My title*

My subtitle if needed

Denise Chang

December 3, 2024

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

1 Introduction

"In an emergency, seconds count." (City of Toronto 2024). Emergency medical services (EMS) are essential to public health by providing care during life-threatening situations. However, Toronto's paramedic services are struggling to meet demand. Toronto Auditor General's Office reports that there were over 1,200 episodes in 2023 where no ambulances were available. (Toronto Auditor General's Office 2024). To echo this report, this paper examines EMS demand using Toronto Paramedic Services' incident data from Open Data Toronto.

In this analysis, I am interested in EMS demand against time-based factors in Toronto from 2017 to 2022. I explore trends in paramedic services, such as dispatch time, incident type, and number of units dispatched per incident to identify periods of high-volume demand and low availability of resources. I find that … [ADD A FEW RESULTS HERE (or in a different paragraph??)]

The remainder of this paper is organized as follows. Section 2 discusses the data source and an overview of the studied variables. Section 3 constructs a model that predicts a shortage in paramedic resources based on time factors. Section 4 presents the results and findings of the exploration of the data. Section 5 discusses implications, limitations, and suggestions for future research. [TELEGRAPH APPENDIX HERE]

*Code and data are available at: https://github.com/DeniseChang9/Emergency_service_demands.git.

2 Data

2.1 Overview

The dataset used for this analysis is titled "Paramedic Services Incident Data" and is published by Toronto Paramedic Services (Toronto Paramedic Services 2023). For this paper, the dataset is retrieved from the City of Toronto Open Data Portal.

The statistical programming language R (R Core Team 2023) is used to process, manage and visualize the data. Specifically, statistical libraries such as `opendatatoronto` (Gelfand 2022), `openxlsx` (Schauberger and Walker 2024) and `janitor` (Firke 2023) are used to simulate, download and clean the raw data. Libraries like `arrow` (Richardson et al. 2024) and `readxl` (Wickham and Bryan 2023) were used to save and read datasets. Other libraries like `knitr` (Xie 2021), `here` (Müller 2020) are used to load and to render tables. The library `tidyverse` (Wickham et al. 2019) is useful throughout the entire data manipulation process.

The initial dataset features data on paramedic dispatch time, type of incident, priority level of each incident, number of paramedic units arrived at scene and forward sortation area of the incident. These features are annually refreshed on Open Data Toronto by Toronto Paramedic Services.

The data used for this paper was retrieved on November 25, 2024 and was last refreshed on October 5, 2023.

2.2 Measurements

The incident data is saved in different files according to the year of incident. The variables and measurement method of the variables are preserved throughout the recorded years.

Table 1: First Ten Rows of the Paramedic Services Incident Data from 2017

Dispatch Time	Incident Type	Priority Number	Units Arrived	Location
2017-01-01 00:01:13	Medical	1	1	M4L
2017-01-01 00:03:27	Medical	1	1	M3M
2017-01-01 00:01:41	Medical	5	1	M5B
2017-01-01 00:05:53	Medical	4	1	M5V
2017-01-01 00:03:55	Medical	3	1	M1P
2017-01-01 00:08:05	Medical	4	1	M5G
2017-01-01 00:11:10	Emergency Transfer	1	1	M2J
2017-01-01 00:06:20	Medical	4	1	M1B
2017-01-01 00:05:31	Medical	3	1	M2R
2017-01-01 00:07:16	Medical	5	1	M5S

Table 1 is a sample of the 10 first entries in the incident data in 2017. Each row in the dataset represents a unique incident. “Dispatch Time” is the precise time when the first paramedic unit was assigned to an incident. This is measured in year, month, date, hour, minutes, and seconds. “Incident Type” is the category assigned to the incident by the dispatcher based on the information provided in the 9.1.1. call. The possible categories of incident are medical emergencies, emergency transfers, fire-related incidents and motor vehicle accidents. “Priority number” represents the urgency of an incident with 1 being the most urgent and 5 being the least. The priority number is measured by the Medical Priority Dispatch System (MPDS) based on the information provided by the 9.1.1. caller(s). “Units Arrived” is the total number of paramedics that arrived on the scene of incident. This is measured by counting the number of different paramedic units who were dispatched and responded to the incident. Units part of this count do not have to be simultaneously present, and a unit who leaves the scene and comes back afterwards is considered 1 count. “Location” is the general location of the incident based on Postal Code Forward Sortation Areas. This is determined as the first three characters of the postal code of the incident location.

2.3 Outcome Variables

This analysis focuses on two outcome variables that represent ambulance response activity:

2.3.1 `avg_units_arrived`

This variable measures the average number of ambulance units arriving at incidents. It is continuous and provides insight into the resource intensity of different types of calls.

- **Visualization**: A violin plot is used to examine the distribution of `avg_units_arrived` across different `incident_type` values. Temporal trends are visualized with a line chart showing annual changes in `avg_units_arrived`.

2.3.2 `count`

This variable captures the number of incidents for each category and is integer-valued. It reflects the frequency of calls and is critical for understanding demand patterns.

- **Visualization**: Bar charts display the total counts of incidents by `incident_type`, while a heatmap reveals temporal patterns by plotting `count` across combinations of `hour`, `day_of_week`, and `month`.

2.4 Predictor Variables

Several variables are explored as predictors to analyze temporal, categorical, and spatial factors influencing ambulance response:

2.4.1 Temporal Predictors

- **`year`**: Indicates the year of each incident, spanning 2017 to 2022.
  - **Visualization**: A line chart visualizes changes in `count` and `avg_units_arrived` over time to detect trends.
- **`month`**: An ordered factor capturing the month of the incident.
  - **Visualization**: A seasonal heatmap overlays `month` and `day_of_week` to analyze patterns in incident frequency and average unit arrival.
- **`day_of_week`**: An ordered factor representing the day of the week.
  - **Visualization**: Temporal variability is further explored with bar charts and heatmaps.
- **`hour`**: Represents the hour of the day (0–23).
  - **Visualization**: A density plot of incident counts by hour reveals peak times for service demands.

2.4.2 Categorical Predictor

- **`incident_type`**: A categorical variable indicating the type of incident (e.g., medical emergencies, vehicle accidents).
  - **Visualization**: Stacked bar charts and facet grids illustrate differences in resource use and frequency across `incident_type`.

2.5 Summary Statistics and Relationships

To understand the dataset, summary statistics are computed for `avg_units_arrived` and `count`, including mean, median, and standard deviation. Visualizations such as histograms and scatter plots capture distributions and relationships between the variables. A scatter plot matrix examines pairwise relationships, while a correlation heatmap identifies patterns among numerical variables.

Together, these outcomes and predictors provide a detailed view of ambulance demand and the factors influencing it.

3 Model

The goal of our modelling strategy is twofold. Firstly,...

Here we briefly describe the Bayesian analysis model used to investigate... Background details and diagnostics are included in Appendix B.

3.1 Model set-up

Define y_i as the number of seconds that the plane remained aloft. Then β_i is the wing width and γ_i is the wing length, both measured in millimeters.

$$
\begin{align}
y_i|\mu_i, \sigma &\sim \text{Normal}(\mu_i, \sigma) \tag{1}\\
\mu_i &= \alpha + \beta_i + \gamma_i \tag{2}\\
\alpha &\sim \text{Normal}(0, 2.5) \tag{3}\\
\beta &\sim \text{Normal}(0, 2.5) \tag{4}\\
\gamma &\sim \text{Normal}(0, 2.5) \tag{5}\\
\sigma &\sim \text{Exponential}(1) \tag{6}
\end{align}
$$

We run the model in R (**citeR?**) using the `rstanarm` package of (**rstanarm?**). We use the default priors from `rstanarm`.

3.1.1 Model justification

We expect a positive relationship between the size of the wings and time spent aloft. In particular...

We can use maths by including latex between dollar signs, for instance θ.

4 Results

Our results are summarized in **?@tbl-modelresults**.

5 Discussion

5.1 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.

5.2 Second discussion point

Please don't use these as sub-heading labels - change them to be what your point actually is.

5.3 Third discussion point

5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

A Additional data details

B Model details

B.1 Posterior predictive check

In **?@fig-ppcheckandposteriorvsprior-1** we implement a posterior predictive check. This shows…

In **?@fig-ppcheckandposteriorvsprior-2** we compare the posterior with the prior. This shows…

Examining how the model fits, and is affected by, the data

Figure 1: **?(caption)**

B.2 Diagnostics

?@fig-stanareyouokay-1 is a trace plot. It shows… This suggests…

?@fig-stanareyouokay-2 is a Rhat plot. It shows… This suggests…

Checking the convergence of the MCMC algorithm

Figure 2: **?(caption)**

References

City of Toronto. 2024. "Public Safety Alerts - City of Toronto." 2024. https://www.toronto.ca/community-people/public-safety-alerts/.

Firke, Sam. 2023. *Janitor: Simple Tools for Examining and Cleaning Dirty Data*. https://CRAN.R-project.org/package=janitor.

Gelfand, Sharla. 2022. *Opendatatoronto: Access the City of Toronto Open Data Portal*. https://CRAN.R-project.org/package=opendatatoronto.

Müller, Kirill. 2020. *Here: A Simpler Way to Find Your Files*. https://CRAN.R-project.org/package=here.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Richardson, Neal, Ian Cook, Nic Crane, Dewey Dunnington, Romain François, Jonathan Keane, Dragoș Moldovan-Grünfeld, Jeroen Ooms, Jacob Wujciak-Jens, and Apache Arrow. 2024. *Arrow: Integration to 'Apache' 'Arrow'*. https://CRAN.R-project.org/package=arrow.

Schauberger, Philipp, and Alexander Walker. 2024. *Openxlsx: Read, Write and Edit Xlsx Files*. https://CRAN.R-project.org/package=openxlsx.

Toronto Auditor General's Office. 2024. "Toronto Paramedic Services: Rising Response Times Caused by Staffing Challenges and Pressures in the Healthcare System." 2024. https://www.torontoauditor.ca/report/toronto-paramedic-services-rising-response-times-caused-by-staffing-challenges-and-pressures-in-the-healthcare-system/.

Toronto Paramedic Services. 2023. "Paramedic Services Incident Data." 2023. https://open.toronto.ca/dataset/paramedic-services-incident-data/.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.

Wickham, Hadley, and Jennifer Bryan. 2023. *Readxl: Read Excel Files*. https://CRAN.R-project.org/package=readxl.

Xie, Yihui. 2021. *Knitr: A General-Purpose Package for Dynamic Report Generation in r*. https://yihui.org/knitr/.