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

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First sentence. Second sentence. Third sentence. Fourth sentence.

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Quorto can only read data we load into it, so if we have data in global enviornment, quorto isnt able to use it

*Code and data are available at: https://github.com/abdullah-motasim/Analyzing-Ambulance-Response-Times use (here::here("/path/to/folder)) to force quorto to look for folder outside of quorto working directory

use citation("library name") to get citation for a library

ggplot(cleaned_data, aes(x=year))+ geom_bar(position = "dodge")+ theme_minimal()

ggplot(cleaned_data, aes(x=year, fill=(units_arrived_at_scene)))+ geom_bar(position = "dodge")+ theme_minimal()+ # theme(axis.text.x = element_text(angle = 45, hjust = 1))

1 Introduction

Efficient ambulances response times play a key role in saving saving peoples lives, especially in severe and sudden health complications such as cardiac arrests, trauma, and motor vehicle accidents. A medical study from 2011 found for cardiac arrest a 1 minute reduction in response time improved a persons 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 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 <talk about how we found that the number of calls was increasing each year and the so was the severity. Analyze the severity data to see of higher severity means more dispatchers and if so say that the increase in the severity led to more calls and also more units needed per call, coupled with ems workers facing shortages and burnout led to poor ems services available to Canadians. Say thus is important as experts can now better tackle the underlying issues causing delayed ems response times, saving lives.>

The remainder of this paper is structured as follows. Section 2 discusses the datatypes included in the raw data, the cleaning process for the data, and reason for selecting the data set we did. Section 3 analyzes the trends and correlations present between different variables utilizing tabular and graphical means. Section 4 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), and knitr Xie (2014). The chosen data set is called "Paramedic Services Incident Data" "Paramedic Services Incident Data" (n.d.) and contains information about ambulances dispatches sent within Toronto from 2017-2022, the data is refreshed annually and was last updated October 5, 2023. The data is sourced and published by Toronto Paramedic Services meaning they decide the type of data collected and the method of collection. 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** - 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 .1 for details).
- **Units_Arrived_At_Scene** - Number of Paramedic units that arrived on scene of incident
- **Forward_Sortation_Area** - General location of incident based on Postal Code Forward Sortation Area
- **Field Name** - Gives names of field such as ID, Dispatch_Time, Incident_Type, etc.
- **Desctiption/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

During the creation of the raw data set the Field Names, Desctiption/Definition, and Comments/Examples columns were added as part of the process combining the data for all 5 years. However, we don't use these columns within our numerical analysis so they were removed within the data cleaning to reduce the data size. Furthermore, the dispatch_time column was formatted from type dbl to type POSIXct and two new columns were added containing the year and month of the report in order to allow for efficient plotting of dates. Lastly, the cleaned data was tested to ensure no missing values and all given values fell within their predetermined values. The cleaned data is shown in Table 3 and Table 4, Figure 1 showcases the total number of dispatches per year.

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

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

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

id	dispatch_time	incident_type	priority_number	units_arrived_at_scene
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 4: First 6 entires of the cleaned ambulance response data (cont.)

forward_sortation_area	year	month
M4L	2017	01
M3M	2017	01
M5B	2017	01
M5V	2017	01
M1P	2017	01
M5G	2017	01

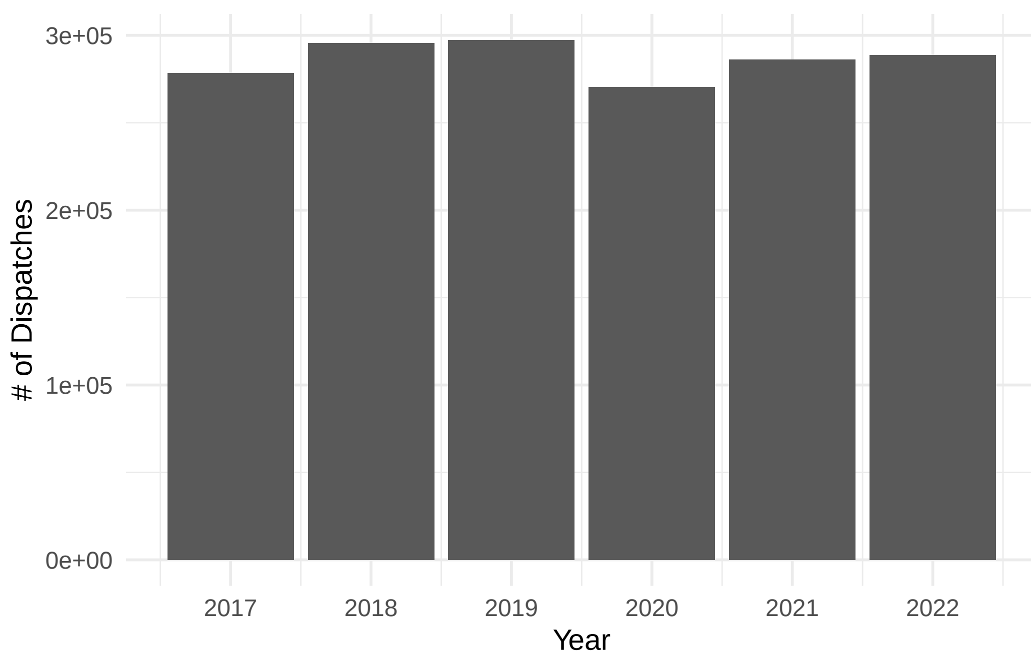

Figure 1: Year vs. Total Number of Dispatches

2.3 Summary of Data

We are only interested in the trend in dispatches over the years and Figure 1 shows that there isn't much change in total number of dispatches over years meaning any calculated statistic on dispatch_time would not be of use. Thus,the only data types for which we can compute useful statistics are incident_type, priority_number, and units_arrived_at_scene. Table 5 shows the summary of these calculated statistics with mean for continuous data and mode for categorical data.

Table 5: Summary of Incident Data Statistics

Field_Name	Value
Units Arrived at Scene	1.10751941745028
Mode Incident Type	Medical
Mode Priority Number	1

3 Results

4 Discussion

4.1 First discussion point

If my paper were 10 pages, then should be be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

4.2 Second discussion point

4.3 Third discussion point

5 Weaknesses and next steps

Data doesn't have arrival times

Appendix

.1 Appendix A

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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