Investigating Persons in Crisis Calls for Service Attended*

Yetao Guo

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This term paper examines the increase in crisis-related calls in Toronto from 2014 to 2024, using the 'toronto_Crisis.csv' dataset to explore their distribution and frequency. The research, conducted with R programming and various packages, investigates multiple crises, including attempted suicide and overdose, and reveals a significant uptick during economic hardships and events like the COVID-19 pandemic. The findings highlight the complex nature of these incidents and their impact on urban crisis management. This study underscores the need for improved crisis response strategies and mental health management in cities, offering valuable insights into the challenges faced by emergency services.

Table of contents

Introduction **2**

Data **2**

Persons in Crisis Calls for Service Attended 2

Discussion **6**

References **8**

*Code and data are available at: https://github.com/yetaoguo/termpaper.git

Introduction

In the bustling urban landscape of Toronto, the increasing number of "Persons in Crisis" (PIC) call incidents has been observed, reflecting the intricate challenges of city life and the growing mental health concerns among its citizens. This study looks deeply into these PIC calls by delving into their spread, frequency, and impact on Toronto's residents. Spanning a decade from 2014 to 2024, the research draws on data from the "toronto_Crisis.csv" dataset, aiming to unearth essential insights for managing urban crises effectively. The research uses detailed, data-focused methods and tools like R(R Core Team 2020) programming and packages including "tidyverse," (Wickham et al. 2019)"dplyr," (Wickham et al. 2021) "janitor,"(Firke 2021)"kableExtra,"(Zhu 2021)"lubricate,"(Grolemund and Wickham 2021) and "knitr"(Xie 2021).This approach facilitates a detailed examination and presentation of the data. The data set from the Toronto Open Data Portal(Gelfand 2020) covers a wide variety of crises, including suicide attempts, people in crisis, and drug overdoses. Analysis of this data is critical to discern underlying patterns and trends in crisis calls, providing a valuable tool for policymakers and emergency services to develop more effective crisis response strategies.

Preliminary data analysis reveals the multifaceted nature of crisis events, characterized by varying frequency and type. Trend analysis shows that crisis calls have increased significantly over the years, especially during economic stress and social tension, such as the COVID-19 pandemic. These initial observations highlight the need to delve deeper into the drivers behind these trends and develop better crisis management strategies in urban Settings. In addition, the report also mentions the categories of crisis events and their corresponding duration, shown in the bar and box charts. It highlights the potential impact of significant trends on public health strategies and resource allocation.

Therefore, this paper wishes to present a comprehensive, data-oriented survey of PIC calls in Toronto, providing insight into the operational challenges facing the city's emergency services, as well as the broader implications for crisis management in urban areas. Through this analysis, this paper hopes to provide valuable perspectives and solutions for strengthening the management of mental health crises in urban environments.

Data

Persons in Crisis Calls for Service Attended

To investigate the Persons in Crisis Calls for Service Attended, I downloaded the dataset 'About Persons in Crisis Calls for Service Attended' from the Toronto Open Data Portal (Gelfand 2020). This document is provided by the Toronto police service, encompassing all Calls for Service Attended (CFSA) related to Persons in Crisis (PIC), covering a range of Event Types such as Attempted Suicide, Person in Crisis, Jumper, Overdose, and Threats of Suicide. These events occurred in Toronto between January 2014 and December 2024 and were organized based on the reported date. To keep the privacy of those in the incident, the location has been changed to the closest road crossing. This means the location details are not accurate. Also, due to these changes, the count of incidents in each area or neighborhood might not match the actual number of events there.

This data set includes the following variables: 291991 observations of calls and 16 variables of background information regarding the person. There are four variables will be displayed respectively in the report: event_year,event_month,event_type,event_hour)

Table 1: Extracting the first six rows from data regarding persons in Crisis Calls for Service Attended

event_year	event_month	event_type	event_hour
2014	January	Suicide-related	9
2014	January	Person in Crisis	2
2014	January	Suicide-related	16
2014	January	Suicide-related	0
2014	January	Person in Crisis	12
2014	January	Overdose	3

Table 1 extracts the first six rows from data. The variable 'event_year' represents the year of the week of the event. 'event_month' shows the month of the week of the event. 'event_hour' represents the hour of the day while the event happened.'event_type' shows the classification of each crisis, including three types: suicide-related, Person in Crisis and overdose. Table 1 gives us a brief understanding of the data.

event_year	event_type	Count
2014	Overdose	1654
2014	Person in Crisis	13967
2014	Suicide-related	6608
2015	Overdose	1673
2015	Person in Crisis	14397
2015	Suicide-related	7108
2016	Overdose	1963
2016	Person in Crisis	15926
2016	Suicide-related	7578
2017	Overdose	2497
2017	Person in Crisis	16361
2017	Suicide-related	8488
2018	Overdose	2693
2018	Person in Crisis	17433
2018	Suicide-related	9573
2019	Overdose	3274
2019	Person in Crisis	17267
2019	Suicide-related	10351
2020	Overdose	3855
2020	Person in Crisis	19519
2020	Suicide-related	9769
2021	Overdose	5628
2021	Person in Crisis	19210
2021	Suicide-related	10556
2022	Overdose	3952
2022	Person in Crisis	18288
2022	Suicide-related	10831
2023	Overdose	4555
2023	Person in Crisis	16378
2023	Suicide-related	10639

Table 2 was created based on the data from cleaned_toronto_Crisis.csv .It provides a summary of 'Persons in Crisis' calls for service attended. It is segmented by year, starting from 2014 to the latest year. Also, there is a corresponding count of the number of times that event was recorded for each year and each type. The table helps to see trends over time regarding the frequency of different kinds of crisis events and makes it easier to create a graph.

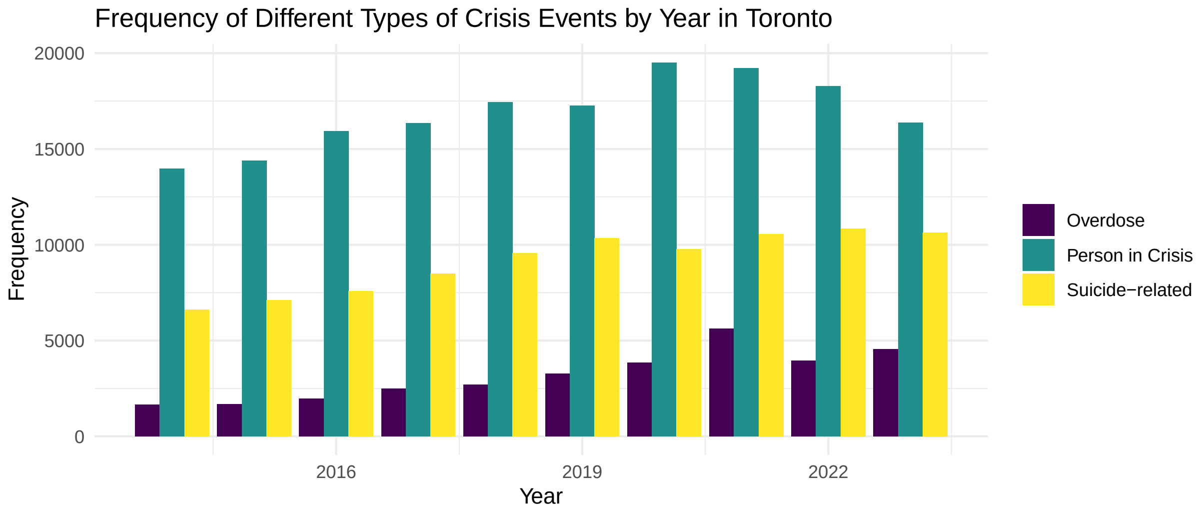

Figure 1: The frequency of different type of crisis event by year in Toronto

Figure 1 demonstrates a time series analysis of crisis event frequencies in Toronto, segmented into three principal categories: "Overdose," "Person in Crisis," and "Suicide-related" occurrences. "People in crisis" is the most common type of crisis incident each year, possessing the most significant trend. This trend may reflect an escalating demand for mental health support and crisis intervention resources. The yellow section represents overdose incidents, which, although a small percentage of the population, have been on a consistent upward trend. It could indicate evolving substance use patterns or the efficacy of public health strategies. While "Suicide-related" incidents demonstrate a relatively stable pattern, they show some minor fluctuations in 2019. It is worth noting that the overall frequency of all types of crisis events seems to peak in particular years. For example, during the emergence of COVID-19, the number of people in each of these three types has increased to varying degrees. The economic downturn and increased social pressure caused by the epidemic have led citizens to take some harmful drastic actions. In addition, we can also attribute this result to the abuse of opioids, mainly in the North American region. The pandemic has exacerbated ongoing problems. These insights call for proactive and flexible public health policies to navigate the fluctuating landscape of urban crisis management adeptly.

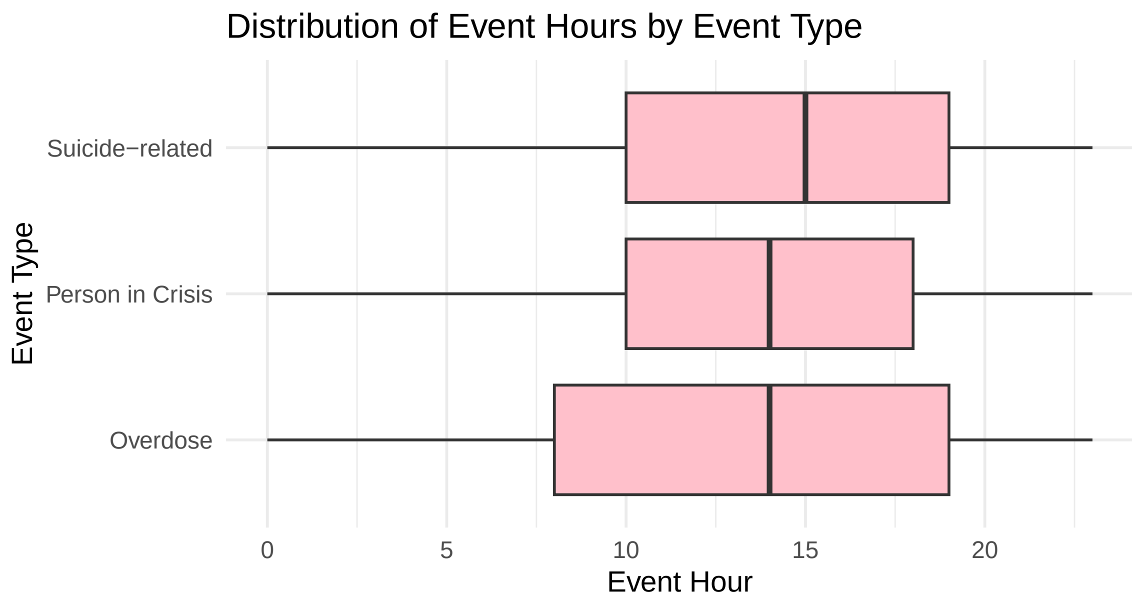

Figure 2: The Distribution of Event Hours by Event Type

Figure 2 is a box plot titled "distriution of event hour by event name" .It describes the spread and central tendency of the hours at which different types of events occur. For the x-axis, it labeld "Event Hour" which ranges from 0 to approximately 25, indicating the hours of the day when events happened. The y-axis is labeled "Event type, which appears to represent different types of events or categories such as"Suicide-related", "Person in Crisis", and "Overdose".Within the box, a horizontal line represents the median, marking the data's middle value. The breadth of the boxes along with the whiskers' reach illustrates the range in hours attributed to each event type. The chart indicates that "Person in Crisis" events generally have a higher median duration, discernible by the median line's position near the upper quartile. While the distributions for "Suicide-related" and "Overdose" events are closely aligned, the median for "Overdose" events appears to be subtly less than that for "Suicide-related" events.This information is vital for emergency service planning and allocation of support for crisis management teams.

Discussion

Exploring "Persons in Crisis" (PIC) calls within Toronto from 2014 to 2024 reveals a profound and complex interplay of societal, economic, and mental health factors. The rising trend in such calls, especially during periods of economic downturn and societal stress like the COVID-19 pandemic, shows an underlying vulnerability in urban populations. This vulnerability is not just a matter of public health. However, it is also a significant urban management challenge, so seeking an approach to crisis intervention and mental health support is necessary. We analyzed the data using R and its associated software packages and found that the results indicate the need for targeted measures. I found articles studying the phenomenon of the increasing frequency of calls associated with suicide and drug overdoses. For instance, a study by Marsella (Marsella 1998) noted that Mental health crises in urban areas are escalating and linking them to socioeconomic stressors. This underscores the importance of current research in identifying specific patterns and trends in Toronto, thereby providing a reference approach to a global issue. However, there are certain limitations to the analysis; for example, location details are changed to protect privacy, which may affect the accuracy of the geographic analysis and strategies for specific communities. As Ramanuj et al(Ramanuj et al. 2018) argue, there is a need to integrate qualitative data to get a complete picture of these crises. Understanding the individual and social environment to improve the effectiveness of crisis intervention strategies. Based on these findings, it is clear that while data analysis can provide important information about the data that has been selected, it is equally important to link these figures to the broader social and economic fabric. This is critical to developing solutions that allow for a timely response to crises as they occur and work to prevent them from occurring. To meet the needs of Toronto's diverse population, a combination of community mental health services, economic support measures, and public health campaigns may be required. This study highlights the importance of data-driven investigations when responding to urban emergencies. At the same time, it demonstrates how important it is to take an integrated problem-solving approach. As cities such as Toronto continue to change, strategies for dealing with crises must change to adapt to the ever-changing nature of urban life.

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