

A Comprehensive Analysis of Mental Health Act Apprehensions in Toronto*

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This paper examines trends in Mental Health Act (MHA) apprehensions in Toronto from 2014 to 2024, focusing on the timing, location, and demographic distribution of incidents. Using detailed data on occurrence year, occurrence hour, premises type, and age cohort, we analyze patterns in MHA apprehensions across various locations and times of day. The results reveal that younger individuals, particularly those aged 25 to 34, are more likely to be apprehended during night hours in residential areas. These findings underscore the need for targeted mental health interventions that account for the time and location of crisis incidents, potentially improving resource allocation and response strategies in high-risk areas.

1 Introduction

Mental health crises can have a profound impact on individuals, families, and communities, often resulting in involuntary apprehensions under the Mental Health Act (MHA). MHA apprehensions are legal interventions aimed at individuals who pose a risk to themselves or others due to a mental health condition. These apprehensions serve as a key intersection between mental health services and law enforcement, raising questions about the role of public policy in addressing mental health issues (Government of Ontario (2018)). The importance of timely and appropriate mental health interventions is further underscored by research showing that mental health crises are more likely to lead to adverse outcomes when proper support mechanisms are unavailable (Organization (2022)). In urban centers such as Toronto, understanding the patterns of these apprehensions is crucial for developing effective mental health policies and resource allocation strategies. In this paper, we focus on analyzing MHA apprehensions in Toronto from 2014 to 2024. Using a dataset provided by the Toronto Police Service, we examine key features including the year and hour of occurrence, the premises type where the incident took place, and the age cohort of the individuals apprehended. Previous research

*Code and data are available at: https://github.com/lauragao75/Analysis_About_Mental_Health_Act_Apprehensions

has highlighted the disproportionate representation of younger individuals in mental health-related incidents (Reavley and Jorm (2011)), and our study builds on this by exploring how factors such as time of day and location influence the likelihood of apprehension. Specifically, this paper investigates whether certain age groups, particularly younger individuals, are more prone to MHA apprehensions during specific times and in particular locations. Our analysis reveals that younger individuals, especially those between 25 and 34 years old, are significantly more likely to be apprehended during late-night hours and in residential areas. This finding aligns with existing literature suggesting that younger adults are more vulnerable to mental health crises that require police intervention (Gulliver, Griffiths, and Christensen (2010)). Additionally, our results indicate that the timing and setting of apprehensions follow identifiable patterns, which can inform future efforts to improve the availability of mental health services in high-risk areas and at high-risk times. The broader implications of this study point to the need for targeted mental health interventions and more strategic deployment of resources to better serve at-risk populations. The remainder of this paper is structured as follows. Section 2 discusses the dataset and the cleaning process used to prepare the data for analysis. Section 2 also includes trends in occurrence year, occurrence hour, premises type, and age cohort. Section 3 provides a discussion of these findings, comparing them to trends found in other studies. Finally, Section 4 addresses the limitations of the study.

2 Data

2.1 Data Source and Background

The dataset used in this study is drawn from the Toronto Police Service and documents all Mental Health Act (MHA) apprehensions from 2014 to 2023. Under the MHA, individuals can be involuntarily detained by law enforcement officers if they are deemed to be a danger to themselves or others due to a mental health condition (Mental Health Act, Ontario 2023). The dataset provides detailed information on:

Occurrence Year (`occ_year`): The year the apprehension occurred. Occurrence Hour (`occ_hour`): The hour of the day the incident was reported. Premises Type (`premises_type`): The location where the apprehension took place (e.g., house, apartment, commercial space). Age Cohort (`age_cohort`): The age group of the apprehended individual (e.g., 18 to 24, 25 to 34).

The data was extracted from the Open Data Toronto portal using the `opendatatoronto` package in R (Gelfand (2022)). The analysis was conducted using the open-source statistical programming language R (R Core Team (2023)). Several R libraries were employed throughout the process: `tidyverse` for data manipulation and visualization (Wickham et al. (2019)), `janitor` for cleaning and formatting the dataset (Firke (2023)), `knitr` for creating tables (Xie (2022)), `dplyr` for data transformation (Wickham et al. (2023)), and `lubridate` for managing date and time data (Grolemund and Wickham (2011)). The visualizations and graphics were produced

using the ggplot2 package (Wickham (2016)). This dataset was chosen due to its comprehensive coverage of MHA apprehensions, enabling us to explore temporal and spatial patterns of such incidents across Toronto. Given the sensitive nature of mental health data, all individual identifiers have been anonymized to protect privacy.

2.2 Data Cleaning

Before analysis, the raw dataset underwent several cleaning and preprocessing steps to ensure its integrity and usability. The data was first inspected for missing or erroneous entries, especially in key variables such as occurrence year, occurrence hour, premises type, and age cohort. Any rows containing missing or ambiguous values were removed to maintain the consistency and accuracy of the analysis. In addition, categorical variables such as age cohort and premises type were standardized to ensure consistency in naming conventions across all entries. The resulting cleaned dataset was then used to generate the descriptive statistics and visualizations that form the foundation of this analysis.

2.3 Summary of Variables

The primary variables of interest in this study are the year of occurrence, hour of occurrence, premises type, and age cohort of the individuals involved. Table 1 provides a sample of the summary of these key variables, highlighting the temporal and spatial distribution of MHA apprehensions as well as the age profile of those apprehended.

Table 1: Table 1: Sample of the Key Variables in the MHA Apprehensions Dataset

Occurred_Year	Occurred_Hour	Premises_Type	Age_Cohort	count
2014	1	Apartment	18 to 24	21
2014	1	Apartment	25 to 34	27
2014	1	Apartment	35 to 44	17
2014	1	Apartment	45 to 54	9
2014	1	Apartment	55 to 64	8
2014	1	Apartment	65 and above	5
2014	1	Commercial	18 to 24	3
2014	1	Commercial	25 to 34	5
2014	1	Commercial	35 to 44	1
2014	1	Commercial	45 to 54	2
2014	1	Commercial	55 to 64	1
2014	1	Commercial	65 and above	1
2014	1	Educational	18 to 24	2
2014	1	Educational	25 to 34	1
2014	1	House	18 to 24	16

Occurred_Year	Occurred_Hour	Premises_Type	Age_Cohort	count
2014	1	House	25 to 34	9
2014	1	House	35 to 44	4
2014	1	House	45 to 54	7
2014	1	House	55 to 64	2
2014	1	House	65 and above	2

Table 1 shows that MHA apprehensions have been recorded across a wide range of premises types, with residential locations accounting for a significant proportion of the total incidents. The data also indicates that younger age cohorts, particularly individuals aged 25 to 34, are over represented in these apprehensions, which raises important questions about the vulnerability of this demographic to mental health crises.

2.4 Visualizations of the Data

In order to better understand the trends and patterns present in the dataset, we present several visualizations that provide a detailed look at the distribution of MHA apprehensions over time, by location, and across different age groups.

Figure 1: Distribution of Apprehensions by Year

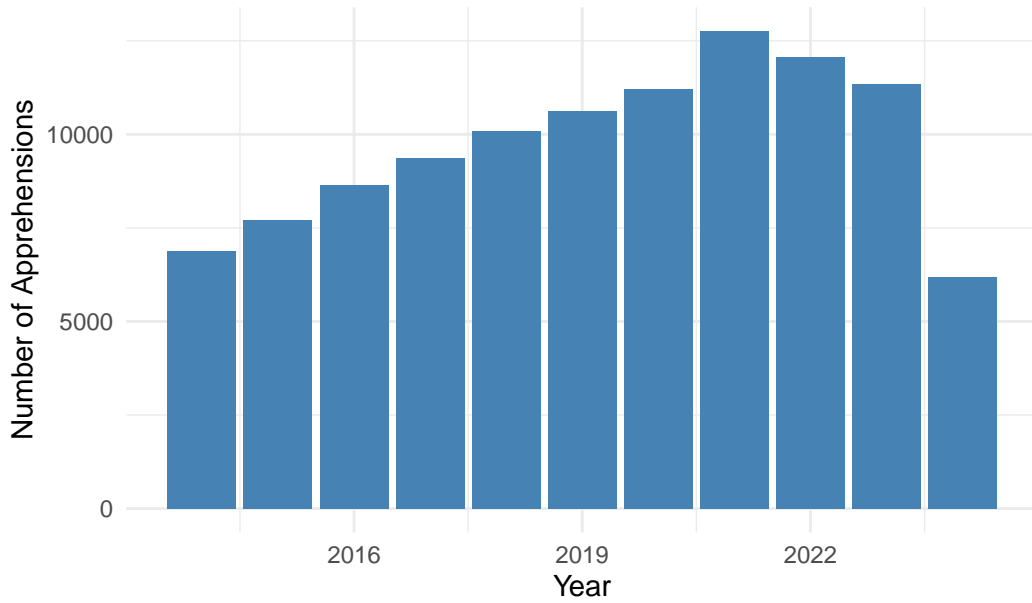


Figure 1 illustrates the temporal distribution of MHA apprehensions from 2014 to 2024. The data shows a steady increase in apprehensions over this period, with a notable rise beginning in 2020. This upward trend may reflect broader social and economic pressures, or changes

in law enforcement practices in response to the mental health needs of the population. Further research could explore whether the increase in apprehensions correlates with specific public health initiatives or external events, such as economic downturns or the COVID-19 pandemic.

Figure 2: Apprehensions by Premises Type

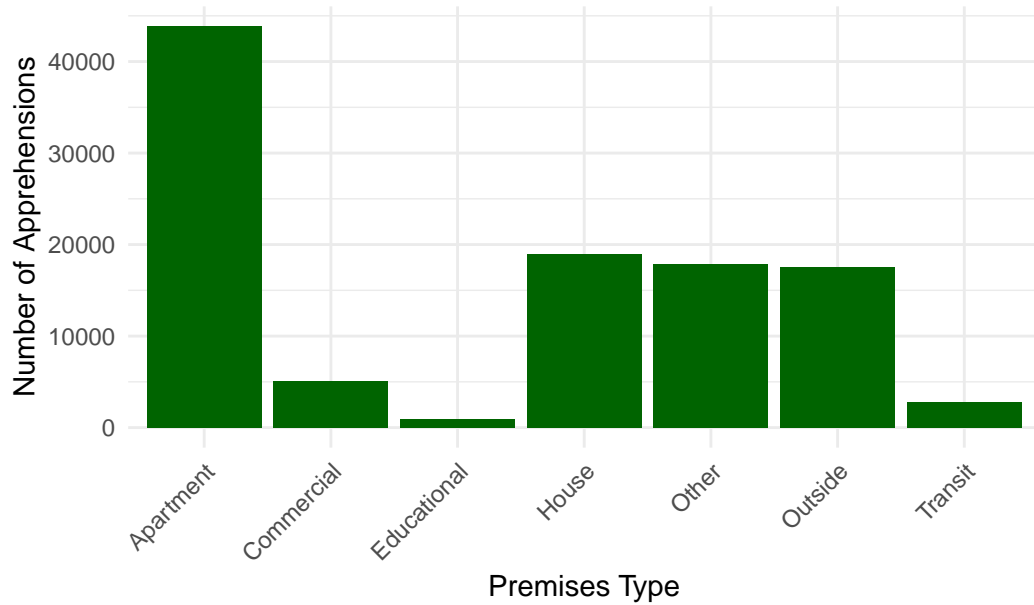


Figure 2 provides a breakdown of MHA apprehensions by premises type. As expected, residential locations dominate the dataset, suggesting that mental health crises are most likely to occur in familiar environments.

Figure 3: Distribution of Apprehensions by Age Cohort and Hour of the Day

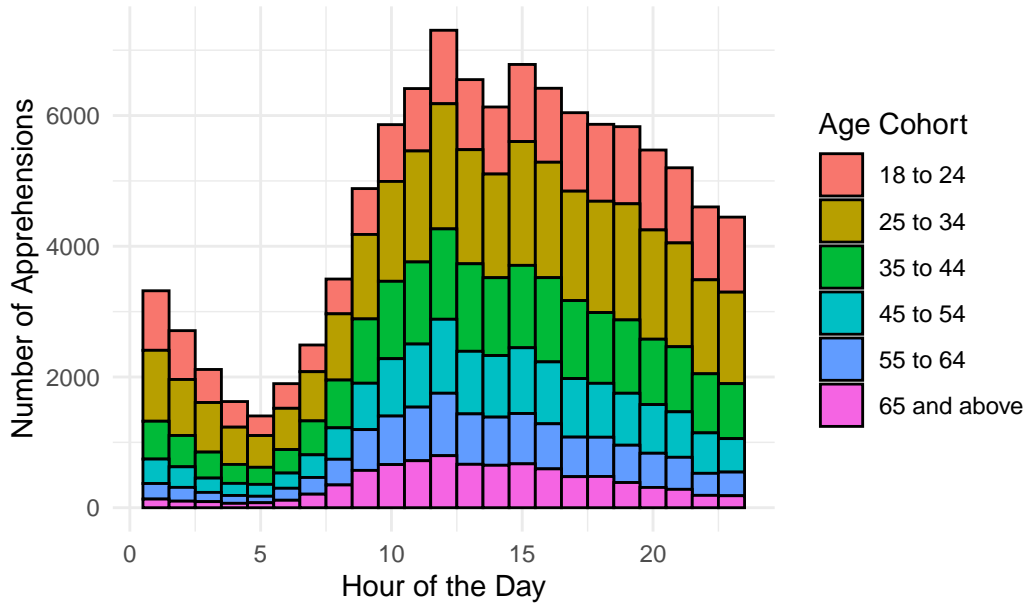


Figure 3 illustrates the distribution of Mental Health Act (MHA) apprehensions across different hours of the day, segmented by age cohort. The x-axis represents the hour of the day (from 0 to 23), while the y-axis shows the total number of apprehensions. Each age cohort is color-coded, ranging from individuals aged 18 to 24 to those aged 65 and above.

The data reveals several important patterns. Apprehensions increase sharply during the early morning hours, peaking around noon and again between 8 PM and midnight. The 25 to 34 age cohort, represented by the green color, accounts for the largest share of apprehensions across all time periods, particularly during the late evening and nighttime hours. This suggests that individuals in this age group are more prone to mental health crises during times when typical social or medical support services may be less accessible.

The consistent rise in apprehensions during nighttime hours (8 PM to midnight) across all age cohorts indicates that mental health crises tend to escalate during periods of reduced public activity. These findings have significant implications for emergency mental health services, highlighting the need for increased availability of crisis intervention services during late hours to address the needs of younger populations more effectively.

2.5 Conclusion of Data Section

In conclusion, the dataset provides a comprehensive view of MHA apprehensions in Toronto, offering valuable insights into the temporal, spatial, and demographic dimensions of mental health crises in the city. Table 1 summarizes the key variables, while Figures 1-3 offer a visual

representation of the patterns observed in the data. These findings serve as the foundation for the more detailed analysis presented in the following sections.

3 Discussion

3.1 Summary of Findings

This paper analyzed Mental Health Act (MHA) apprehensions in Toronto from 2014 to 2024, focusing on key variables such as occurrence year, occurrence hour, premises type, and age cohort. The analysis demonstrated that younger individuals, particularly those aged 25 to 34, are disproportionately represented in the data. Furthermore, the analysis revealed that most apprehensions occur during late-night and early morning hours, particularly in residential locations. These findings provide valuable insights into the demographics, timing, and geography of MHA apprehensions, which can inform future mental health policy and interventions.

3.2 Temporal Patterns and Their Implications

The data highlights that MHA apprehensions have increased over time, with a sharp rise starting around 2017 and peaking in 2021. This finding suggests that mental health crises have become more prevalent, potentially due to a combination of factors such as increasing societal stressors, economic challenges, and the effects of the COVID-19 pandemic. Previous research has shown that economic downturns and public health crises tend to exacerbate mental health problems (The Lancet (2018)), which may explain the uptick in apprehensions observed in the data. Additionally, the concentration of incidents during nighttime hours suggests that crises may escalate when social and medical services are less accessible, indicating the need for 24-hour mental health support services.

3.3 Spatial Distribution of Apprehensions

The analysis also showed that the majority of MHA apprehensions occur in residential settings, such as houses and apartments. Residential settings may also offer fewer immediate intervention resources compared to commercial or public spaces, making it more likely that a crisis escalates to the point where law enforcement is involved. These findings underscore the need for more in-home mental health support services, particularly for younger populations.

3.4 Demographic Patterns: The Role of Age

The over representation of individuals aged 25 to 34 in MHA apprehensions is perhaps the most significant finding of this study. This age group, often referred to as the “young adult” demographic, is known to experience high levels of mental health-related stress due to the transition into adulthood, economic pressures, and social challenges (Gulliver, Griffiths, and Christensen (2010)). The data suggests that younger adults may be more vulnerable to mental health crises that necessitate police intervention, particularly during high-risk times such as late at night. This raises important questions about the adequacy of mental health services targeted at this age group. Expanding mental health outreach programs and increasing awareness among young adults about available mental health resources could help reduce the need for MHA apprehensions in this population.

4 Limitations of the Study

While this study provides valuable insights into the patterns of MHA apprehensions in Toronto, several limitations must be acknowledged. First, the dataset does not contain information about the underlying causes of each apprehension, making it difficult to determine whether certain types of crises (e.g., substance abuse, economic hardship, or psychiatric disorders) are more prevalent in certain locations or age groups. Second, the anonymized nature of the dataset prevents any longitudinal analysis that could track repeat apprehensions of the same individuals. It is possible that some individuals may have been apprehended multiple times during the study period, which could skew the results. Lastly, the focus on police-reported data introduces a potential bias, as not all mental health crises result in police intervention. Many crises are managed by healthcare professionals or family members, meaning that the dataset may underrepresent the true prevalence of mental health crises in Toronto.

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