Emergency Medical Response in Toronto: An Analysis of Ambulance Dispatches*

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The Toronto Paramedic Services respond to all ambulance dispatch requests across the city. In recent years, there have been growing concerns about increased call wait times and a shortage of available ambulances. This paper analyzes the number and severity of dispatch requests over the years. Our findings indicate that longer wait times are primarily due to a higher frequency of severe emergency calls following the COVID-19 pandemic, coupled with a shortage of first responders.

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*Code and data are available at: https://github.com/abdullah-motasim/Analyzing-Ambulance-Response-Times

1 Introduction

Efficient ambulance response times play a key role in saving people's lives, especially in severe and sudden health complications such as cardiac arrests, trauma, and motor vehicle accidents. A medical study from 2011 found that for cardiac arrest a 1 minute reduction in response time improved a person's odds of survival by 24% Coats, Michard, and Robinson (2011). Furthermore, Toronto is facing issues retaining Emergency Medical Services (EMS) workers News (2023c) leading to increased call wait times News (2023b) and a lower number of ambulances available to be dispatched News (2023a).

This paper hopes to analyze the number and types of dispatch requests to EMS services within Toronto to identify the reason for the reduced amount of ambulances available and the increased call wait times. This is achieved utilizing a data set procured from OpenDataToronto *Open Data Dataset* (n.d.) containing information on the number of dispatches made per year, the severity of these reports, and the number of units dispatched. We utilize this information to determine that COVID-19 reduced the number of calls received by Toronto Paramedic Services, but also caused EMS workers to change their careers. Paired with an increase in the number of life-threatening and possibly life-threatening incidents the city was under-equipped with experienced first responders to deal with the complex situations. Overall, all these factors lead to an increase in call wait times and a decreased amount of available ambulances.

The remainder of this paper is structured as follows. Section 2 discusses the data types included in the raw data, the cleaning process for the data, and the reason for selecting the data set we did. Section 3 analyzes the trends and correlations between different variables utilizing tabular and graphical means. Section 4 discusses the results of Section 3 going into detail on what these results can tell us about the cause for delayed ems response time. Lastly, Section 5 discusses limitations within the data and steps for improvement.

2 Data

2.1 Raw Data

The data utilized for the analysis was sourced from the Open Data Toronto website and was read into the paper using the opendatatoronto library Gelfand (2022) and all analysis was performed using R R Core Team (2023) and the following packages: tidyverse Wickham et al. (2019), janitor Firke (2023), lubridate Grolemund and Wickham (2011), truncnorm Mersmann et al. (2023), purrr Wickham and Henry (2023), dplyr Wickham et al. (2023), here Müller (2020), ggplot2, Wickham (2016), knitr Xie (2014), and modeest Poncet (2019). The chosen data set is called "Paramedic Services Incident Data" "Paramedic Services Incident Data" (n.d.) and contains information about ambulance dispatches sent within Toronto from 2017-2022, the data is refreshed annually and was last updated on October 5, 2023. The data is sourced and published by Toronto Paramedic Services meaning they decide the type of data collected and the collection method. Online research shows they likely collect the data electronically as ambulance dispatches are made dispatchers manually record information such as the type of incident, priority level, dispatch time, etc. This data is likely combined into the data set and released. Note, that this set was chosen due to the large amount of data it contained, with over 1.7 million entries over the 5 years recorded meaning we could analyze trends over multiple years.

The raw downloaded data is shown in Table 1 and Table 2, as you can see it contains a total of 9 variables:

- **ID** - Incident ID number associated with the Computer Aided Dispatch (CAD) record.
- **Dispatch_Time** - The time the first Paramedic unit was assigned to the incident.
- **Incident_Type** - Type of incident reported; possible values are:
  - '-' (no value)
  - Airport Standby
  - Emergency Transfer
  - Fire
  - Medical
  - Motor Vehicle Accident
- **Priority_Number** - Priority level determined using the Medical Priority Dispatch System (MPDS), (see Section A for details).
- **Units_Arrived_At_Scene** - Number of Paramedic units that arrived on the scene of the incident
- **Forward_Sortation_Area** - General location of the incident based on Postal Code Forward Sortation Area
- **Field Name** - Gives names of field such as ID, Dispatch_Time, Incident_Type, etc.
- **Description/Definition** - Describes what each field name means
- **Comments/Examples** - Provides additional information on field name descriptions

Table 1: First 6 entires of the Paramedic Services Incident Dataset

ID	Dispatch_Time	Incident_Type	Priority_Number	Units_Arrived_At_Scene
5351620	2017-01-01 00:01:13	Medical	1	1
5351621	2017-01-01 00:03:27	Medical	1	1
5351622	2017-01-01 00:01:41	Medical	5	1
5351624	2017-01-01 00:05:53	Medical	4	1
5351625	2017-01-01 00:03:55	Medical	3	1
5351626	2017-01-01 00:08:05	Medical	4	1

Table 2: First 6 entires of the Paramedic Services Incident Dataset (cont.)

Forward_Sortation_Area	Field Name	Desctiption/Definition	Comments/Examples
M4L	NA	NA	NA
M3M	NA	NA	NA
M5B	NA	NA	NA
M5V	NA	NA	NA
M1P	NA	NA	NA
M5G	NA	NA	NA

2.2 Cleaned Data

Since the data set is large, the main goal when cleaning the data was to reduce the size, meaning the cleaned data removed irrelevant columns from the raw data. The cleaned data shown in Table 3 contains fewer columns than the raw data reducing the overall size significantly.

Table 3: First 6 entires of the cleaned ambulance response data

dispatch_time	incident_type	priority_number	units_arrived_at_scene	year
2017-01-01 00:01:13	Medical	1	1	2017
2017-01-01 00:03:27	Medical	1	1	2017
2017-01-01 00:01:41	Medical	5	1	2017
2017-01-01 00:05:53	Medical	4	1	2017
2017-01-01 00:03:55	Medical	3	1	2017
2017-01-01 00:08:05	Medical	4	1	2017

2.3 Summary of Data

As we are interested in understanding the reason behind the reduced ambulance availability the only data types for which we can compute useful statistics are: the number of dispatches per year, incident_type, priority_number, and units_arrived_at_scene. Table 4 shows a summary of the data columns we are interested in, the summary of these calculated statistics with mean for continuous data and mode for categorical data. The total number of dispatches per year is visualized in Figure 2. On average, the Toronto Paramedic Service received 285 000 calls or 780 calls per day, with an average of 1.1 units sent per call which is approximately 860 units dispatched daily.

Table 4: Summary of Incident Data Statistics

Field_Name	Value
Mean Dispatches per Year	286190.166666667
Mean Units Arrived at Scene	1.10751941745028
Mode Incident Type	Medical
Mode Priority Number	1

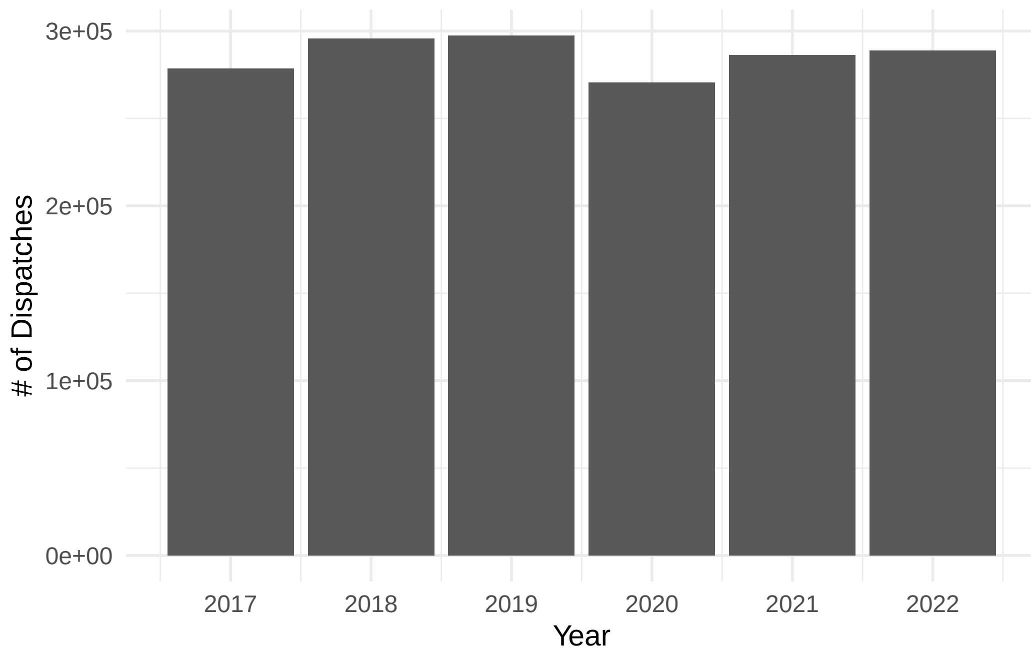

Figure 1: Year vs. Total Number of Dispatches

3 Results

Figure 1 appears to show there isn't much increase in the number of dispatches over the years. However, we have to keep in mind the scale is in the hundreds of thousands, overall there is an increase of 8 000 calls per year with a dip in the number of calls during the COVID-19 pandemic causing people to delay medical care Czeisler et al. (2020). Overall, roughly 860 units were dispatched per day within the city and as of 2024, the Toronto Paramedic Services has a fleet of 236 ambulances City of Toronto (2024) meaning each ambulance would need to be used 3.5 times per day to meet the demand explaining the lack of ambulances available for the city to use. Figure 2 shows the change in priority numbers of the calls over the years, as seen priority numbers 1 and 3 increase and the rest decrease or stay the same near the end of 2022. Also, it is worth noting I have chosen to drop low-priority numbers like 11, 12, 13, and 14 as they occur less than 40 times which is a minuscule amount compared with the rest of the data.

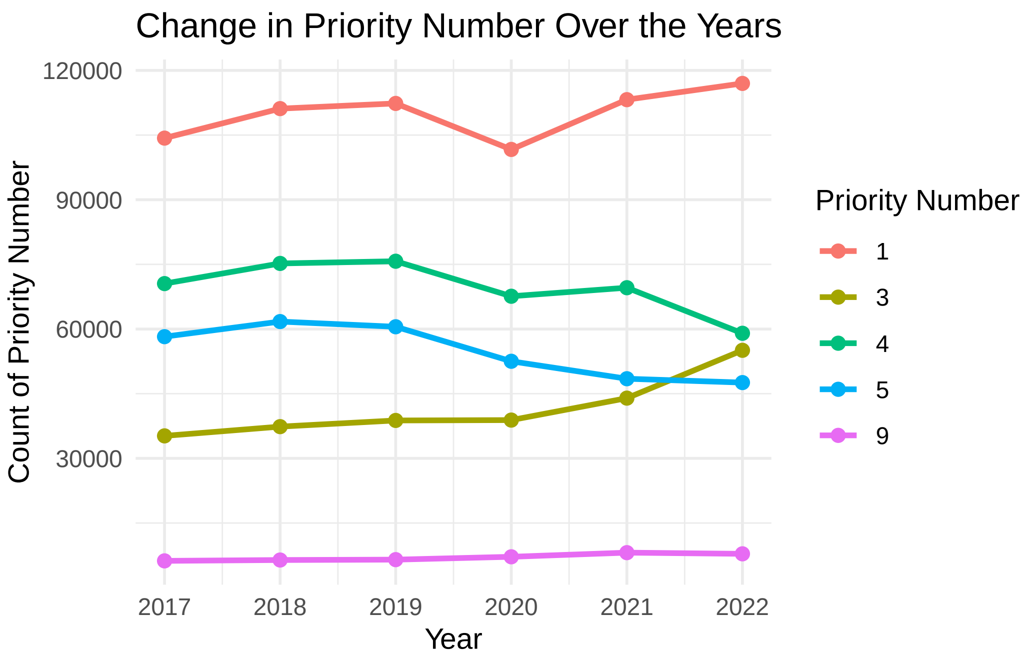

Figure 2: Year vs. Priority Number

Figure 3 and Figure 4 show how the number of units dispatched per year changed, with an overall positive trend until 2020 when the number dropped drastically in line with COVID-19 as mentioned previously. After which, the initial drop numbers jump back up and resume the positive trend. It is worth noting that we only look at 1 and 2 units dispatched as those are by far the most common dispatch numbers and we can see they both follow a similar trend.

4 Discussion

We have seen from the results section that there was a significant drop in the number of calls Toronto Paramedic Services received during the pandemic and a steady increase afterward. However, this doesn't fully account for the increased wait times, as the volume of calls remains lower than pre-COVID levels. A more complete explanation considers the broader context, including many healthcare workers feeling burned out and contemplating career changes Statistics Canada (2022). This coupled with the increase in calls and units dispatched after the COVID-19 pandemic ended resulted in the Toronto Paramedic Services being under-equipped

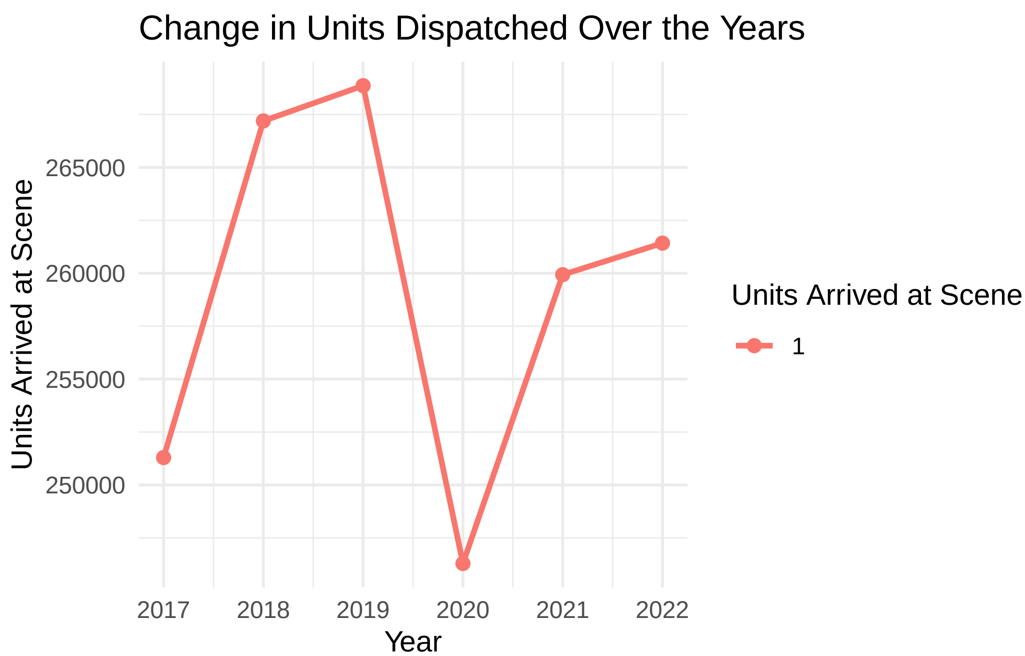

Figure 3: Year vs. Number of Times 1 Unit Arrived at Scene

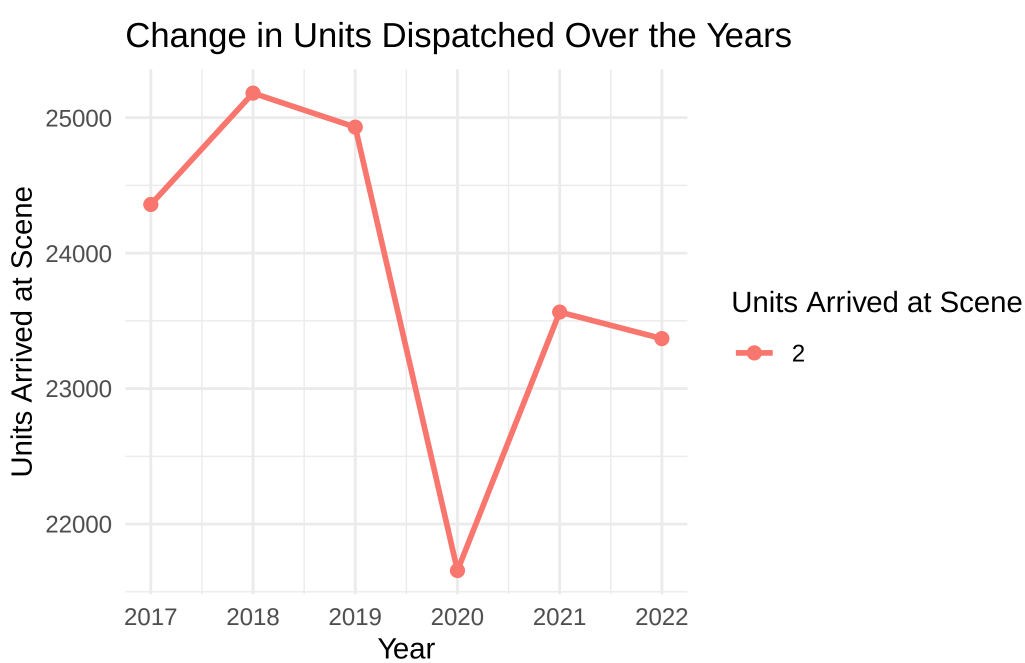

Figure 4: Year vs. Number of Times 2 Units Arrived at Scene

to deal with the increase in call volume. Furthermore, the increase in reports of priority 1 and 3, which are life-threatening or possibly life-threatening situations means that there was a need for experienced medical personnel at a time when there was a shortage. All these factors combined most likely resulted in longer wait times for Torontonians requiring medical assistance.

5 Weaknesses and next steps

A possible next step could be including the dispatch arrival time and seeing if there is any change within the time paramedic units take to respond to a request. As the data set I analyzed only contained the dispatch time I couldn't perform this calculation, however, if completed we could get information on whether the increased call wait times resulted in increased response times as well.

A Appendix

Information on priority levels of Medical Priority Dispatch System (MPDS) ratings was sourced from Author (2000). Below is the severity of each level.

Priority #	Description
5	Alpha (Low Priority)
4	Bravo (Mid Priority)
3	Charlie (Possibly Life Threatening)
1	Delta (Life Threatening)
9	Echo (Full Arrest or Imminent Death)
11	Alpha1 (Most Urgency within Alpha)
12	Alpha2 (Mid Urgency within Alpha)
13	Alpha3 (Least Urgency within Alpha)
14	Code 2 (Non-emergency transport requests.)

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