Behind the Delays: Exploring Variations in Toronto's Transit Disruptions*

A Comparative Analysis of Delay Duration Across TTC Subway, Streetcar, and Bus Systems

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This paper uses a Bayesian Linear Regression Model to examine which Toronto Transit Commission (TTC) transit mode—subway, streetcar, or bus—experiences the highest duration of delays. We found that buses experience significantly longer delays compared to subways and streetcars. This finding is important because it highlights critical areas where transit improvements could alleviate the impact of delays on daily commuters. Overall, our study provides valuable insights into TTC transit reliability, informing efforts to enhance urban transportation efficiency and passenger experience.

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*Code and data are available at: [https://github.com/ClaireUoft/Toronto_TTC_Transportation).

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1 Introduction

Overview paragraph

Estimand paragraph

Results paragraph

Why it matters paragraph

The remainder of this paper is structured as follows. Section 2 discusses the data used for this analysis, including key variables and sources, with particular attention to the quality metrics that affect polling accuracy. Section 3 outlines our modeling approach…, incorporating lessons learned from recent electoral cycles. Our predictions are under section of each model. Section 5 discusses the implications of our findings and suggests directions for future research. Finally, Section A evaluates methodology and survey copy.

2 Data

2.1 Overview

In this project, we used data from the opendatatoronto dataset created by (Gelfand 2022). This dataset provided bus, subway, streetcar records essential for our analysis. In this project, we used R(R Core Team 2023) and several R packages for data processing, analysis, and visualization. Specifically, tidyverse (Wickham et al. 2019), arrow(Richardson et al. 2024), here(Müller 2020), ggplot2(Wickham 2016), while dplyr(Wickham et al. 2023) was key for data manipulation tasks. For dynamic report generation, knitr(Xie 2023) and kableExtra (Zhu 2024) used, providing enhanced formatting for outputs. Together, these packages enabled efficient data cleaning, analysis, and visualization throughout the study.

2.2 Measurement

Some paragraphs about how we go from a phenomena in the world to an entry in the dataset.

Table 1: Preview of Cleaned Dataset for Bus, Subway, and Streetcar (One Example Each)

Date	Time	Day	Transit_mode	Line	Location	Incident	Min Delay
2024-01-01	02:08:00	Monday	Bus	89	KEELE AND GLENLAKE	Vision	10
2024-01-01	02:45:00	Monday	Streetcar	505	DUNDAS AND MCCAUL	Security	10
2024-01-01	02:00:00	Monday	Subway	1	SHEPPARD STATION	N/A	0

2.3 Data Cleaning

2.4 Outcome variables

2.4.1 Delay Duration (Min Delay)

The main outcome variable in this study is the duration of delays, measured in minutes (Min Delay). This variable quantifies the length of each delay experienced by the TTC's different transit modes (subway, streetcar, bus). The primary goal of the analysis is to determine which transit mode exhibits the highest average delay duration.

To visualize the distribution of delay durations, a histogram Figure 1 is presented to provide an overview of the range of delay durations for each transit mode. This figure highlights the spread and common ranges of delay times, allowing us to observe whether there are particularly long delays for any given mode.

Lastly, Figure 2 displays a boxplot comparing delay durations across subway, streetcar, and bus transit modes. The boxplot offers insights into the median delays and potential outliers that may suggest unusual or extreme events, while showing variability in delay times across the different transit modes.

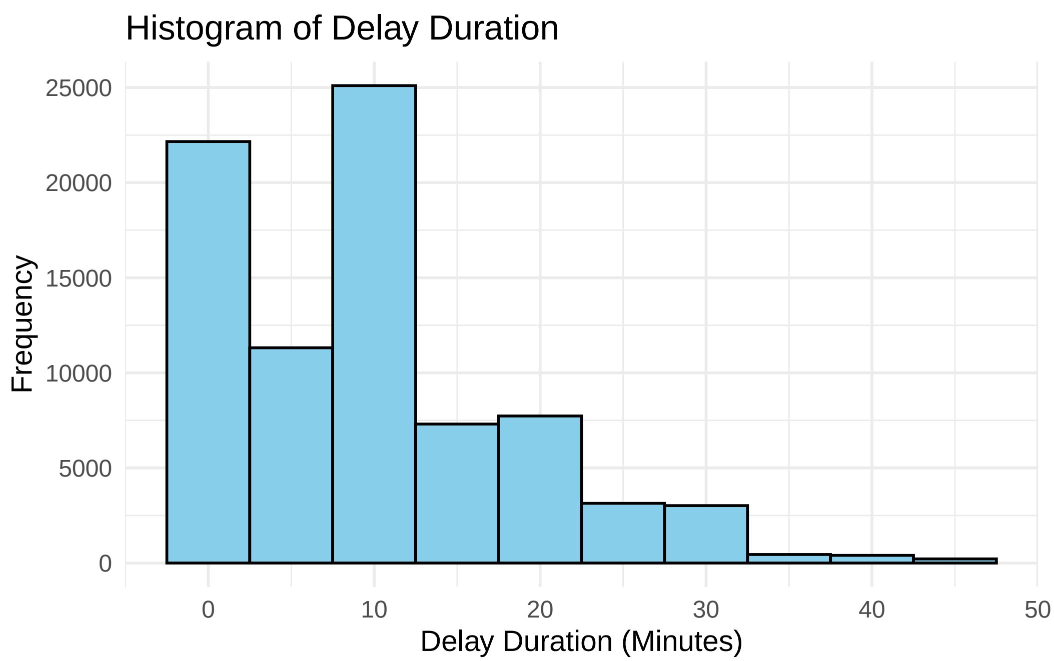

Figure 1: Histogram of Delay Duration (Filtered at 45 Minutes)

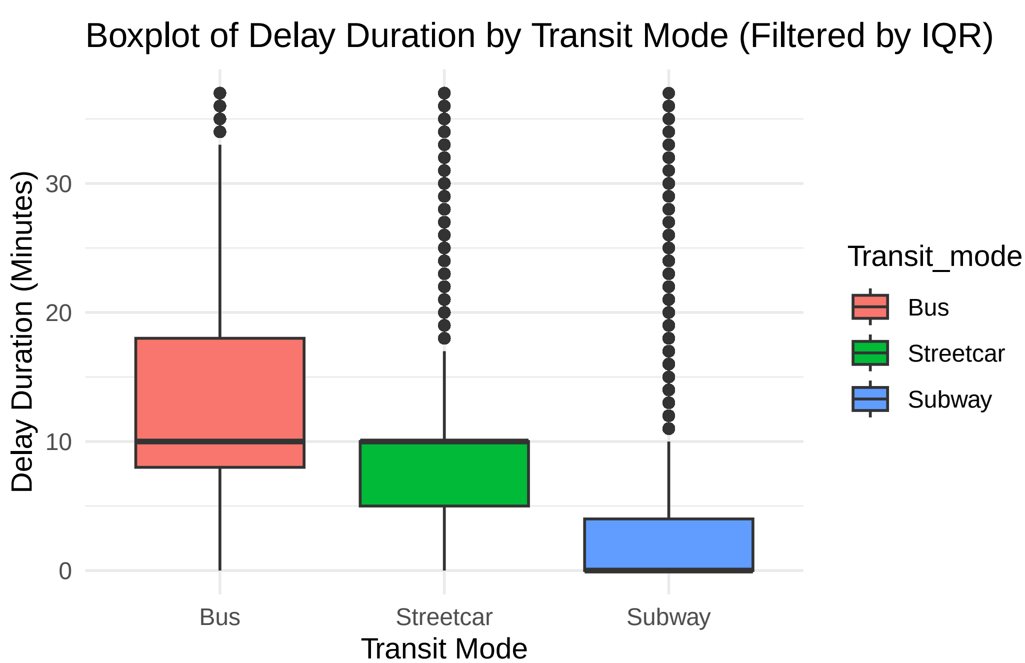

Figure 2: Boxplot of Delay Duration by Transit Mode (Filtered by IQR)

2.5 Predictor variables

2.5.1 Transit Mode

The main predictor variable is Transit Mode, which includes three categories: subway, streetcar, and bus. Each transit mode has distinct characteristics, service areas, and operational challenges that may contribute to variations in delay duration.

To examine this relationship, Figure 3 plots the average delay duration for each transit mode. This chart helps us visualize which transit mode experiences the longest delays on average and illustrates the extent to which each mode contributes to the overall delay picture.

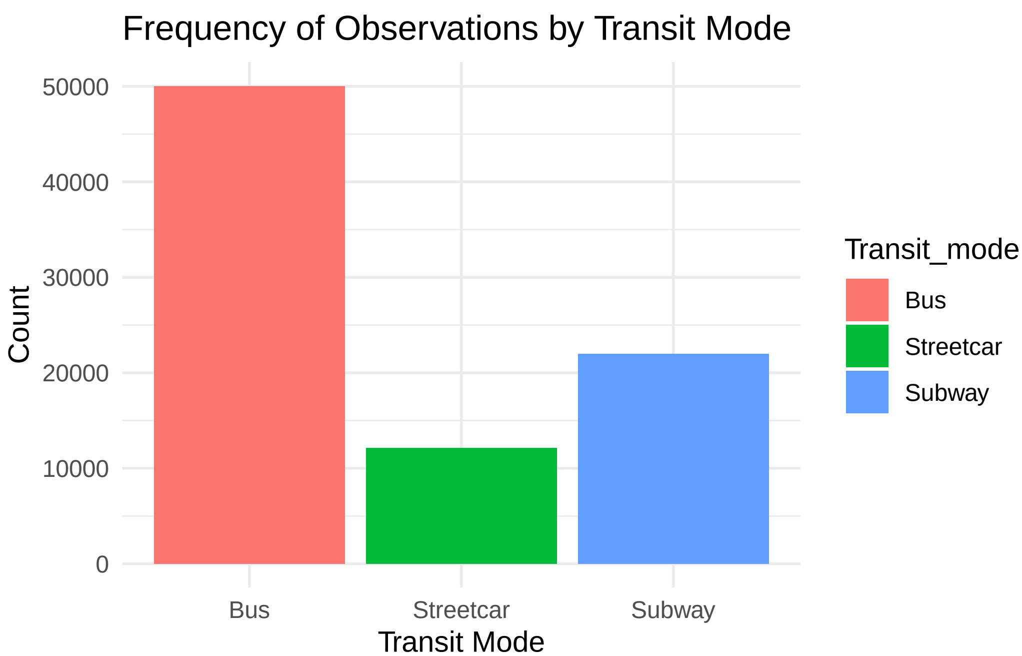

Figure 3: Average Delay Duration by Transit Mode

2.5.2 Time of Day

Another key predictor is Time of Day shown in Figure 4. This variable plays a crucial role in understanding how congestion and operational challenges fluctuate throughout the day. For example, delays might be more frequent and prolonged during peak hours (morning and evening rush periods) due to increased ridership.

Figure 4 shows a line plot representing average delay duration across different hours of the day. This visualization allows us to determine the times at which each transit mode is most

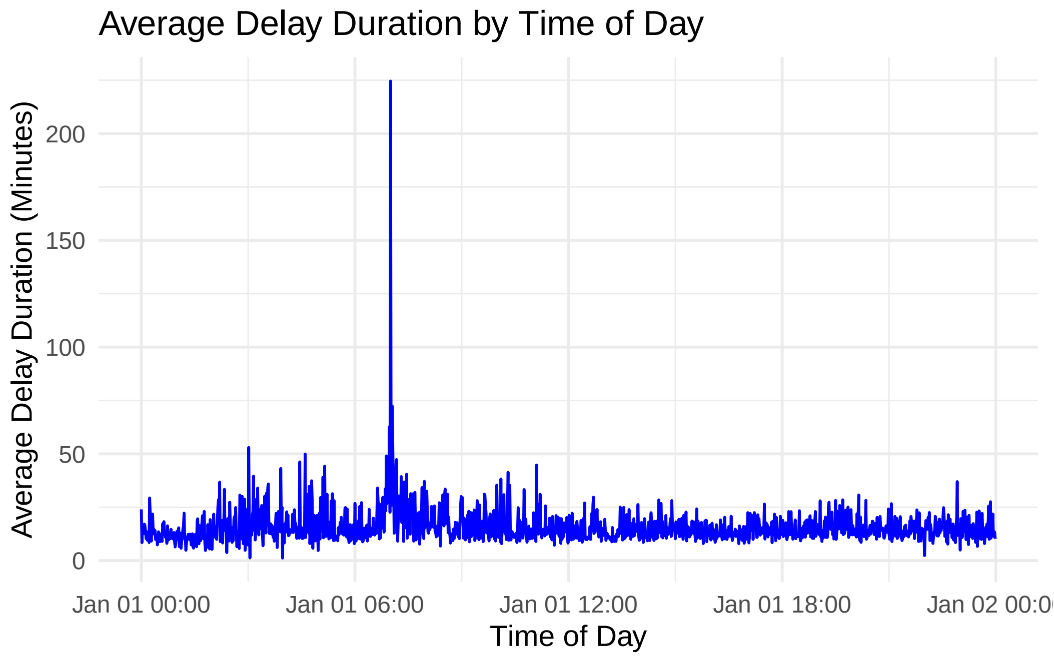

Figure 4: Average Delay by Time of Day

vulnerable to delays, and whether certain transit modes are disproportionately affected during rush hours.

2.5.3 Day of the Week

The Day of the Week is an important predictor that may influence delays due to varying passenger demand and maintenance schedules. Weekdays typically see different patterns compared to weekends, with increased rider demand and therefore greater potential for delays.

Figure 5 is a bar chart that shows the average delay duration for each day of the week, grouped by transit mode. It allows us to observe any weekly trends in delay duration, such as consistent weekday delays or weekend-specific issues, giving more insight into the operational aspects of the different modes. The predictor variables, including transit mode, time of day, and day of the week, help in assessing the specific conditions that affect the delay duration.

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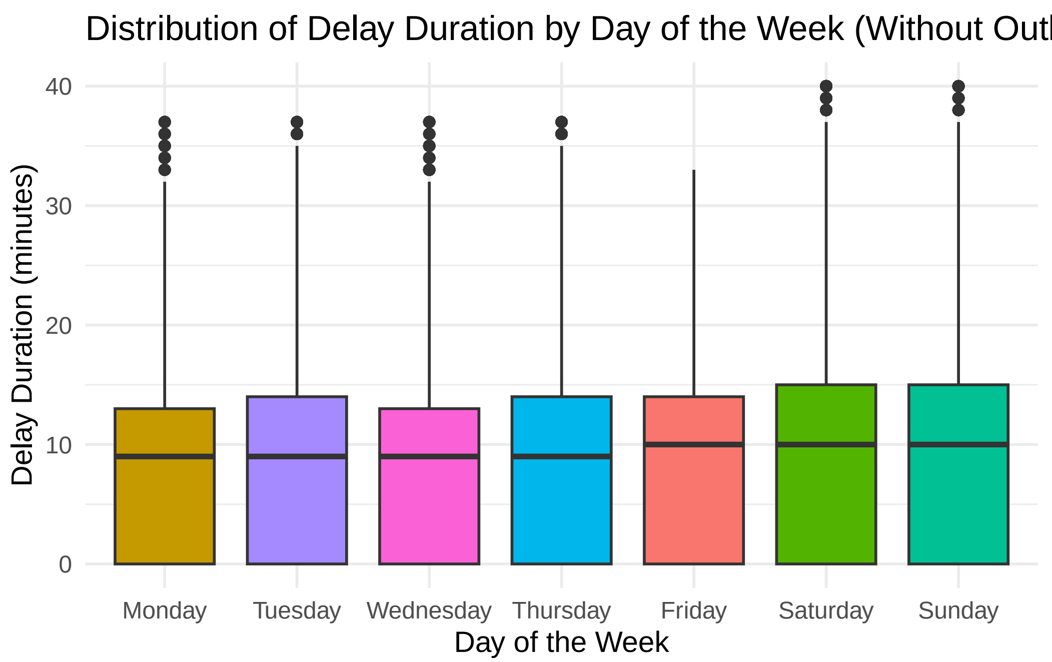


Figure 5: Delay Duration by Day of the Week

3 Model

The Bayesian linear regression model is designed to predict the duration of delays experienced by different TTC transit modes (subway, streetcar, or bus) based on various predictors such as transit mode, time of day, and day of the week. Background details and diagnostics are included in Appendix C.

3.1 Model Set-Up

Define y_i as the duration of the delay (in minutes) for a given transit event. Let β_i represent the transit mode (subway, streetcar, or bus), and γ_i and δ_i represent the time and day of the week, respectively. The generative model is specified as follows:

$$
\begin{aligned}
y_i|\mu_i, \sigma &\sim \text{Normal}(\mu_i, \sigma) && (1)\\
\mu_i &= \alpha + \beta_i + \gamma_i + \delta_i && (2)\\
\alpha &\sim \text{Normal}(0, 2.5) && (3)\\
\beta &\sim \text{Normal}(0, 2.5) && (4)\\
\gamma &\sim \text{Normal}(0, 2.5) && (5)\\
\delta &\sim \text{Normal}(0, 2.5) && (6)\\
\sigma &\sim \text{Exponential}(1) && (7)
\end{aligned}
$$

Here:

- y_i is the observed delay duration for a specific transit event.
- α is the baseline average delay duration.
- β_i captures the effect of transit mode (subway, streetcar, or bus).
- γ_i captures the effect of the time of day (e.g., peak or off-peak).
- δ_i captures the effect of the day of the week.
- σ is the standard deviation, representing unexplained variability in y_i.

This Bayesian model allows for estimating the contributions of transit mode, time, and day to delay durations while accounting for uncertainty in the data.

We run the model in R (R Core Team 2023) using the `rstanarm` package of Goodrich et al. (2022). We use the default priors from `rstanarm`.

3.2 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.

3.3 Assumptions and Limitations

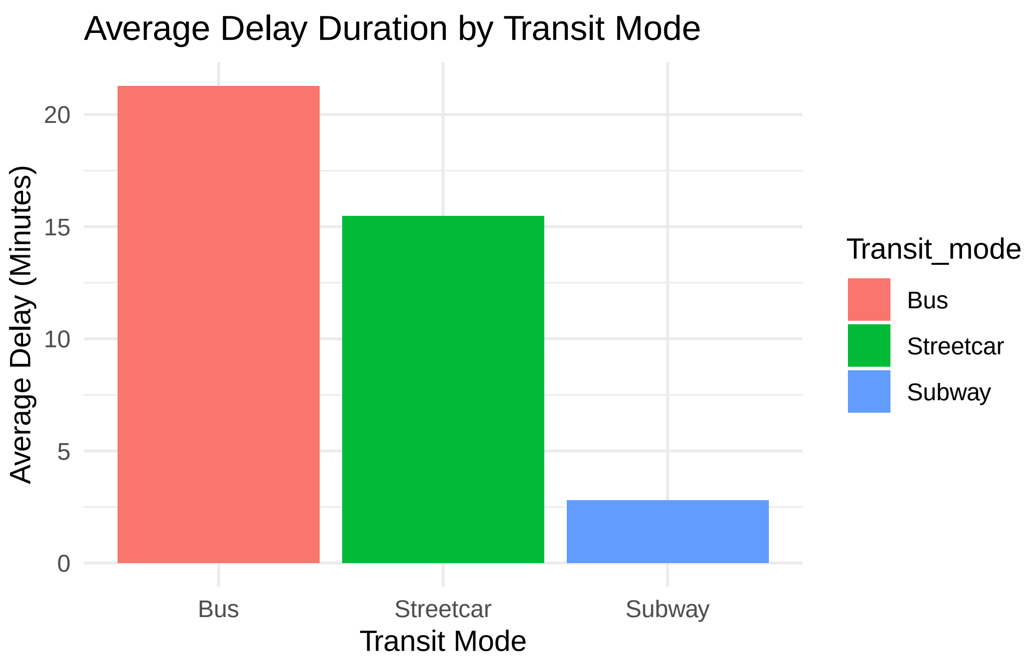
4 Results

These statistics indicate that, on average, TTC streetcars experienced a delay duration of approximately 15.7 minutes, while buses faced an average delay of 12.5 minutes, and subways experienced the shortest average delay of 9.3 minutes. The total number of delay events recorded was 50,039 for buses, 21,979 for subways, and 12,107 for streetcars.

Table 2: Summary statistics of delay events for TTC transit modes

Transit_mode	Average Delay Duration (Minutes)	Count of Events
Bus	21.273167	50039
Subway	2.806497	21979
Streetcar	15.476666	12107

The bar plot visually confirms that streetcars have consistently higher average delay durations compared to buses and subways, aligning with the numerical analysis."



The model summary Table 3 results indicate that, compared to buses, streetcars and subways have shorter delays, with average reductions of 6.8 and 18.8 minutes, respectively. Delays also vary by day of the week, with Tuesday and Wednesday showing slightly shorter delays. However, the model explains only about 3% of the variance in delay duration ($R^2 = 0.033$), and the RMSE of 44.88 suggests moderate prediction error. While transit mode and day of the week have some influence, much of the variation in delay duration remains unexplained.

The Figure 6 graph indicates that bus face the highest average delay durations, peaking at over 40 minutes in the early morning. Streecar have moderate delays throughout the day, averaging between 15-20 minutes, while subways consistently experience the lowest delays, averaging below 10 minutes. The significant early morning peak for streetcars suggests this as a critical period for intervention to reduce delays.

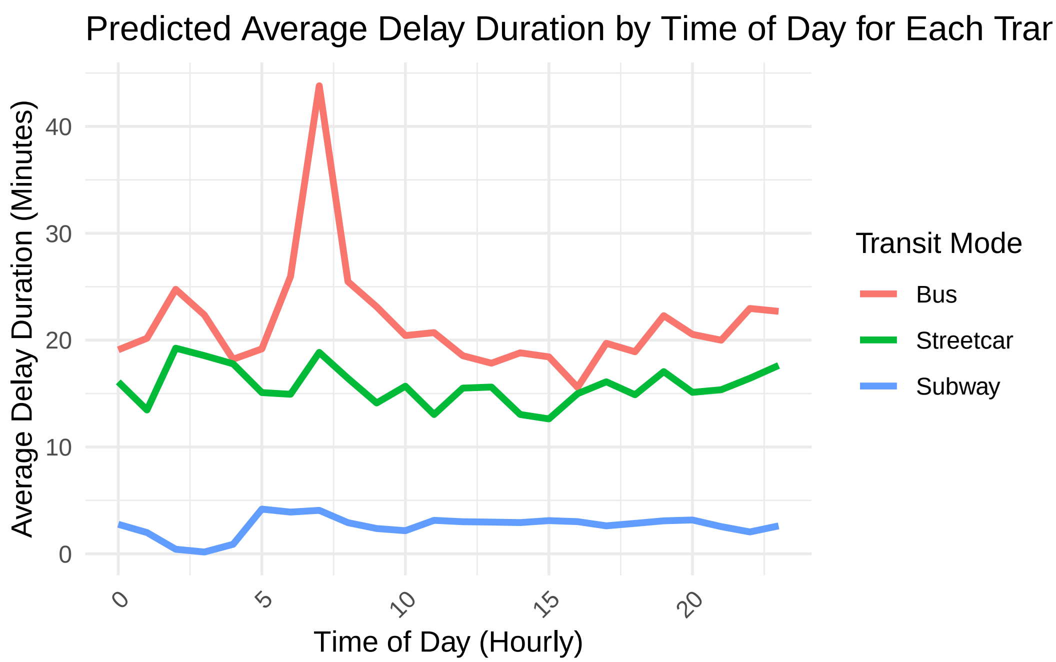


Figure 6: Predicting average delay duration by time of day for each transit mode

5 Discussion

Some questions that a good discussion would cover include (each of these would be a sub-section of something like half a page to a page): What is done in this paper? What is something that we learn about the world? What is another thing that we learn about the world? What are some weaknesses of what was done? What is left to learn or how should we proceed in the future?

Table 3: Summary of model results evaluating the relationship between transit mode and delay duration

	model1
(Intercept)	25.051
Transit_modeStreetcar	−6.799
Transit_modeSubway	−18.849
Time	0.000
DayMonday	−1.043
DaySaturday	−2.160
DaySunday	−1.572
DayThursday	−1.161
DayTuesday	−3.601
DayWednesday	−3.712
Num.Obs.	8412
R2	0.033
R2 Adj.	0.031
Log.Lik.	−43 938.441
ELPD	−43 986.3
ELPD s.e.	622.5
LOOIC	87 972.7
LOOIC s.e.	1245.0
WAIC	87 985.6
RMSE	44.88

5.1 First discussion point

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 Limitations and next steps

A Appendix

Surveys, sampling, and observational data appendix Please include an appendix where you focus on some aspect of surveys, sampling or observational data, related to your paper. This should be an in-depth exploration, akin to the "idealized methodology/survey/pollster methodology" sections of Paper 2. Some aspect of this is likely covered in the Measurement sub-section of your Data section, but this would be much more detailed, and might include aspects like simulation and linkages to the literature, among other aspects.

B Additional data details

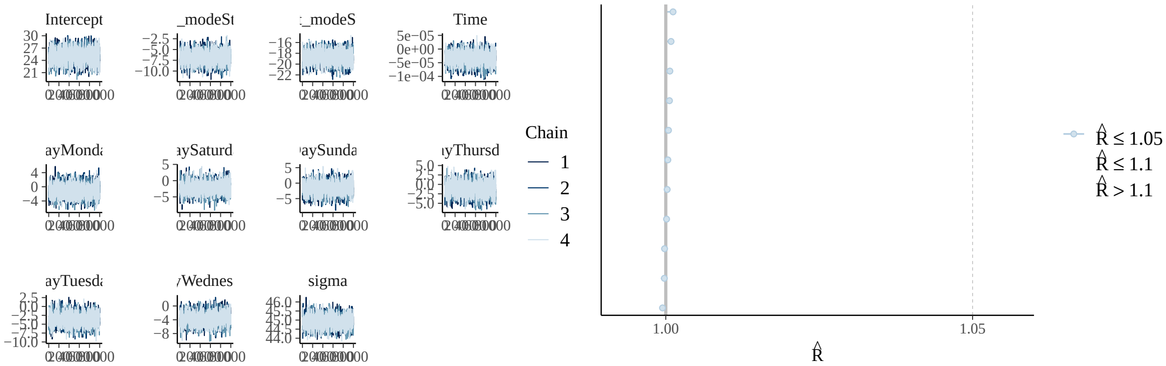
C Model details

C.1 Posterior predictive check

C.2 Diagnostics

Figure 7a is a trace Plot that shows the sampled values of each parameter from the MCMC chains over the iterations. Ideally, these chains should overlap well and display consistent movement across the same regions. From the trace plot, the chains for all parameters appear to have converged and are overlapping consistently, without any clear trends or divergences. This indicates good mixing and suggests the MCMC algorithm has likely converged.

Figure 7b is a Rhat Plot that shows the potential scale reduction factor, which assesses convergence of the MCMC chains. The Rhat statistic should be close to 1, typically below 1.1, to indicate good convergence. In this plot, the Rhat values for all parameters are very close to 1, suggesting the MCMC algorithm has converged, and there is no significant difference between the variances within and across chains.



(a) Trace plot (b) Rhat plot

Figure 7: Checking the convergence of the MCMC algorithm

References

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

Goodrich, Ben, Jonah Gabry, Imad Ali, and Sam Brilleman. 2022. "rstanarm: Bayesian applied regression modeling via Stan." https://mc-stan.org/rstanarm/.

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.

Wickham, Hadley. 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org.

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, Romain François, Lionel Henry, Kirill Müller, and Davis Vaughan. 2023. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Xie, Yihui. 2023. *Knitr: A General-Purpose Package for Dynamic Report Generation in r*. https://CRAN.R-project.org/package=knitr.

Zhu, Hao. 2024. *kableExtra: Construct Complex Table with 'Kable' and Pipe Syntax*. https://CRAN.R-project.org/package=kableExtra.