Beyond Capacity: Analyzing Shelter Use and Government Responses to Homelessness in Toronto*

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The study examines the impact of the COVID-19 pandemic and government policies on Toronto's shelter system in 2022. It analyzes the system's response to external pressures using a dataset that includes shelter occupancy rates, service user counts, and capacity metrics. The findings show significant fluctuations in shelter demand and occupancy, highlighting both the system's resilience and vulnerabilities. The study also offers policymakers valuable insights into how to strengthen support for homeless populations in the face of future challenges. Despite temporary emergency shelters and a plan to transition to permanent affordable housing, the shelter system was under pressure from the pandemic, opioid crisis, and an increase in refugee claimants. The analysis offers useful insights for policymakers looking to improve support for homeless people.

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*Code and data are available at: https://github.com/Sinanma/shelter_in_Toronto.

1 Introduction

During the COVID-19 pandemic, urban shelters faced unprecedented challenges. The pandemic's ripple effects have reached Toronto's shelters, which provide a safety net for the city's homeless population. As public health directives evolved and governmental policies changed, the shelter system's response became a critical area of research to ensure the homeless's safety and well-being during and after the crisis. This paper looks at the complexities of shelter use, service demand, and capacity in Toronto's diverse urban landscape in 2022. Despite previous research on homelessness, there are few comprehensive analyses that combine a Bayesian approach with a visual examination of service patterns across shelter types and demographics.

In this study, our primary estimand is the differential impact of seasonal changes on shelter occupancy rates. We aim to close that gap by providing a nuanced analysis of the current state of the shelter system using sophisticated statistical models and extensive visual data. On the other hand, we discovered some secondary resources about the city of Toronto, as well as any other pertinent resources. According to a City of Toronto article, the city plans to build over 400 affordable homes for homeless people, with 1,100 supportive homes completed in 2020. By 2022, the City of Toronto expects nearly 3,000 new housing opportunities. However, we also cite the article "Prevalence of SARS-CoV-2 infection among people experiencing homelessness in Toronto during the first wave of the COVID-19 pandemic" by the author Linh Luong(Luong et al. 2022) and others that The COVID-19 pandemic has had a significant impact on homelessness, especially among Indigenous and racialized communities. Over 35,000 people in Canada are homeless on a daily basis, with Toronto's homeless population being especially diverse.

Furthermore, our Bayesian analysis reveals an unexpected pattern: men account for a disproportionately high proportion of all shelter occupants. This is especially noticeable in the colder winter months, indicating a seasonal susceptibility that corresponds to Toronto's lower temperatures. Furthermore, the data show a troubling pattern of men repeatedly using short-term shelters, indicating potential gaps in services designed to promote long-term housing stability.

These discoveries are undeniably significant. The high proportion of men in shelter occupancy data necessitates a thorough reassessment of existing support structures designed specifically for men. It requires that resource allocation and policy making be gender-sensitive. The high turnover rates and seasonal peaks in occupancy among men highlight the need for targeted interventions that address not only immediate shelter needs but also more general systemic issues such as employment, mental health, and substance abuse—all of which are frequently associated with homelessness. By highlighting these issues, our research contributes to a more informed conversation, which is critical for developing strong, long-term solutions for Toronto's homeless men.

2 Data

The dataset was collected by the city of Toronto and obtained from OpenDataToronto (Gelfand 2022). This dataset captures the shelter use throughout the diverse urban landscape of Toronto in 2022, which is a year marked by the ongoing impacts of the COVID-19 pandemic, economic fluctuations, and changes in governmental policies affecting the homeless population. We analysis the data in R(R Core Team (2023)), with additional tools for support the analysis, including `tidyverse`(Wickham et al. 2019), `here`(Müller 2020), `dplyr`(Wickham et al. 2023), `readr`(Wickham, Hester, and Bryan 2023), `modelsummary`(Arel-Bundock 2022), `janitor`(Firke 2023), `tibble`(Müller and Wickham 2023), `ggplot2`(Wickham 2016), and research method is from Alexander (2023).

2.1 Variables

The primary factor being examined is the average number of rooms occupied daily in shelters, indicating the demand for shelter services and how it varies throughout the year of 2022. This analysis is further detailed by distinguishing between types of shelter programs—emergency shelters for immediate needs, and transitional shelters for longer-term stays. Furthermore, the study considers demographic segments such as families, men, women, mixed adults, and youth to provide insight into the diverse populations utilizing these services. Geographic analysis divides the data by city areas, including Etobicoke, North York, Scarborough, Toronto, and

Vaughan, offering a clear view of where the demand for shelters is most pronounced within the metropolitan region.

Key variables were constructed to enhance the analysis, such as categorizing months into seasons to explore potential weather-related trends in shelter usage. Data cleaning efforts involved addressing missing values and outliers, ensuring the reliability of the analysis. Details on these processes are transparently documented in our code repository.

2.2 Alternative Data Considerations

While other datasets might have been available, such as individual level admission statistics or broader homelessness data. These were not utilized for specific reasons. The selected dataset's aggregate nature avoids the privacy concerns associated with individual data and provides a consistent, high-level view suitable for policy analysis. Additionally, the dataset's reliability and the authority of the source OpenDataToronto (Gelfand 2022) ensure a robust foundation for the investigation.

2.3 Visualizations and Summary Statistics

To provide a better understanding in comprehension of the dataset, visualizations such as statistic (Table 1) and scatter plots (Figure 1, Figure 2) have been included. These visuals depict monthly occupancy trends, and geographic distribution of shelter use.

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Table 1: Shelter usage in Toronto in 2022

Month	Avg daily occupied rooms
January	65.8
February	67.0
March	66.4
April	66.2
May	68.1
June	69.1
July	68.5
August	70.6
September	70.9
October	71.5
November	68.7
December	68.2

The statistics from Table 1 and scatter plot in Figure 1 illustrated the mean daily occupancy rates for Toronto's shelter system in 2022, offering a detailed perspective on the impact of seasonal variations and other factors on shelter utilization. The occupancy rate starts at a reasonable level during the winter months and gradually increases, reaching its highest point in October at 71.5, before slightly declining towards the end of the year. This pattern indicates a growing demand for shelter as the year advances, especially during the autumn season. This increase could be linked to cooler temperatures, changes in socioeconomic conditions, or alterations in policies that impact the homeless community.

The following abstract highlights the influence of COVID-19, the opined crisis, and increasing refugee claims on the shelter system, suggesting that these issues are major contributors to the observed changes in shelter usage. Although there have been efforts to make housing more accessible and provide temporary emergency shelters, the shelter system is still being challenged, as shown by the consistently high occupancy rates, especially towards the end of the year. This suggests that the shelter system is both adaptable and under significant strain, highlighting the urgent requirement for policymakers to modify and strengthen their assistance for the homeless population. This is particularly important in anticipation of future issues that could further burden the system.

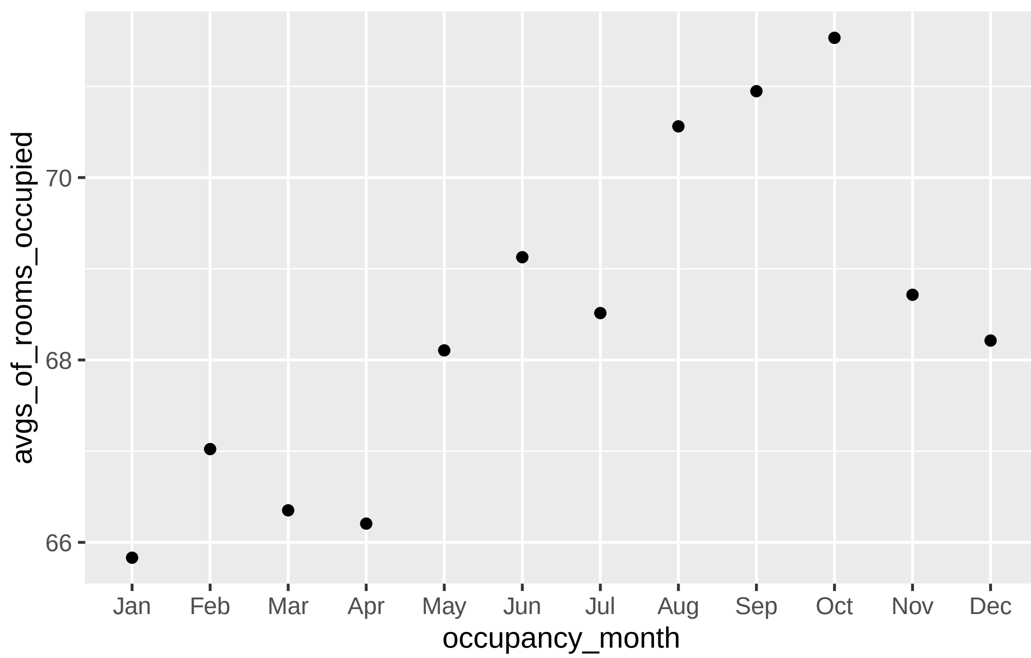


Figure 1: Toronto shelter rooms average usage in 2022

The scatter plot (Figure 2) that depicts the distribution of occupied rooms by several sectors, such as families, males, mixed adults, women, and youth, across several places, including Etobicoke, North York, Scarborough, Toronto proper, and Vaughan. Each dot shows the amount of rooms inhabited by a sector within a certain city. The most notable finding here is that Toronto has the highest occupancy rate across all categories, notably for families and mixed adults, showing a concentrated demand for shelters in the city's core.

Figure 2: Occupancy of Shelter Rooms by Sector Across Toronto Cities

2.4 Measurements

The data measures demonstrate the systemic influence of COVID-19 and other crises on shelter demands when paired with the contextual information given in the introduction and abstract. The high occupancy rates, particularly in emergency shelters, indicate a severely overburdened shelter system despite efforts like the establishment of emergency shelters and the shift to permanent housing. This thorough data analysis confirms the necessity for well-informed policy responses that improve the support given to different demographic groups and the system's capability, especially in light of impending and continuing challenges. Data on shelter occupancy in the Toronto area is shown in a scatter plot and bar graph. The first graph summarises total occupancy in emergency versus transitional shelters, while the second shows individual occupancy by sector (families, men, mixed adults, women, and youth) across several cities. The scatter plot's data points give an overview of demand within each demographic sector. At the same time, the graph's stacked bars show the overall occupancy levels and emphasize the need for emergency shelters, especially in central Toronto. The y-axes of both visualizations quantify the number of rooms occupied and use numerical measures of occupancy.

3 Model

In our study, the study used a Bayesian analysis model to investigate occupancy patterns and service utilization in Toronto's shelter system in 2022. The model was chosen because of its ability to account for prior knowledge and uncertainty, resulting in a probabilistic approach to understanding shelter usage data. The model used a hierarchical structure to account for the different effects of factors like location, demographic groups, and time of year on shelter occupancy rates. The posterior distributions of model parameters revealed information about the relationships between these factors and shelter usage, particularly across different parts of the city and demographic groups.

However, The Bayesian model used in the analysis was effective in drawing significant conclusions about Toronto's shelter service usage trends. The study provided a multidimensional view of the shelter system by combining quantitative analysis and data visualization, as well as identifying significant trends and patterns that can inform service delivery and policy. Instead of being based on an image, the information about the priors being normally distributed with a location of 0 and a scale of 2.5 is based on a standard Bayesian statistics method for defining model priors. A normal distribution is frequently used as a weakly informative prior. This option represents a baseline assumption that, prior to data observation, the coefficients should be centered around 0, indicating no effect with a degree of uncertainty represented by the scale.

The model specified occupancy rates as a function of several covariates, including time (months), city location (e.g., Etobicoke, North York, Scarborough, Toronto, Vaughan), and shelter demographics. Specifically, we used the number of occupied rooms (number_occupied) as a response variable, with (occupancy_month) and (location_city) as predictor variables, as well as sectors to account for different demographic groups.

3.1 Model set-up

$y_i|\mu_i \sim \text{Normal}(\mu_i, \sigma)$: Following the Bayesian model, we know that this implies that the outcome variable y_i, conditioned on the mean μ_i, has a normal distribution with standard deviation σ. For the Toronto shelter, y_i can represent the number of people who come to the shelter on day i, or other relevant response metric, such as the number of occupied beds.

$\mu_i = \beta_0 + \beta_1 \cdot x_i$: This is the linear model, where μ_i represents the expected value of y_i. The intercept β_0 and slope $beta_1$ are multiplied by the predictor x_i. In the Toronto shelter, x_i represents a variable of interest, it could represent the variables such as the capacity of the shelter, the number of services offered, location factors, or the time of year.

$\beta_0, \sim \text{Normal}(0, 2.5)$: The intercept term β_0 is assumed to be centred around 0 with a standard deviation of 2.5. This means that you do not expect a strong relationship between the predictor variable x_i and the outcome y_i before analyzing the data, but you are open to the possibility of discovering one.This expresses modest prior knowledge about shelter occupancy rates, allowing the data to significantly influence the posterior distribution β_0.

$\beta_1 \sim \text{Normal}(0, 2.5)$: In a comparable way, this indicates the previous consensus regarding the slope 1 was that it has a standard deviation of 2.5 and is centered around 0. This implies that, prior to data analysis, you do not expect a strong relationship between the predictor variable x_i and the outcome of y_i.

$\sigma \sim \text{Exponential}(1)$: This implies that the prior belief for the standard deviation of the outcome variable's distribution is an exponential distribution with a rate parameter of one. This suggests lower values, indicating less variability in daily shelter use. However, you are open to learning from the data if there is more variability than expected.This distribution is commonly used for scale parameters like in Bayesian models because it is constrained to positive values and can represent a wide range of variability.

Furthermore, the Bayesian model is used in our study to examine occupancy rates in Toronto's shelter system, allowing for a thorough understanding of the uncertainties and variables associated with shelter use. This method generates preliminary estimates, which can be refined as more data becomes available, resulting in a probabilistic forecast. The model's predictive power stems from its ability to differentiate between the effects of various factors on the number of people seeking shelter. By assigning priors to model parameters and tracking their evolution through posterior distributions, the model learns about the relative weight of each factor, allowing it to identify which signals are genuine and worth paying attention to. The Bayesian framework allows for a dynamic dialogue between data and theory, challenging and refining our understanding of the relationship between socioeconomic factors and shelter demand. This dialogue lays the groundwork for developing targeted policies that are both responsive to immediate needs and proactive in promoting long-term solutions to homelessness. The model's findings serve as an empirical foundation for resource allocation discussions, allowing policymakers to prioritize funding, tailor services to demographic needs, and design interventions that directly address identified causes of shelter overuse.

$$
\begin{aligned}
y_i | \mu_i &\sim \text{Normal}(\mu_i, \sigma) && (1) \\
\mu_i &= \beta_0 + \beta_1 x_i && (2) \\
\beta_0 &\sim \text{Normal}(0, 2.5) && (3) \\
\beta_1 &\sim \text{Normal}(0, 2.5) && (4) \\
\sigma &\sim \text{Exponential}(1) && (5)
\end{aligned}
$$

3.2 Model justification

The Bayesian model was used to analyzing in Toronto's shelter occupancy rates since it is reliable, adaptable, and possesses a lot of information. The model analyzes what it currently knows and adds it to the data it has seen to make an accurate assessment that is based on both past events and present conditions. It finds possible correlations in nested data, which lets you get an accurate understanding of how individual and group-level covariates affect occupancy rates. Thus, the Bayesian approach measures uncertainty by giving a full probabilistic account of all unknowns.

However, the model are also flexible, since it can be updated all the time as new data comes in. This makes it a dynamic tool for ongoing policy change and assessment. The Bayesian model also lets us examine at the complicated connections and interactions between covariates like demographic variables, economic factors, and neighbourhood characteristics. It Figuring out these connections can help you see deeper patterns and trends that other modelling methods might miss. Lastly, the Bayesian model was picked because it is reliable, adaptable, and gives a lot of information. This makes it an important tool for understanding the Toronto shelter system and making it work better and have a bigger effect.

4 Results

In this section, we present the outcomes of our investigation into the Toronto shelter system during 2022, focusing on shelter demand, occupancy rates, and demographic distributions through data analysis and visual representations. We identified the critical trends that have influenced the shelter system's capacity and its response to the needs of the homeless population by examining shelter usage across different sectors and service programs, alongside the occupancy rates.

The stacked bar graph (Figure 3) provides a detailed breakdown of room occupancy within Toronto's shelter system, comparing emergency and transitional program usage across different sectors and cities. The data reveals a pronounced reliance on emergency shelters, with Toronto showing the highest occupancy rates, particularly for men and mixed adults. In contrast, transitional shelters are utilized less, though they play a critical role for youth and women in Toronto.This difference in shelter usage indicates a urgent need for targeted policies to support sustainable housing and services. Such policies should aim to decrease the heavy reliance on immediate, short-term shelters and enhance the use of transitional shelters that support the progression toward stable, long-term accommodation.

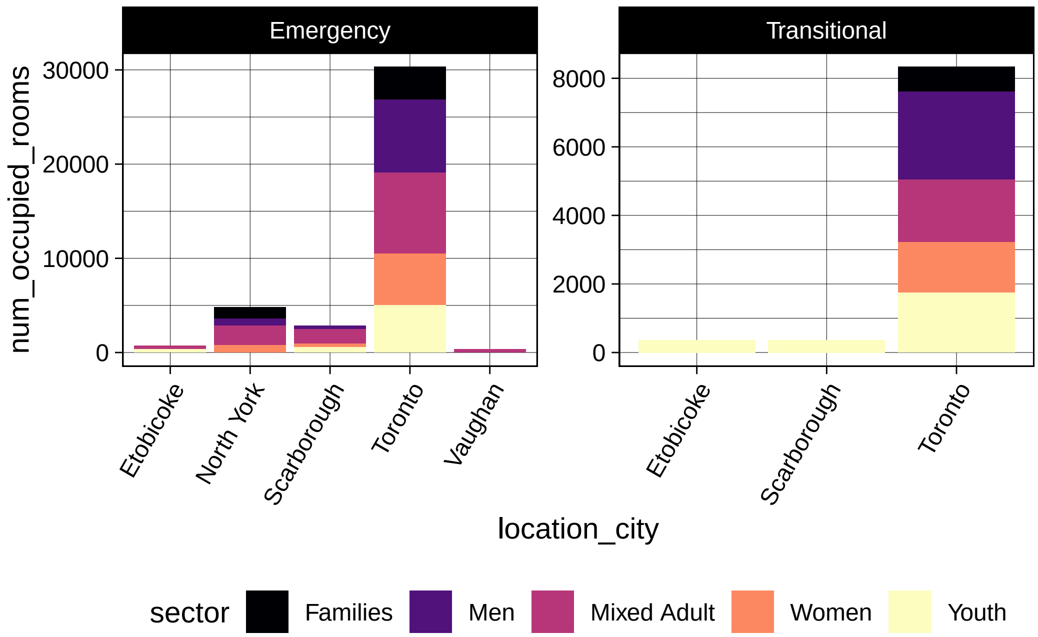


Figure 3: The shelter rooms usage based on different sector and services program in Toronto.

The scatter plot(Figure 4) illustrates the relationship between the occupancy rate of rooms and the actual room capacity in Toronto's shelters. Each point represents a data pairing of these two variables, showing a positive trend: as the occupancy rate increases, the actual capacity used also tends to increase. The red line indicates the average trend, cutting through the data to demonstrate the general direction of this relationship. This graph indicats that as more people use the shelters, the actual number of rooms occupied goes up, which could strain the shelter system. The analysis underscores the importance of using predictive models to inform policy decisions and resource allocation, ensuring that the shelter system can accommodate the needs of Toronto's homeless population effectively.

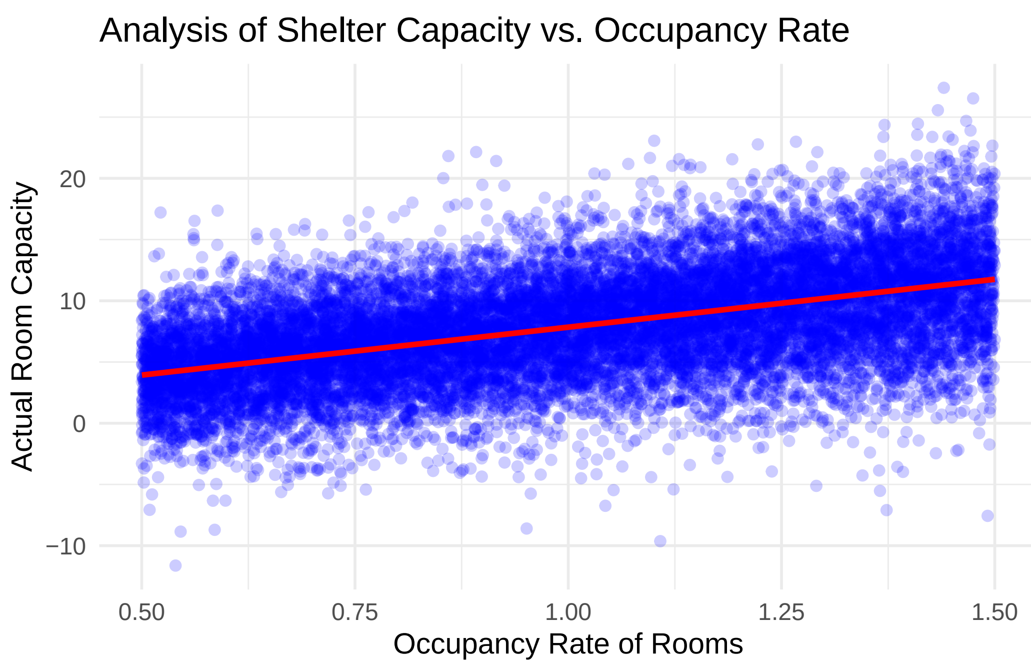


Figure 4: The relationship between the occupancy rate and actual room occupied.

Table 2: Explanatory models of Toronto's shelters usage based on occupancy rate and service user count

	(1)
(Intercept)	11.556
occupancy_rate_rooms	−0.471
service_user_count	0.558
Num.Obs.	337
R2	0.430
R2 Adj.	0.078
Log.Lik.	−1886.786
ELPD	−1890.1
ELPD s.e.	13.5
LOOIC	3780.2
LOOIC s.e.	27.0
WAIC	3780.1
RMSE	65.07

The table (Table 2) presents a statistical model summarizing the factors influencing shelter usage in Toronto based on occupancy rate and service user count. The model intercept suggests that when occupancy rates and service user counts are at zero, the baseline number of occupied rooms is approximately 11.6. The occupancy rate coefficient is negative (-0.471), indicating a decrease in room count with higher occupancy rates. While the negative coefficient may seem perverse, the service user count presents a positive relationship, indicating that as more individuals use the shelter services, the number of rooms used increases. The R-squared value of model is 0.430, which indicates that approximately 43% of the variation in room occupancy is explained by these variables, although the low adjusted R-squared suggests that additional factors not included in the model could significantly impact shelter use. These findings highlight the complexity of predicting shelter usage and the need for more nuanced models to inform policy decisions and resource distribution effectively.

Our findings point to the critical need for policy makers and shelter administrators to implement targeted interventions that address the specific needs of Toronto's homeless population. The evidence supports the call for an expansion of shelter capacity and the development of comprehensive long-term housing strategies. These actions are imperative to ensure that the shelter system can adequately respond to the demands of a diverse and growing homeless population, paving the way for more sustainable and inclusive solutions to homelessness in Toronto and beyond.

5 Discussion

5.1 Findings

This study aimed to analyze the trends in shelter usage across Toronto in 2022, focusing on average usage rates of beds and rooms, the impact of different shelter program models, and the capacity needs across various demographics and city regions. The findings reveal significant insights into the dynamics of shelter usage and the pressing needs within the community, reflecting broader social issues.

The analysis indicates a clear seasonal trend in shelter usage, with occupancy rates peaking during the colder months. This pattern underscores the critical role of weather in influencing the demand for shelter services, aligning with previous research highlighting the vulnerability of homeless populations to adverse weather conditions (City of Toronto 2023a). Furthermore, the distinction between emergency and transitional shelter types revealed diverse needs within the homeless population, suggesting a complex landscape of shelter requirements that vary not only by season but also by individual circumstances.

5.2 Expanding Solutions: Toronto's Comprehensive Strategy Against Homelessness

Toronto's government has been proactive in responding to the homelessness crisis, with several plans aimed at alleviating the strain on the city's shelter system.

For the winter of 2023/2024, the City of Toronto has laid out a comprehensive Winter Services Plan to support those experiencing homelessness. This plan includes the activation of Warming Centres when temperatures drop to critical lows, addition of up to 180 shelter spaces by optimizing the existing shelter sites, and the creation of 170 spaces at Warming Centres during periods of cold weather. Importantly, the city acknowledges the increasing demand for shelter and housing, highlighting the need for urgent support from federal and provincial governments to manage capacity pressures (City of Toronto 2023a).

Furthermore, Toronto has been actively working on creating more permanent solutions to homelessness. The city has purchased properties to be transitioned into affordable and supportive housing, with projects at 222 Spadina Ave. and 4626 Kingston Rd. already underway, providing homes for those at risk of or currently experiencing homelessness (City of Toronto 2023b). This approach not only addresses immediate needs but also focuses on long-term solutions to prevent chronic homelessness by moving individuals from shelter systems into stable housing with necessary supports.

These efforts reflect a multifaceted approach to tackling the challenges highlighted in our paper, demonstrating the city's commitment to not just managing but resolving the issue of homelessness. The initiatives underscore the importance of collaborative efforts between different levels of government and the community to address a complex issue that affects many in Toronto. The city's plans align with our findings, suggesting that while significant steps are being taken, continued and enhanced support is necessary to meet the growing demand for shelter and affordable housing in the face of various contributing factors such as pandemic, the opioid crisis, and an influx of refugee claimants and asylum seekers.

5.3 Implications

The implications of these findings are multifaceted. Firstly, the seasonal surge in shelter demand highlights the necessity for scalable solutions in Toronto's shelter services to accommodate fluctuating needs. This could involve dynamic resource allocation strategies that adjust in anticipation of seasonal trends. Secondly, the varied demands between emergency and transitional shelters suggest a need for a more nuanced approach to shelter provision, one that caters to the specific needs of different demographic groups.

5.4 Limitations

This study is not without limitations. The reliance on publicly available data may introduce biases, as not all instances of shelter usage or homelessness are captured within the dataset. Additionally, the analysis does not account for the potential impact of policy changes or other external factors that may influence shelter demand. These limitations suggest caution in generalizing the findings without consideration of the broader context.

5.5 Suggestions for Future Research

Future research should aim to address the identified limitations by incorporating more comprehensive datasets, potentially including qualitative data that captures the lived experiences of those utilizing shelter services. Furthermore, exploring the impact of policy interventions on shelter usage trends could offer valuable insights into effective strategies for managing shelter capacity and meeting the needs of vulnerable populations.

5.6 Conclusion

The study of Toronto's shelter usage in 2022 provides critical insights into the challenges faced by homeless populations and the services designed to support them. By understanding the trends and factors influencing shelter demand, policymakers and service providers can better prepare for and address the complex needs of those seeking shelter. Continued research and innovation in this field are essential to developing effective solutions that ensure no individual is left without refuge in times of need.

Appendix

A Model details

A.1 Posterior predictive check

we implement a posterior predictive check. This shows... we compare the posterior with the prior. This shows...

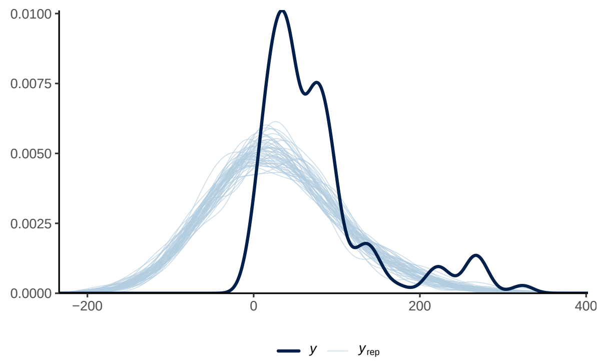
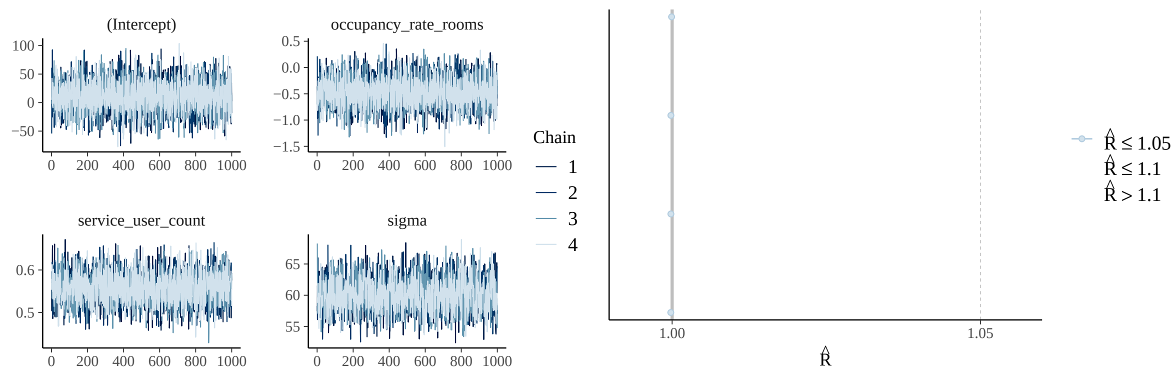


Figure 5: Examining how the model fits, and is affected by, the data

A.2 Diagnostics

is a trace plot. It shows... This suggests...

is a Rhat plot. It shows... This suggests...



(a) Trace plot

(b) Rhat plot

Figure 6: Checking the convergence of the MCMC algorithm

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