.243 | 5.086 | -1.224 | 2.338 | -4.986 | 3.517 | 7.201 | 12.539 |
| Violence to others: 24 hrs | 18.327 | 6.749 | 0.718 | 20.917 | 19.187 | 18.693 | -0.272 | -1.051 | -3.007 | 18.637 | 2.762 | 2.199 | 6.561 | 22.558 | 13.843 | 12.882 | 19.048 | 13.458 | 14.138 | 1.469 | -1.001 | 5.751 | 6.516 | 11.175 |
| Self injurious attempt last 7 days | 11.840 | 14.049 | 10.583 | 11.668 | 31.859 | 15.984 | 0.445 | 6.204 | 6.244 | 4.115 | 17.074 | 1.445 | 0.911 | 15.981 | 14.305 | 8.156 | 26.812 | 10.045 | 7.940 | 3.995 | -2.575 | 1.824 | 10.666 | 1.291 |
| Considered self injury last 30 days | 7.395 | 17.537 | 8.496 | 10.511 | 42.327 | 7.205 | 4.638 | 14.747 | 3.617 | 1.002 | 24.268 | 3.449 | 3.891 | 24.248 | 7.946 | 9.269 | 32.126 | 7.522 | -2.395 | 3.355 | -1.413 | 1.533 | 8.467 | 3.483 |
| Suicide Plan | 9.289 | 12.770 | 7.372 | 17.517 | 28.005 | 14.932 | 1.360 | 4.060 | 4.925 | 13.157 | 20.305 | 2.637 | 2.450 | 22.030 | 2.499 | 10.737 | 25.933 | 6.424 | 5.921 | 3.138 | -1.344 | 3.806 | 5.112 | 4.985 |
| Others concerned about self-injury | 15.322 | 10.277 | 3.014 | 9.989 | 14.340 | -3.071 | 5.914 | 11.053 | 0.142 | 19.308 | 24.273 | 1.141 | 4.892 | -1.400 | -0.051 | 8.981 | -1.800 | -2.724 | 9.049 | 4.844 | 1.506 | 0.628 | 1.758 | 1.463 |
| Squalid condition | 4.227 | 8.729 | 4.278 | 11.602 | 14.060 | 4.121 | -0.276 | 8.110 | -3.782 | 8.123 | 7.989 | -0.926 | 1.893 | 10.161 | 9.991 | 7.090 | 7.732 | 4.757 | -4.549 | 2.975 | 0.543 | 0.394 | 1.594 | 3.251 |
| Refused Medication | -7.403 | 0.515 | -4.550 | -3.641 | 10.874 | 4.334 | -3.201 | 1.106 | -1.861 | -3.948 | -0.826 | 0.287 | -2.312 | 9.442 | 5.349 | 4.698 | 9.208 | 8.878 | -1.632 | 1.779 | 1.279 | -0.311 | 5.953 | 2.803 |
| Voluntary Escort to Hospital | 6.867 | 8.184 | 12.782 | 7.789 | 12.254 | 19.225 | 0.892 | -2.603 | 0.034 | -1.861 | -18.567 | 0.744 | 4.642 | 20.758 | 12.983 | 2.997 | 20.106 | 4.291 | 17.034 | 3.163 | 4.799 | 4.058 | 8.094 | 12.247 |
| Transferred to EMS/MCRRT | 2.883 | 9.847 | 4.023 | 1.064 | 20.306 | 3.959 | 0.419 | -2.160 | 3.071 | -1.006 | -1.251 | -1.425 | 0.224 | 22.610 | 3.217 | 3.215 | 13.604 | 2.947 | 3.888 | 3.310 | -0.067 | 2.710 | 5.506 | -3.142 |
| Caseworker/Probation notified | 2.338 | 3.902 | 1.953 | -1.406 | 6.604 | 0.825 | -0.050 | -4.240 | -3.127 | 2.694 | -1.031 | -1.127 | -0.549 | 4.905 | 9.625 | 0.785 | -1.828 | -0.547 | -1.107 | 0.281 | -0.818 | 0.693 | 1.209 | -0.682 |
| Referred to CMH | -1.760 | 0.819 | 2.398 | 4.771 | 10.049 | 5.149 | 3.718 | -2.545 | 3.925 | 7.225 | -1.951 | 2.224 | 2.257 | 10.634 | 6.127 | 3.994 | 6.840 | 8.404 | -0.517 | -0.057 | -1.602 | -0.644 | -0.181 | -4.350 |
| Apprehended under existing order | 5.881 | 4.595 | 3.953 | 6.037 | 12.022 | 5.594 | -0.892 | 0.539 | 1.623 | 0.328 | 2.313 | 1.849 | 2.821 | 17.349 | 9.273 | 3.971 | 18.233 | 3.551 | 0.148 | 1.810 | 2.807 | -0.355 | 3.038 | 1.863 |
| Involuntarily Apprehended | 30.801 | 18.919 | 23.889 | 25.606 | 34.357 | 29.181 | 3.600 | 10.784 | 11.268 | 17.857 | 6.645 | 4.395 | 3.904 | 24.261 | 20.142 | 7.507 | 23.981 | 10.790 | 25.232 | 5.971 | 7.422 | 7.683 | 7.928 | 16.433 |
| Harm to Others Scale | 20.557 | 13.070 | 11.636 | 23.485 | 45.501 | 17.306 | 5.836 | 10.388 | 7.240 | 16.489 | 20.426 | 3.161 | 7.011 | 27.743 | 13.086 | 15.149 | 31.728 | 9.069 | 14.049 | 6.963 | 3.418 | 6.252 | 15.551 | 13.434 |
| Harm to Self Scale | 24.967 | 17.447 | 19.541 | 25.810 | 47.904 | 23.282 | 11.548 | 11.701 | 15.664 | 21.814 | 25.953 | 6.004 | 6.236 | 28.934 | 20.592 | 18.387 | 33.552 | 10.488 | 19.220 | 5.294 | 5.940 | 5.906 | 13.298 | 11.101 |
| Self Harm Scale | 21.631 | 19.880 | 18.169 | 22.607 | 51.286 | 26.430 | 10.291 | 12.882 | 8.892 | 21.633 | 26.621 | 5.672 | 4.991 | 33.363 | 18.707 | 17.107 | 41.593 | 10.907 | 9.979 | 5.159 | 1.966 | 3.279 | 11.335 | 8.550 |
| Age | 12.125 | 3.088 | 13.197 | 11.699 | 8.626 | 12.287 | 4.289 | 0.070 | 7.542 | 17.733 | 5.567 | 4.030 | 2.691 | -3.836 | 7.685 | 3.153 | 7.152 | 5.264 | 7.183 | -1.452 | 2.189 | 1.946 | 0.979 | 5.048 |

Appendix xiv Variable Importance Type 2 (Mean Decrease Gini)

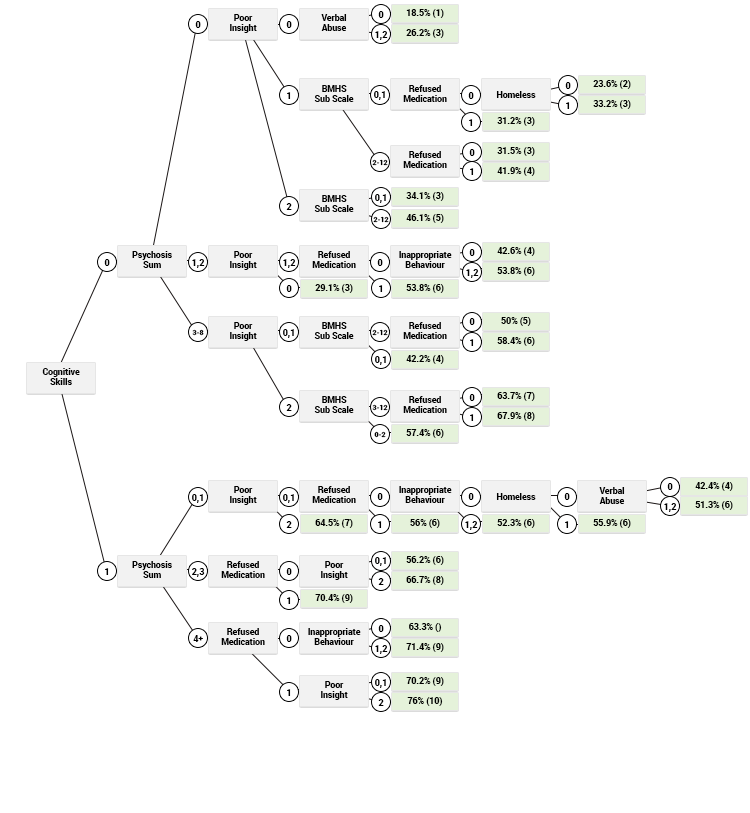
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **MERGED TRAINING** | | | | | | **BRANTFORD TRAINING** | | | | | | **LONDON TRAINING** | | | | | | **NIAGARA TRAINING** | | | | | |
| **HO24** | **SH24** | **SC24** | **HO72** | **SH72** | **SC72** | **HO24** | **SH24** | **SC24** | **HO72** | **SH72** | **SC72** | **HO24** | **SH24** | **SC24** | **HO72** | **SH72** | **SC72** | **HO24** | **SH24** | **SC24** | **HO72** | **SH72** | **SC72** |
| Region | 8.669 | 14.476 | 11.004 | 18.127 | 30.437 | 17.319 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Homeless | 2.455 | 3.325 | 3.164 | 5.145 | 7.152 | 4.546 | 1.226 | 1.156 | 0.883 | 1.889 | 1.674 | 1.699 | 0.546 | 1.143 | 0.915 | 0.952 | 2.041 | 1.263 | 0.857 | 0.751 | 0.707 | 1.299 | 2.043 | 1.336 |
| Gender | 2.481 | 4.063 | 3.573 | 6.354 | 11.220 | 5.345 | 1.002 | 1.741 | 0.837 | 2.226 | 2.642 | 1.623 | 0.940 | 2.302 | 1.075 | 1.830 | 3.331 | 1.398 | 0.506 | 0.720 | 0.472 | 0.943 | 2.952 | 1.358 |
| Irritability: 24 hrs | 2.464 | 4.732 | 4.381 | 5.975 | 12.201 | 6.655 | 0.968 | 1.975 | 1.145 | 2.200 | 2.361 | 2.564 | 0.763 | 2.474 | 1.761 | 1.952 | 3.860 | 2.297 | 0.471 | 0.946 | 0.651 | 0.716 | 2.509 | 1.065 |
| Hallucinations: 24 hrs | 1.968 | 3.093 | 3.507 | 5.278 | 6.833 | 5.552 | 0.359 | 0.958 | 1.129 | 1.395 | 1.089 | 2.016 | 0.787 | 1.322 | 0.857 | 1.826 | 2.412 | 1.521 | 0.636 | 0.585 | 0.771 | 0.983 | 1.661 | 1.280 |
| Command hallucinations: 24 hrs | 1.729 | 2.045 | 2.300 | 4.045 | 6.047 | 4.033 | 0.264 | 0.104 | 0.505 | 0.423 | 0.637 | 0.618 | 0.614 | 1.182 | 0.608 | 1.578 | 2.529 | 1.575 | 0.588 | 0.255 | 0.466 | 0.924 | 1.305 | 1.044 |
| Delusions: 24 hrs | 2.379 | 2.743 | 2.834 | 6.197 | 7.194 | 5.715 | 1.027 | 0.515 | 0.959 | 2.022 | 1.356 | 2.109 | 0.742 | 1.440 | 0.809 | 1.812 | 2.896 | 1.759 | 0.671 | 0.352 | 0.609 | 1.033 | 1.335 | 1.209 |
| Hyper-arousal: 24 hrs | 2.721 | 3.628 | 3.079 | 6.378 | 9.078 | 5.619 | 1.278 | 1.400 | 0.933 | 2.308 | 1.591 | 1.884 | 0.867 | 1.697 | 0.879 | 1.616 | 2.805 | 1.627 | 0.624 | 0.597 | 0.528 | 1.173 | 2.337 | 1.262 |
| Pressured speech: 24 hrs | 3.015 | 4.841 | 3.565 | 6.454 | 10.807 | 6.326 | 1.226 | 1.559 | 1.157 | 2.300 | 2.219 | 2.426 | 0.950 | 2.386 | 0.929 | 1.865 | 3.603 | 1.608 | 0.993 | 0.942 | 1.089 | 1.130 | 2.035 | 1.479 |
| Abnormal thought processes: 24 hrs | 2.949 | 4.256 | 3.400 | 6.973 | 11.288 | 5.366 | 1.401 | 1.578 | 1.407 | 2.334 | 2.471 | 2.912 | 1.024 | 2.155 | 1.014 | 2.185 | 3.943 | 1.559 | 0.565 | 0.567 | 0.548 | 0.874 | 1.725 | 0.800 |
| Socially inappropriate: 24 hrs | 3.126 | 4.444 | 3.111 | 6.642 | 10.788 | 5.281 | 1.962 | 1.738 | 1.072 | 2.985 | 2.388 | 2.193 | 0.774 | 2.182 | 0.671 | 2.009 | 3.360 | 1.354 | 0.394 | 0.694 | 0.329 | 0.751 | 2.063 | 0.886 |
| Verbal abuse: 24 hrs | 2.871 | 3.422 | 3.141 | 6.499 | 8.204 | 4.996 | 1.026 | 1.070 | 0.762 | 1.952 | 1.637 | 1.609 | 1.144 | 1.509 | 1.106 | 2.101 | 2.259 | 1.311 | 0.690 | 0.592 | 0.656 | 1.166 | 1.944 | 1.503 |
| Intoxication: 24 hrs | 3.937 | 5.204 | 6.361 | 10.126 | 12.864 | 8.468 | 1.661 | 1.653 | 2.054 | 3.147 | 2.916 | 3.762 | 1.221 | 2.562 | 1.695 | 2.616 | 3.735 | 1.839 | 0.995 | 0.841 | 0.999 | 1.227 | 2.262 | 1.596 |
| Degree of insight | 4.179 | 6.467 | 5.620 | 10.760 | 14.939 | 8.340 | 1.935 | 3.177 | 1.562 | 3.434 | 3.265 | 2.995 | 1.463 | 3.256 | 1.844 | 2.813 | 4.719 | 2.759 | 0.946 | 0.913 | 0.805 | 1.828 | 3.120 | 1.644 |
| Daily Decision Making (CA) | 2.319 | 3.778 | 2.672 | 5.459 | 8.702 | 4.207 | 1.054 | 0.986 | 0.861 | 1.738 | 1.530 | 1.622 | 0.946 | 2.045 | 0.889 | 1.618 | 3.194 | 1.336 | 0.626 | 0.779 | 0.516 | 0.906 | 1.839 | 0.833 |
| Previous Police Contact | 5.124 | 9.016 | 6.473 | 11.211 | 18.836 | 9.982 | 2.370 | 3.941 | 1.807 | 4.196 | 4.615 | 3.750 | 1.920 | 4.923 | 2.296 | 3.801 | 8.100 | 3.430 | 1.380 | 1.274 | 0.866 | 1.781 | 3.617 | 1.583 |
| Carries Weapon | 2.619 | 4.737 | 3.424 | 6.396 | 10.536 | 5.285 | 1.139 | 2.319 | 0.573 | 1.940 | 2.548 | 1.331 | 0.715 | 2.619 | 1.547 | 2.005 | 3.769 | 2.037 | 0.952 | 0.495 | 0.721 | 1.140 | 1.434 | 1.092 |
| Violent ideation: 24 hrs | 2.511 | 3.605 | 2.284 | 5.451 | 8.099 | 4.733 | 0.785 | 0.990 | 0.366 | 1.712 | 1.456 | 1.001 | 0.953 | 1.378 | 0.836 | 1.547 | 2.875 | 1.729 | 0.790 | 0.820 | 0.573 | 1.290 | 2.048 | 1.254 |
| Intimidation of others: 24 hrs | 2.387 | 3.258 | 1.955 | 5.202 | 7.170 | 3.984 | 0.715 | 0.867 | 0.316 | 1.898 | 1.824 | 0.921 | 1.209 | 1.483 | 0.773 | 1.897 | 2.129 | 1.151 | 0.505 | 0.626 | 0.516 | 1.037 | 1.576 | 1.135 |
| Violence to others: 24 hrs | 2.839 | 3.098 | 2.212 | 5.543 | 5.942 | 4.098 | 0.523 | 0.563 | 0.322 | 1.626 | 1.165 | 1.221 | 1.354 | 1.616 | 0.931 | 2.108 | 1.852 | 1.192 | 0.830 | 0.633 | 0.513 | 1.276 | 1.542 | 1.148 |
| Self injurious attempt last 7 days | 1.843 | 3.810 | 2.163 | 4.191 | 7.576 | 3.252 | 0.407 | 1.366 | 0.385 | 0.789 | 1.748 | 0.425 | 0.708 | 2.231 | 1.042 | 1.616 | 3.229 | 1.586 | 0.615 | 0.850 | 0.338 | 0.885 | 1.878 | 0.768 |
| Considered self injury last 30 days | 1.908 | 2.420 | 1.710 | 3.811 | 4.502 | 3.220 | 0.725 | 1.107 | 0.371 | 1.112 | 1.999 | 0.738 | 0.684 | 1.363 | 0.736 | 1.447 | 2.233 | 1.366 | 0.387 | 0.441 | 0.394 | 0.596 | 0.994 | 0.682 |
| Suicide Plan | 1.826 | 3.490 | 1.853 | 4.074 | 6.594 | 3.126 | 0.433 | 1.204 | 0.271 | 0.814 | 1.748 | 0.453 | 0.664 | 2.134 | 0.703 | 1.676 | 3.025 | 1.237 | 0.506 | 0.608 | 0.283 | 0.898 | 1.173 | 0.781 |
| Others concerned about self-injury | 2.521 | 4.123 | 2.334 | 5.231 | 8.561 | 3.648 | 0.982 | 1.912 | 0.506 | 1.645 | 2.273 | 1.226 | 0.907 | 1.931 | 0.931 | 2.034 | 2.887 | 1.293 | 0.648 | 0.660 | 0.579 | 0.873 | 1.190 | 0.888 |
| Squalid condition | 3.576 | 5.361 | 5.216 | 9.020 | 13.123 | 7.261 | 1.145 | 2.035 | 1.064 | 2.259 | 2.475 | 2.091 | 1.162 | 2.530 | 1.834 | 2.852 | 3.704 | 2.434 | 0.837 | 1.129 | 0.938 | 1.601 | 2.441 | 1.670 |
| Refused Medication | 2.256 | 3.497 | 2.998 | 5.325 | 8.599 | 4.754 | 0.554 | 1.134 | 0.562 | 1.272 | 1.272 | 1.035 | 0.781 | 1.912 | 1.187 | 1.770 | 2.672 | 1.882 | 0.618 | 0.685 | 0.748 | 0.169 | 2.925 | 1.319 |
| Voluntary Escort to Hospital | 1.891 | 4.012 | 3.256 | 4.589 | 9.565 | 4.737 | 0.508 | 1.982 | 0.705 | 0.802 | 1.769 | 1.452 | 0.758 | 2.499 | 1.126 | 1.766 | 2.965 | 1.448 | 0.780 | 0.766 | 0.573 | 0.928 | 2.058 | 0.917 |
| Transferred to EMS/MCRRT | 1.699 | 3.487 | 2.275 | 4.192 | 9.209 | 3.455 | 0.710 | 1.162 | 0.185 | 1.047 | 1.283 | 0.540 | 0.691 | 2.632 | 1.402 | 1.952 | 3.454 | 1.642 | 0.294 | 0.537 | 0.315 | 0.550 | 1.726 | 0.769 |
| Caseworker/Probation notified | 2.790 | 4.209 | 2.467 | 5.085 | 8.032 | 3.875 | 1.927 | 2.155 | 0.652 | 2.439 | 2.472 | 1.412 | 0.473 | 2.073 | 0.663 | 1.067 | 2.647 | 1.055 | 0.494 | 0.604 | 0.385 | 0.504 | 1.590 | 0.525 |
| Referred to CMH | 2.533 | 4.445 | 4.285 | 6.920 | 10.444 | 5.887 | 1.430 | 1.972 | 1.288 | 2.481 | 2.337 | 2.298 | 0.859 | 2.902 | 1.211 | 1.720 | 3.754 | 2.007 | 0.456 | 0.548 | 0.296 | 0.741 | 2.087 | 0.686 |
| Apprehended under existing order | 0.912 | 0.640 | 1.178 | 1.702 | 1.897 | 1.626 | 0.437 | 0.114 | 0.062 | 0.442 | 0.128 | 0.135 | 0.349 | 0.432 | 0.847 | 0.768 | 0.995 | 1.029 | 0.087 | 0.113 | 0.139 | 0.141 | 0.252 | 0.236 |
| Involuntarily Apprehended | 2.854 | 4.108 | 3.232 | 5.948 | 9.752 | 4.675 | 0.755 | 1.837 | 0.453 | 1.604 | 1.715 | 1.200 | 0.944 | 2.282 | 1.387 | 1.701 | 3.000 | 1.499 | 1.153 | 0.857 | 0.896 | 1.227 | 1.961 | 1.217 |
| Harm to Others Scale | 6.152 | 10.498 | 8.143 | 15.664 | 26.022 | 12.622 | 2.689 | 4.519 | 2.177 | 5.320 | 5.272 | 4.615 | 2.493 | 5.783 | 2.821 | 4.926 | 7.814 | 4.004 | 1.412 | 1.908 | 1.248 | 2.676 | 6.057 | 2.628 |
| Harm to Self Scale | 6.679 | 10.524 | 8.736 | 17.450 | 26.145 | 12.723 | 3.264 | 4.734 | 2.573 | 5.683 | 5.317 | 5.135 | 2.008 | 5.707 | 2.817 | 5.311 | 7.855 | 3.816 | 1.982 | 1.865 | 1.457 | 2.476 | 6.149 | 2.539 |
| Self Harm Scale | 7.193 | 10.128 | 9.203 | 16.870 | 22.075 | 12.735 | 3.350 | 4.089 | 1.916 | 4.762 | 5.783 | 3.957 | 2.622 | 6.185 | 3.824 | 6.024 | 8.714 | 4.767 | 1.914 | 1.628 | 1.600 | 2.654 | 3.677 | 2.709 |
| Age | 13.865 | 21.633 | 23.766 | 38.162 | 57.640 | 27.319 | 6.882 | 11.293 | 4.850 | 11.393 | 10.135 | 9.580 | 4.305 | 13.320 | 7.653 | 10.412 | 16.182 | 6.922 | 3.385 | 2.787 | 2.599 | 4.586 | 11.260 | 4.699 |



Appendix xv interRAI BMHS Harm to Others Scale



Appendix xvi interRAI BMHS Harm to Self Scale



Appendix xvii interRAI BMHS Risk of Failure to Care for Self Scale

Appendix xviii Descriptive Statistics, Homelessness by Intoxication by Drugs or Alcohol, All Reports, All Communities (n=13,057)

|  |  |  |
| --- | --- | --- |
|  | **No intoxication** | **Intoxication** |
| **Not Homeless** | 7794 (67%) | 3807 (33%) |
| **Homeless** | 802 (55%) | 654 (45%) |

Appendix xix Number of Unique Persons by Region (n=9334)

|  |  |  |
| --- | --- | --- |
| **Region** | **Unique Persons** | |
| Brantford | 2190 | (23.46%) |
| Brockville | 183 | (1.96%) |
| Cobourg | 177 | (1.9%) |
| Gananoque | 35 | (0.37%) |
| Guelph | 754 | (8.08%) |
| Kawartha Lakes | 78 | (0.84%) |
| London | 2972 | (31.84%) |
| Niagara | 2043 | (21.89%) |
| Orangeville | 43 | (0.46%) |
| Ottawa | 339 | (3.63%) |
| Regina | 278 | (2.98%) |
| Saskatoon | 198 | (2.12%) |
| Smiths Falls | 44 | (0.47%) |
| **Total** | **9334** | |

Appendix xx Number of Reports by Region (N=13,058)

|  |  |  |
| --- | --- | --- |
| **Region** | **BMHS Reports** | |
| Brantford | 3800 | (29.1%) |
| Brockville | 229 | (1.75%) |
| Cobourg | 219 | (1.68%) |
| Gananoque | 36 | (0.28%) |
| Guelph | 1008 | (7.72%) |
| Kawartha Lakes | 93 | (0.71%) |
| London | 4079 | (31.24%) |
| Niagara | 2606 | (19.96%) |
| Orangeville | 51 | (0.39%) |
| Ottawa | 356 | (2.73%) |
| Regina | 315 | (2.41%) |
| Saskatoon | 214 | (1.64%) |
| Smiths Falls | 52 | (0.4%) |
| **Total** | **13,058** | |

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