My title*

My subtitle if needed

Denise Chang

November 27, 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 4 constructs a model that predicts a shortage in paramedic resources based on time factors. Section 5 presents the results and findings of the exploration of the data. Section 6 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

what data was used (from Open Data Toronto) + name and mention last dat accessed. What frequency it's updated etc etc which libraries were used

We use the statistical programming language R (R Core Team 2023)…. Our data (**shelter?**)…. Following (**tellingstories?**), we consider…

3 Data

3.1 Measurements

The dataset captures ambulance incident records by translating real-world emergency service activities into structured data entries. Each row in the dataset corresponds to an incident, defined by the nature of the emergency, the time and place it occurred, and the response provided.

The temporal variables (`year`, `month`, `day_of_week`, and `hour`) are derived from timestamps recorded during each incident. These entries allow for the analysis of seasonal, weekly, and daily patterns, as well as shifts in demand over multiple years. The variables are pre-processed to ensure consistency, with `month` and `day_of_week` encoded as ordered factors to preserve their sequential nature.

The incident type (`incident_type`) represents a classification provided by dispatchers or paramedics based on the nature of the call. This variable reflects categories such as medical emergencies, vehicle accidents, and fires. It ensures that diverse incidents are grouped into manageable classifications for analysis.

The response metrics (`avg_units_arrived` and `count`) represent operational data tied to each incident. The `avg_units_arrived` variable is calculated by averaging the number of units dispatched to each type of incident within specific time intervals. The `count` variable represents the number of incidents recorded for each combination of temporal and incident characteristics. These variables quantify resource utilization and demand, enabling a detailed exploration of service patterns.

Through this systematic representation of real-world phenomena, the dataset provides a foundation for analyzing ambulance demand and the factors influencing emergency service delivery.

3.2 Outcome Variables

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

3.2.1 `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`.

3.2.2 `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`.

3.3 Predictor Variables

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

3.3.1 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.

3.3.2 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`.

3.4 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.

4 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.

4.1 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.

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

We run the model in R (R Core Team 2023) using the `rstanarm` package of (**rstanarm?**). We use the default priors from `rstanarm`.

4.1.1 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.

5 Results

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

6 Discussion

6.1 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.

6.2 Second discussion point

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

6.3 Third discussion point

6.4 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/.

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

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/.