Balancing Efficiency and Equity in Urban Waste Management in Toronto from 2021 to 2024*

A Data-Driven Analysis of Demographics, Housing, and Waste Collection Patterns with Bayesian Logistic Regression Model

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Effective urban waste management is essential for sustainability, yet many cities face challenges in balancing efficiency with equitable resource distribution. This paper examines demographic and housing characteristics in Toronto to assess their impact on waste generation and collection patterns with Bayesian logistic regression model. The analysis indicates that high-density areas often experience greater servicing demands, while low-density areas may underutilize resources. The findings support recommendations to improve waste management strategies, ensure fairness, and strengthen sustainability initiatives, providing a model that other cities can adapt.

1 Introduction

Effective waste management is vital for sustainable urban living, yet balancing efficiency and equity in servicing remains a challenge. As cities expand and diversify, it is important to understand the demographic, dwelling, and household factors that influence waste generation and collection patterns. This paper examines these dynamics using datasets from Toronto, integrating demographic and waste collection data to identify operational inefficiencies and disparities in service.

This research examines the overlooked relationship between localized demographic and housing characteristics and their effect on waste generation and service frequency. While previous studies offer general overviews of urban waste management, they often lack detailed analyses

*Code and data are available at: https://github.com/jwonc4602/Waste-and-Recycling-in-Toronto.

linking demographic factors to service patterns. This study focuses on (1) the role of age distribution, household size, and housing type in shaping waste generation, and (2) the operational implications of these factors for resource planning and optimization.

Through statistical and predictive modeling, this study examines how demographic and housing factors influence waste management needs across Toronto's wards. The analysis identifies disproportionate servicing of specific asset types in high-density areas and resource underutilization in low-density neighborhoods. These findings point to opportunities for improving service allocation and ensuring equitable resource distribution.

The findings of this study contribute to optimizing waste management in Toronto while informing broader policy discussions on urban sustainability. By integrating demographic data with operational metrics, this research offers a framework that cities can replicate to balance efficiency and equity in public services. The paper is organized as follows: Section 2 details the data sources and key estimands, Section 3 explains the modeling approach and its diagnostics, Section 4 presents the results, and Section 5 discusses the implications, limitations, and future research directions. Section A includes additional details on model diagnostics, figures, and idealized survey and methodology.

2 Data

2.1 Overview

This research is based on two datasets: Litter Bin Collection Frequency (Services 2024) and Ward Profiles (Planning 2024), which are accessible through the City of Toronto's OpenData-Toronto Library (Gelfand 2022). Litter Bin Collection Frequency dataset contains more than 10,000 garbage/recycling street litter bins across the city and the frequency of collection varies based on the location and/or usage of each bin and seasonality. Ward Profiles dataset contains the 2021 Ward Profiles based on the 25-Ward model (effective December 1, 2018) are available from City Planning and each Ward Profile provides a snapshot of the population and households in the Ward.

The data was compiled and examined using the Python: A programming language for clear and concise code (Foundation 2024) and R statistical programming software (R Core Team 2023), supplemented by various tools such as `tidyverse` (Wickham et al. 2019), `ggplot2` (Wickham 2016), `dplyr` (Wickham et al. 2023), `readr` (Wickham, Hester, and Bryan 2023), `knitr` (Xie 2014), and `here` (Müller and Bryan 2020).

2.2 Estimand

The primary objective of this analysis is to estimate the relationship between demographic, dwelling, and household characteristics in Toronto neighborhoods and their impact on waste

Table 1: Sample of Cleaned Litter Data

WARD	DAYS.SERVICED	ASSET.TYPE	STATUS
Ward4	5	WR1	Existing
Ward4	7	WR4	Existing
Ward4	7	WR2	Existing
Ward4	7	WR4	Existing
Ward4	7	WR1	Temporarily Removed

generation and collection patterns. Specifically, the analysis focuses on:

1. The influence of demographic factors, such as age distribution, on waste generation across wards.

2. The contribution of dwelling types and household sizes to variations in waste output and service frequency.

3. The predictive power of these factors in estimating waste generation for planning and optimization.

2.3 Litter Data

The dataset contains metrics on waste collection across Toronto's 25 wards, detailing the types of litter bins (WR1-WR5), their status, and servicing frequency. Service levels indicate how often bins are collected, but this applies only to bins labeled "existing." Bins marked "planned" or "temporarily removed" are not currently serviced. This data is critical for analyzing waste collection distribution and infrastructure usage in Toronto (refer to Table 1). It supports evaluations of service efficiency, identifies underperforming areas, and informs equitable allocation of waste management resources citywide.

The dataset provides essential information on litter bin operations. Days Serviced indicates the collection frequency for active bins, categorized as once, three times, or five times per week. Bin Status identifies whether a bin is "Existing" (currently deployed and serviced) or "Temporarily Removed" (out of service for repairs or reallocation). Ward Identifiers are numerical labels for Toronto's 25 wards, enabling analysis of bin distribution and servicing patterns across the city.

Figure 1 illustrates the distribution of Bin Status across Toronto's 25 wards, categorizing bins as "Existing" or "Temporarily Removed." "Existing" bins dominate across all wards, underscoring their central role in waste management, while "Temporarily Removed" bins are fewer and vary significantly.

Wards 13 and 14 show notably higher counts of "Temporarily Removed" bins, possibly due to ongoing maintenance or reallocation efforts. In contrast, wards like 1, 5, and 25 have very few removed bins, indicating a more stable deployment. Wards 10, 13, and 14 also have the highest overall bin counts, suggesting these areas may have higher population density or waste generation. Conversely, wards such as 19 and 23 have fewer bins, reflecting lower demand or differing waste management strategies. This variability highlights how bin allocation and maintenance are tailored to the specific needs of each ward.

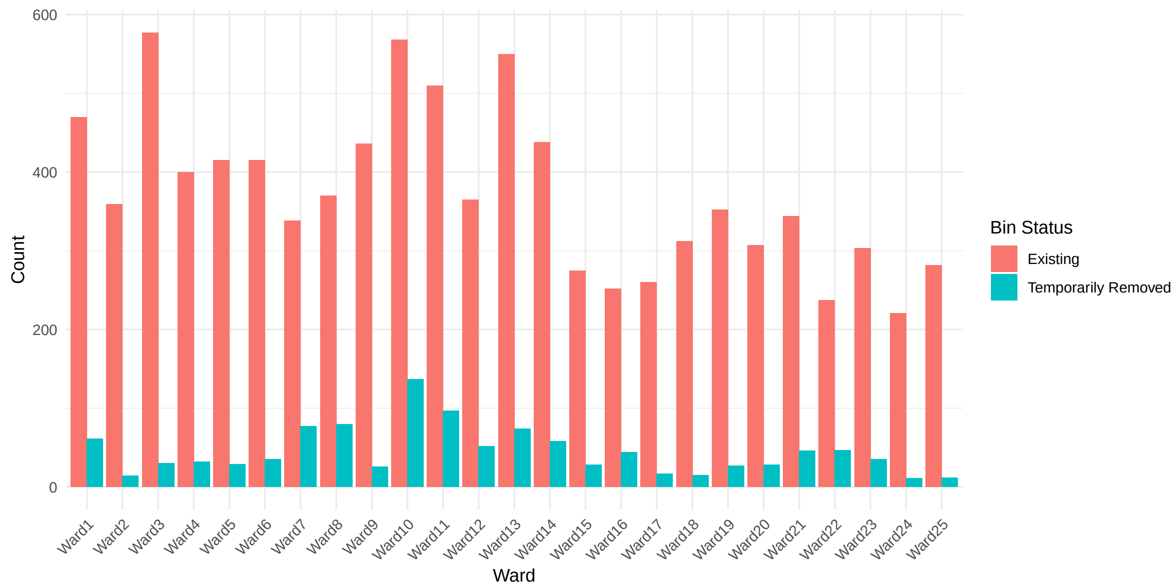

Figure 1: Distribution of Bin Status by Ward

The waste receptacles (WRs) in the dataset are categorized into five asset types, each designed for specific functions and usage scenarios:

- **WR1**: A plastic litter bin with two entry ports—one for litter and one for recycling—supporting basic waste segregation.

- **WR2**: A plastic litter bin with three entry ports, offering expanded recycling options with one for litter and two for recycling.

- **WR3**: A steel litter bin elevated on a concrete pedestal, featuring two entry ports for litter and recycling.

- **WR4**: A steel bin similar to WR3 but with three entry ports—one for litter and two for recycling—accommodating larger waste disposal needs.

- **WR5**: The newest model, featuring larger ports for high-volume waste handling, with two ports for litter and one for recycling, enhancing efficiency.

Figure 2 summarizes the distribution of asset types in the dataset. WR2 is the most prevalent, with over 4,000 bins recorded, followed by WR1, which also constitutes a significant portion of the bins. WR4 ranks third in prevalence, while WR3 has the lowest representation. Notably, WR5 is absent from this figure, likely due to its status as a newer model that may not yet be widely deployed.

Figure 3 examines the distribution of asset types across Toronto's wards, revealing notable deployment patterns. WR2 is the most common type in most wards, suggesting its general suitability for widespread use. WR1 and WR4 show moderate but variable distributions, with some wards having noticeably higher counts. In contrast, WR3 remains consistently low across all wards, indicating its specialized or limited use. These variations suggest that asset type allocation is influenced by factors such as population density, waste generation patterns, or local recycling priorities.

Figure 2: Frequency of Litter Bins by Asset Type across the City

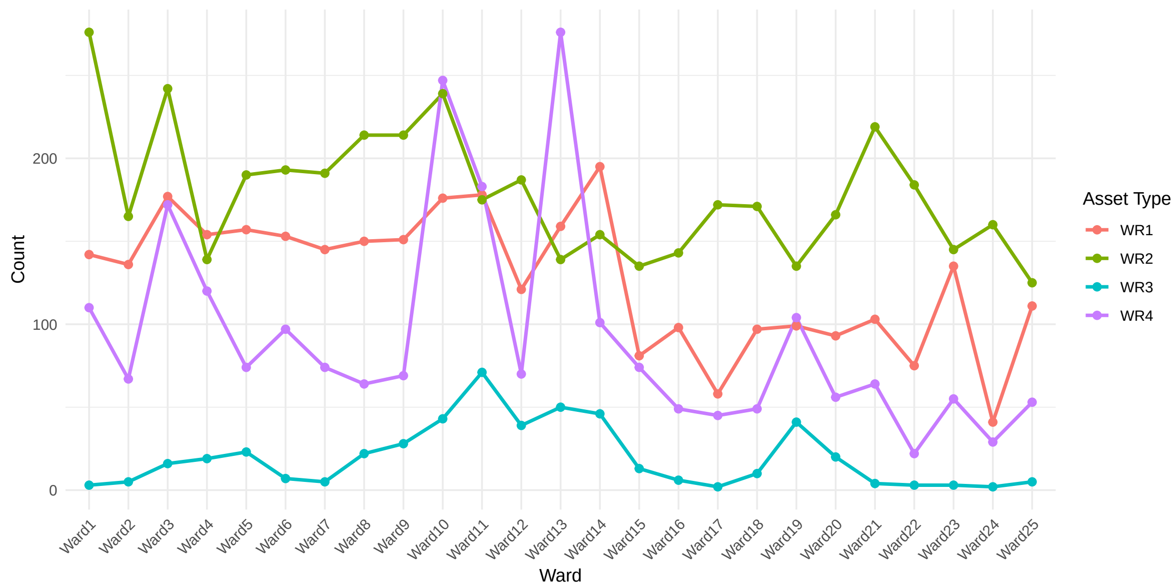

Figure 3: Distribution of Asset Types by Ward

2.4 Ward Profile Data

2.4.1 Age Demographics

The dataset includes age distribution data for Toronto, categorized into age groups (e.g., "0 to 4 years," "15 to 19 years") and organized by ward (refer to Table 2). This information is essential for understanding how population composition influences waste generation, as waste production varies by age due to different consumption patterns. For example, younger age groups may generate more waste from disposable products, while older populations might contribute differently to waste streams. Key variables include total population, specific age groups (e.g., "0 to 4 years" and "65+ years"), and ward identifiers. Differences in age distributions across wards can provide insight into variations in waste types, such as recyclable versus organic materials, emphasizing the need for waste management strategies tailored to demographic profiles.

Figure 4 illustrates population distribution across Toronto's 25 wards, segmented into four age groups: Minors (0–19), Adults (20–39), Middle-Age Adults (40–59), and Senior Adults (60+). The Adult group has the highest population counts in most wards, with a notable peak in Ward 13, likely reflecting a concentration of working-age individuals or young families. The Middle-Age Adult group shows consistent numbers across wards, with minor variations but no significant outliers. The Senior Adult population is evenly distributed across wards, maintaining lower but steady counts compared to younger groups. Minors exhibit consistent trends across wards, though their population is generally smaller than Adults and Middle-Age

Table 2: Sample of Cleaned Age Data

Variable	Minors	Adult	Middle_Age_Adult	Senior_Adult
Ward1	25585	35130	29380	25020
Ward2	23840	27570	32090	33700
Ward3	23620	44935	38605	32760
Ward4	19695	32780	30745	21485
Ward5	24855	32545	32015	26260

Adults. Ward 13 stands out with a significantly larger Adult population, potentially linked to areas with higher-density housing or urban hubs. These variations in age distribution provide context for understanding how demographics influence waste generation, consumption patterns, and service needs across the city.

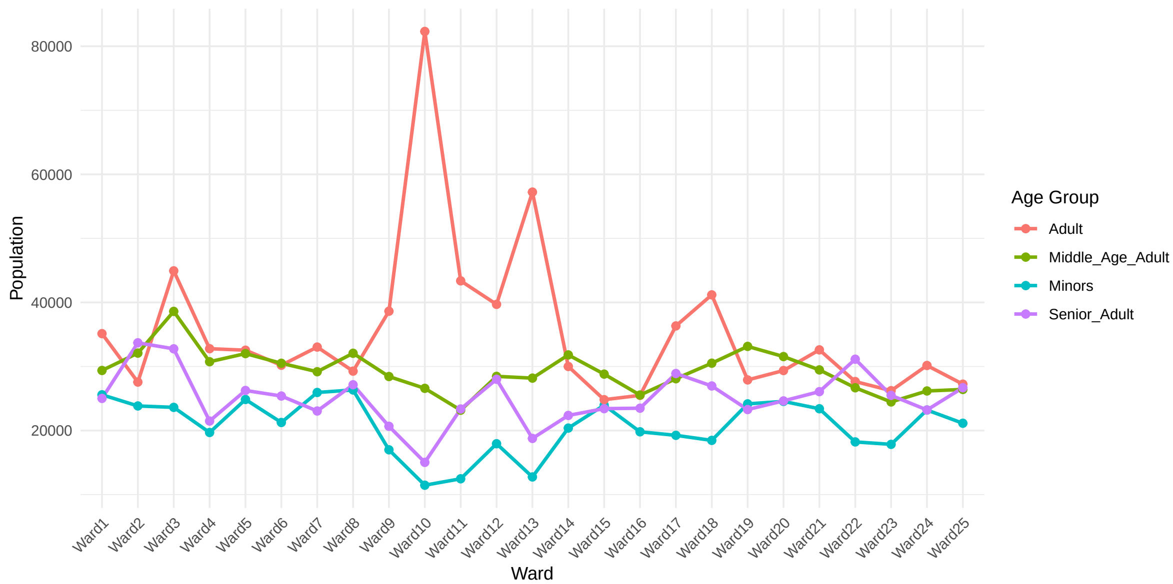

Figure 4: Population Trends Across Wards by Age Group

2.4.2 Dwelling Type

The dataset provides information on housing structures across Toronto's wards (see Table 3), categorized into High-Density Housing (e.g., apartments with five or more storeys), Medium-Density Housing (e.g., row houses, duplexes), Low-Density Housing (e.g., single-detached and semi-detached homes), and Other Types (e.g., movable dwellings or single-attached houses). This categorization helps analyze housing diversity and its potential influence on waste generation. For instance, single-detached and semi-detached homes may produce more organic waste

Table 3: Sample of Cleaned Dwelling Data

[!h]

Variable	Low_Density_Housing	Medium_Density_Housing	High_Density_Housing	Other_Types
Ward1	12695	7435	17995	10
Ward2	22735	2790	19785	25
Ward3	19950	3840	41745	35
Ward4	13070	3295	32995	85
Ward5	16505	3110	25405	35

due to gardens and outdoor spaces, while high-rise apartments are likely to generate more recyclable waste. Key variables include total dwellings, dwelling type categories, and ward identifiers. The distribution of dwelling types across wards offers critical context for designing waste management strategies and resource allocation, as housing types often correlate with unique waste generation patterns and service requirements.

Figure 5 illustrates the distribution of housing types across Toronto's 25 wards. High-Density Housing is the most prevalent, particularly in Ward 13 and Ward 14, reflecting urban centers dominated by apartment buildings. Low-Density Housing is more evenly distributed, with higher proportions in wards such as Ward 15 and Ward 25, indicative of suburban or less densely populated areas. Medium-Density Housing remains consistent across wards with minor variations, while Other Types are minimal and stable citywide.

This distribution underscores how different housing types shape the urban environment and influence waste management. High-density areas typically generate more recyclables, whereas low-density areas may produce higher volumes of organic and mixed waste due to larger properties and gardens. These variations emphasize the need for waste services tailored to local housing patterns.

2.4.3 Household Size

The dataset details the distribution of households by size across Toronto's wards, categorized into three groups (see Table 4): Small Households (1–2 persons), Medium Households (3–4 persons), and Large Households (5 or more persons).

This classification provides insight into how household size influences waste generation and management needs. Small households, often comprising one or two people, may generate more packaging and convenience waste due to individual consumption patterns. Medium and Large households typically produce higher overall waste volumes but less per capita, as resources are shared among members.

Key variables include the total number of households, household size categories, and ward identifiers. Larger households may require additional or larger bins to handle increased waste, while smaller households may benefit from more frequent waste collection. Understanding

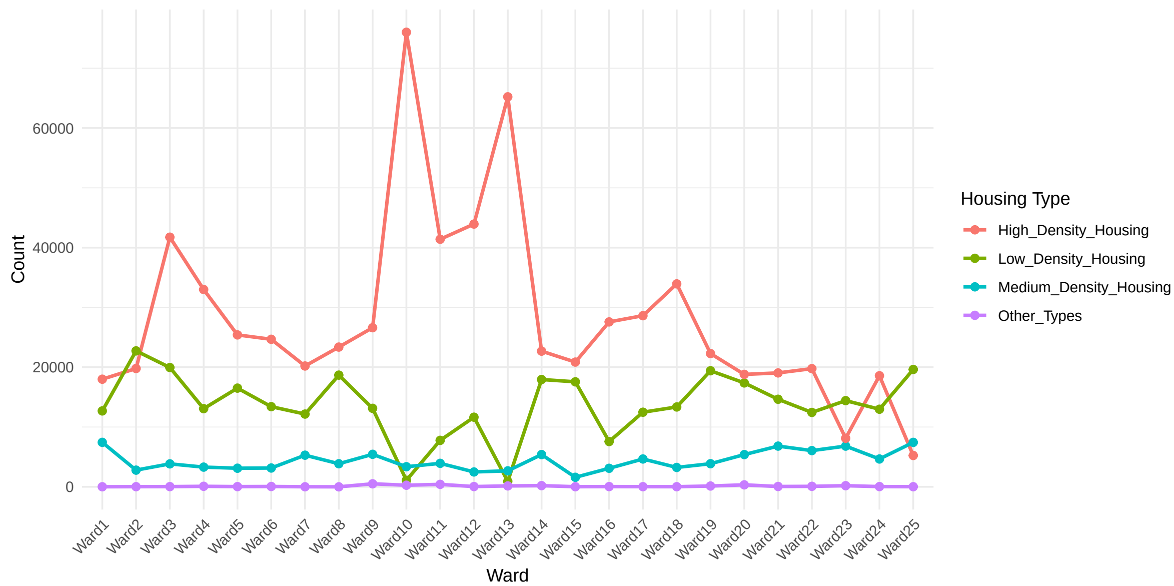

Figure 5: Trends in Housing Types Across Wards

Table 4: Sample of Cleaned Household Size Data

Variable	Small_Households	Medium_Households	Large_Households
Ward1	17425	13920	6795
Ward2	25460	15840	4045
Ward3	46340	16385	2850
Ward4	34805	12475	2165
Ward5	25495	14930	4620

these patterns supports the optimization of waste collection services and resource allocation tailored to household composition across wards.

Figure 6 displays the distribution of household sizes across Toronto's 25 wards, divided into Small Households (1–2 persons), Medium Households (3–4 persons), and Large Households (5 or more persons).

Small households are the most common in all wards, with notably higher counts in Ward 13 and Ward 14, likely reflecting urban areas with a greater prevalence of apartments or smaller housing units. Medium households show relatively consistent numbers across wards, representing stable family-sized living arrangements. Large households, though the least common, are evenly distributed, often corresponding to areas with larger homes suitable for extended or multi-generational families.

The dominance of small households suggests higher per capita waste generation, especially from packaging and convenience items, while medium and large households generate greater overall waste but benefit from resource sharing. These patterns highlight the need for tailored waste collection strategies—such as larger bins in areas with more medium and large households and frequent servicing in wards with a concentration of small households.

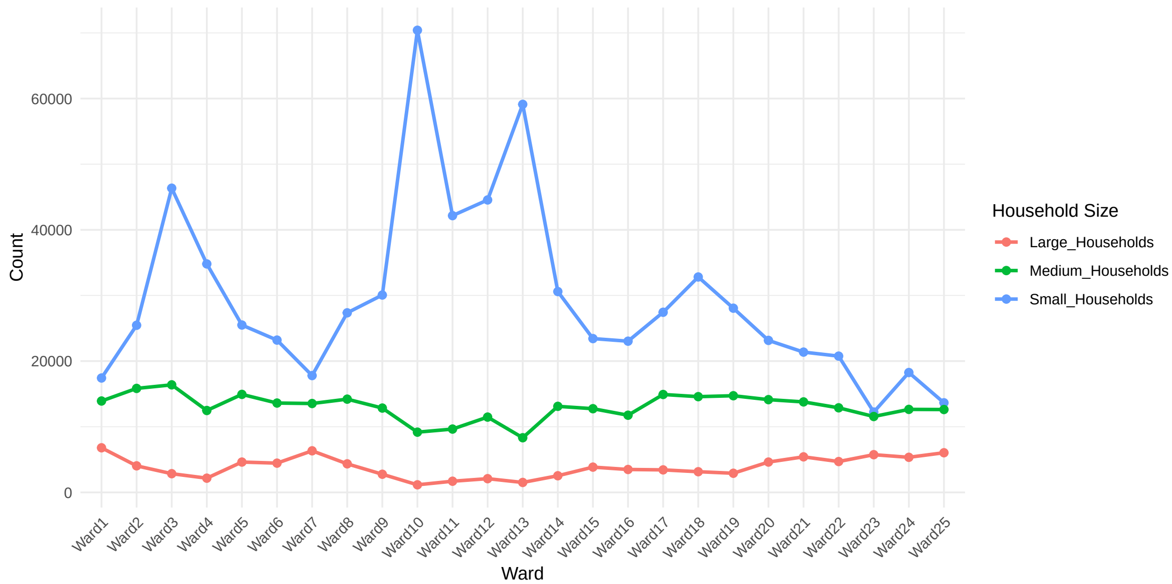

Figure 6: Distribution of Household Sizes by Ward

2.5 Measurement

The litter data were sourced from municipal waste management systems, capturing service frequency, bin asset types, and statuses. Only bins with a status of "existing" are actively serviced, highlighting the operational relevance of this subset. This data reflects the daily functioning of waste collection systems and informs analyses of infrastructure usage and service patterns.

Age demographics data were obtained from census or municipal records, offering detailed population breakdowns by ward. These measurements link demographic factors, such as age distribution, to waste generation trends. Similarly, data on dwelling types and household sizes were derived from housing and census records, providing insight into the physical and social structures within each ward. These variables reveal the influence of housing density and household composition on waste production and service requirements.

Together, these datasets integrate real-world waste management practices with demographic dynamics, forming the foundation for the structured analyses in this study.

3 Model

To predict the binary status of litter bins (STATUS), where 1 represents "Existing" and 0 represents "Not Existing," we use a Bayesian logistic regression model. This method incorporates prior knowledge and accounts for uncertainty, offering a robust framework for making predictions based on the observed data.

The logistic regression model is defined as follows:

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \beta_0 + \beta_1 x_{STATUS} + \beta_2 x_{ASSET.TYPE} + \beta_3 x_{DAYS.SERVICED} + \beta_4 x_{Low.Density.Housing} + \beta_5 x_{High.Density.Housing} \tag{1}$$

In this model:

- STATUS_i represents the binary outcome variable for the i-th observation, where 1 indicates "Existing" and 0 indicates "Not Existing."
- ASSET.TYPE_i is a categorical variable that captures the type of litter bin asset.
- DAYS.SERVICED_i denotes the number of days per week the litter bin is serviced.
- $\text{Low.Density.Housing}_i$, $textMedium.Density.Housing_i$, and $textHigh.Density.Housing_i$ represent the proportions of low-, medium-, and high-density housing in the corresponding ward, respectively.
- β is the intercept term, while β_1, β_2, ..., β_5 are the coefficients corresponding to each predictor.

In Equation 1, each β represents a coefficient estimated through Bayesian regression analysis. The predictors for this model include ASSET.TYPE, DAYS.SERVICED, and housing density variables (Low.Density.Housing, Medium.Density.Housing, and High.Density.Housing). These variables were selected to capture critical dimensions of waste management dynamics. ASSET.TYPE reflects characteristics of litter bins that may influence their operational status. DAYS.SERVICED represents the frequency of maintenance, which likely correlates with a bin's likelihood of remaining operational. Housing density variables account for levels of urbanization, as areas with higher population density often exhibit different waste management requirements and bin usage patterns compared to less dense areas.

After developing the Bayesian logistic regression model, we will use the 'predict()' function from R's rstanarm package (R Core Team 2023) to generate posterior predictions for bin statuses. This approach incorporates uncertainty into the predictions, allowing us to estimate the probability of each litter bin being classified as "Existing" or "Not Existing." These predictions will be analyzed by asset type and servicing frequency, offering practical insights for optimizing waste management strategies.

The regression analysis will be conducted using the 'stan_glm()' function in R (R Core Team 2023), selected for its capability to handle binary outcomes such as the operational status of litter bins. Logistic regression is well-suited to this analysis, given the binary response variable and the anticipated S-shaped relationship between the predictors and the probability of bin existence. The Bayesian framework enhances this approach by incorporating prior knowledge and providing a robust method to quantify uncertainty in parameter estimates and predictions.

The model does have some limitations. The binary outcome restricts the analysis to whether a bin is classified as "Existing" or "Not Existing," without accounting for intermediate states like partial serviceability or variations in operational efficiency. Additionally, the model's accuracy depends on the quality and representativeness of the input data. Unobserved factors, such as policy changes or environmental conditions, are not included, which may affect the generalizability of the findings to other contexts or time periods.

4 Results

4.1 Overview of Coefficients from the Bayesian Logistic Regression Model

The Bayesian logistic regression model was applied to estimate the probability of a litter bin's status as "Existing," based on predictors such as asset type, days serviced, and housing density. The results, summarized in the table and visualization below, include estimated coefficients, standard errors, and 95% credible intervals for each predictor (Table 6).

4.1.1 Key Findings

- **ASSET.TYPE**:
  - Asset Type 3 and Asset Type 4 had significant positive effects on the likelihood of a bin being "Existing."
  - Asset Type 2 showed a slightly negative but non-significant effect.
- **DAYS.SERVICED**:
  - This variable was negatively associated with a bin's status, suggesting that bins serviced more frequently were less likely to remain "Existing."
- **Housing Density**:
  - Low-density housing had a strong positive association with the likelihood of a bin being "Existing."

– Medium-density housing exhibited a small, non-significant negative effect.

– High-density housing had a modest positive effect.

4.1.2 Visualization

Figure 7 depicts the estimated coefficients along with their 95% credible intervals, offering a clear view of the direction and strength of each predictor's influence. This analysis provides actionable insights for understanding how asset characteristics, servicing patterns, and housing contexts impact bin operability.

4.2 Predicted Probabilities

Using the fitted Bayesian model, predicted probabilities for the bins' statuses were calculated to estimate the likelihood of a bin being classified as "Existing" based on its characteristics (refer to Table 5). Bins in low-density housing areas consistently had higher probabilities of being "Existing," indicating a relationship between housing density and bin operability. Bins serviced less frequently were more likely to remain "Existing," suggesting that reduced servicing frequency might correlate with longer operational durability. Bins of Asset Types 3 and 4 were more likely to be "Existing," while bins of Asset Type 2 showed lower predicted probabilities.

While the model performed well overall, some limitations should be noted. Predictions depended on the categorization of asset types, which might oversimplify variability within these groups. Additionally, unobserved factors, such as environmental conditions or policy changes, were not included, which could limit the applicability of the findings to other contexts. Future analyses could address these gaps by including interaction terms or hierarchical modeling to capture ward-level differences and improve model robustness.

This analysis identifies predictors of litter bin statuses and offers a framework for improving waste management strategies. By addressing patterns in servicing frequency and asset type deployment, waste management can be made more efficient and better suited to local conditions.

5 Discussion

5.1 Prediction of Waste Bin Servicing

The predictions in the Table 5, indicate the likelihood of waste bins requiring servicing. Evaluating the model's accuracy is crucial for assessing its reliability. Metrics such as precision,

Table 5: Sample of Predicted Litter Bin Prediction

Ward	ASSET.TYPE	STATUS	Predicted_Probability
Ward4	WR1	1	0.8949138
Ward4	WR4	1	0.9028629
Ward4	WR2	1	0.8558629
Ward4	WR4	1	0.9028629
Ward4	WR1	0	0.8674690

Table 6: Coefficients from the GLM Model

term	estimate	std.error	conf.low	conf.high
(Intercept)	2.15	0.06	2.05	2.24
ASSET.TYPEWR2	-0.10	0.08	-0.22	0.02
ASSET.TYPEWR3	0.46	0.19	0.16	0.77
ASSET.TYPEWR4	0.35	0.09	0.20	0.51
DAYS.SERVICED	-0.26	0.04	-0.32	-0.19
Low_Density_Housing	0.38	0.06	0.28	0.48
Medium_Density_Housing	-0.07	0.04	-0.14	0.00
High_Density_Housing	0.16	0.07	0.05	0.28

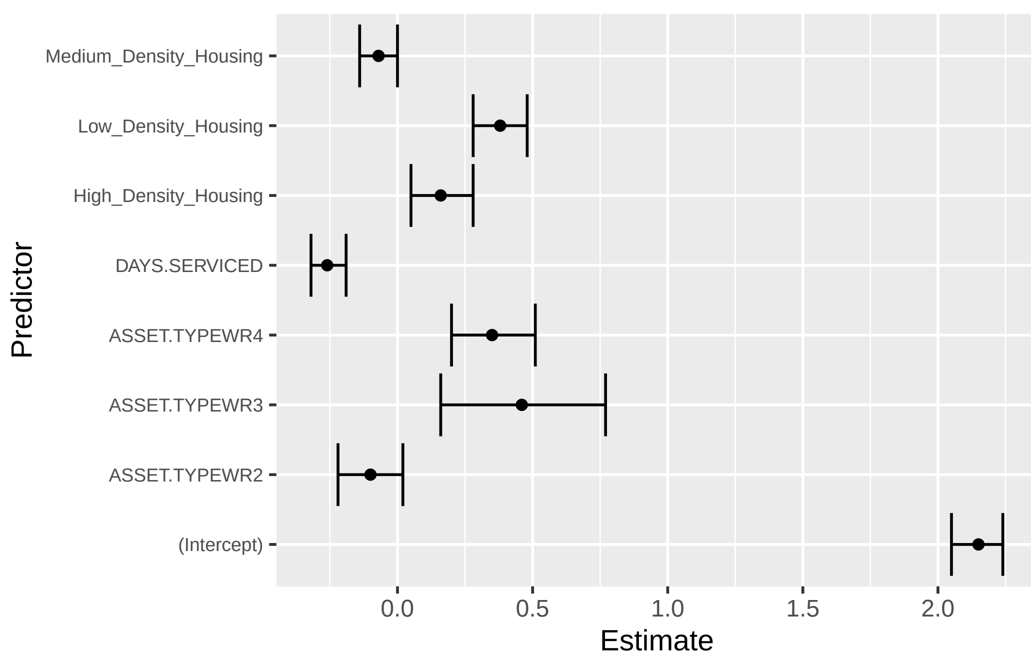

Figure 7: Coefficient Estimates for Predictors

recall, and overall accuracy should be analyzed to identify performance strengths and weaknesses. Attention should also be given to potential systematic biases, such as overestimating servicing needs in certain wards or underestimating them for specific asset types. Additionally, comparing the predicted probabilities with actual servicing outcomes (STATUS) can reveal areas where the model may require refinement, improving its alignment with real-world servicing patterns.

Key predictors influencing these probabilities merit further discussion. Variables such as housing density, household size, and demographic composition play an important role in shaping waste servicing patterns. Understanding how these factors impact the model's predictions can provide valuable context for its decision-making process. This understanding can also guide refinements to the model, ensuring it captures context-specific drivers of waste generation and collection needs.

The operational implications of these predictions are equally important. A reliable model can improve resource allocation by prioritizing bins that truly require servicing, reducing unnecessary efforts and associated costs. This not only enhances efficiency but also improves the overall quality of waste management services, ensuring they better align with the needs of specific areas.

The model's performance should also be evaluated across wards to assess its consistency. Localized conditions, such as differences in population density or ward-specific waste management policies, may influence servicing patterns and affect the accuracy of predictions. Identifying and addressing these discrepancies is essential to ensure that the predictions are both actionable and equitable across all areas. This approach avoids applying a uniform strategy to waste management and instead tailors solutions to the unique needs of each ward.

5.2 Demographic and Housing Influence

Demographic and housing characteristics are key factors in shaping waste generation patterns and servicing requirements. Variables such as Minors, Adults, and Senior Adults offer insights into the population composition of different wards. Areas with higher proportions of specific age groups may display distinct waste generation behaviors. For example, regions with a larger senior population might produce less waste per household compared to areas with larger families or young children. Understanding these demographic patterns can support the development of waste management strategies tailored to the behaviors and needs of specific populations.

The type of housing in a ward—whether low, medium, or high-density—directly influences waste generation and collection needs. High-density areas, often dominated by apartment buildings, tend to have concentrated waste disposal points that may require more frequent servicing. In contrast, low-density residential areas typically generate less concentrated waste but can present logistical challenges due to the greater distances between bins. Examining these patterns is essential for determining whether waste management resources are allocated efficiently and appropriately based on housing type and density.

In addition to understanding waste generation patterns, ensuring equity in servicing is crucial. Spatial disparities in servicing frequency may arise, particularly in areas with varying socio-economic profiles. For example, high-density, lower-income neighborhoods might produce more waste but experience under-servicing due to resource limitations. Addressing these inequities is essential for creating a fair and effective waste management system that meets the needs of all residents, regardless of their location or demographic characteristics.

5.3 Performance Across Asset Types

The ASSET.TYPE variable provides a useful perspective on the performance of different waste bin types in terms of servicing needs. Analyzing the servicing frequency for each asset type can help determine whether certain bins require more frequent collection. For instance, some asset types may be deployed in high-traffic areas, such as commercial zones, leading to higher servicing demands. Understanding these patterns can inform assessments of operational efficiency in asset deployment and identify opportunities for optimizing waste collection strategies.

Asset design and usage significantly influence servicing demands. Certain bin types may struggle to handle the volume or type of waste they encounter, leading to inefficiencies. For example, bins with smaller capacities in high-traffic areas may require frequent emptying, while larger bins in underutilized locations might remain underfilled. Identifying and addressing these mismatches between bin design, placement, and actual usage can optimize bin distribution, improve resource allocation, and reduce servicing costs.

Optimizing asset performance requires data-informed strategies to refine placement and resource allocation. Bins with higher servicing demands may be better suited for replacement with larger or more efficient designs, while underutilized bins can be relocated to areas with greater need. Using insights from the dataset, waste management systems can align asset deployment with actual servicing requirements, enhancing both operational efficiency and service effectiveness.

5.4 Weaknesses and next steps

Despite the strengths of the dataset and analysis, several limitations may affect the insights and practical applications of the findings. Gaps or inaccuracies in the dataset, particularly in the STATUS and Predicted_Probability columns, could indicate inconsistencies in data collection or recording. The absence of key variables, such as weather conditions, waste volume, or nearby commercial activity, limits the understanding of factors influencing waste generation and servicing.

The model may also be biased if certain wards or asset types dominate the dataset, reducing its ability to generalize across all neighborhoods. Additionally, the lack of spatial coordinates or robust time-series data restricts the analysis from capturing precise location-based trends or long-term patterns, both of which are critical for designing and optimizing waste management strategies. Addressing these limitations in future studies could enhance the robustness and applicability of the findings.

To address these limitations, several steps can enhance the analysis's quality and applicability. Expanding the dataset to include variables such as waste volume, commercial activity levels, and real-time updates would provide a more detailed understanding of waste generation and servicing dynamics. Exploring advanced machine learning models, such as Gradient Boosted Trees or neural networks, could improve prediction accuracy, especially when paired with rigorous cross-validation techniques to minimize overfitting and bias.

Integrating geospatial data would allow for precise mapping of servicing patterns, while time-series analysis could identify seasonal or long-term trends. Conducting operational simulations would provide insights into the real-world impact of implementing model-driven recommendations, such as optimizing bin placement or adjusting service schedules. Additionally, an equity-focused evaluation would ensure that high-demand or underserved areas receive adequate resources, promoting fair and effective waste management. Finally, predictive insights can support sustainability initiatives aimed at reducing waste and optimizing resource use, creating a more efficient and environmentally conscious system.

A Appendix

A.1 Diagnostics for model

Figure 8 compares observed data (dark line) with replicated posterior predictions (lighter lines). The close alignment suggests that the model accurately captures the data's central tendency and variability. Figure 9 and Figure 10 show that the sampling algorithm used, the Markov chain Monte Carlo (MCMC) algorithm, did not run into issues as the posterior distribution for the model was created. Using the checks presented by Alexander (2023), both graphs do not show anything abnormal since the trace plots in Figure 9 display substantial horizontal fluctuation across chains, indicating good mixing, while the Rhat values in Figure 10 are close to 1 and well below 1.1, further supporting convergence.

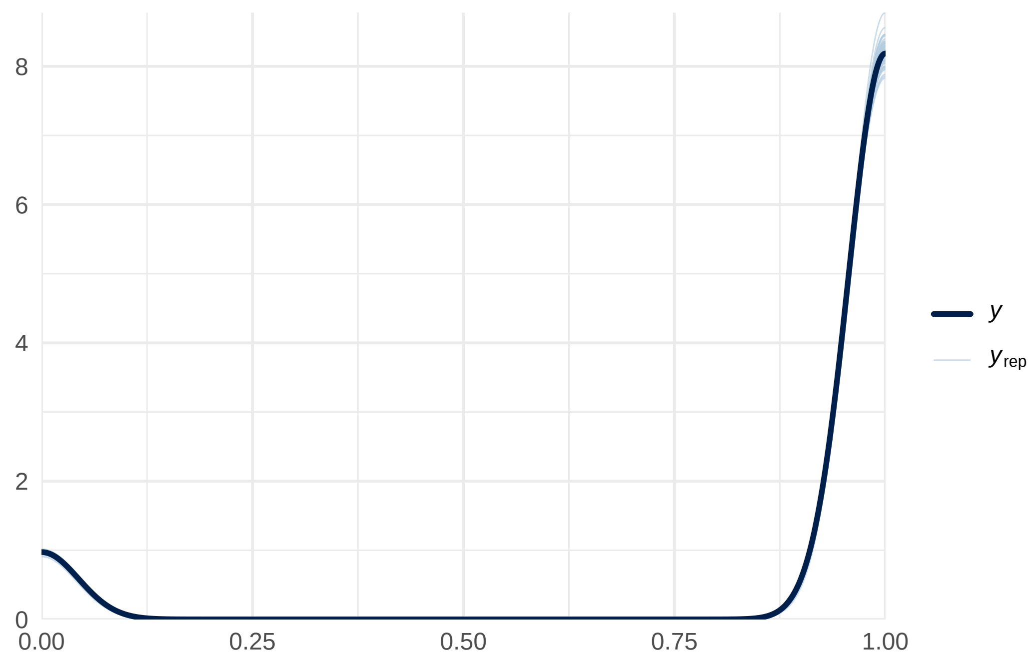

Figure 8: Posterior Predictive Check: Comparison of Observed and Replicated Data

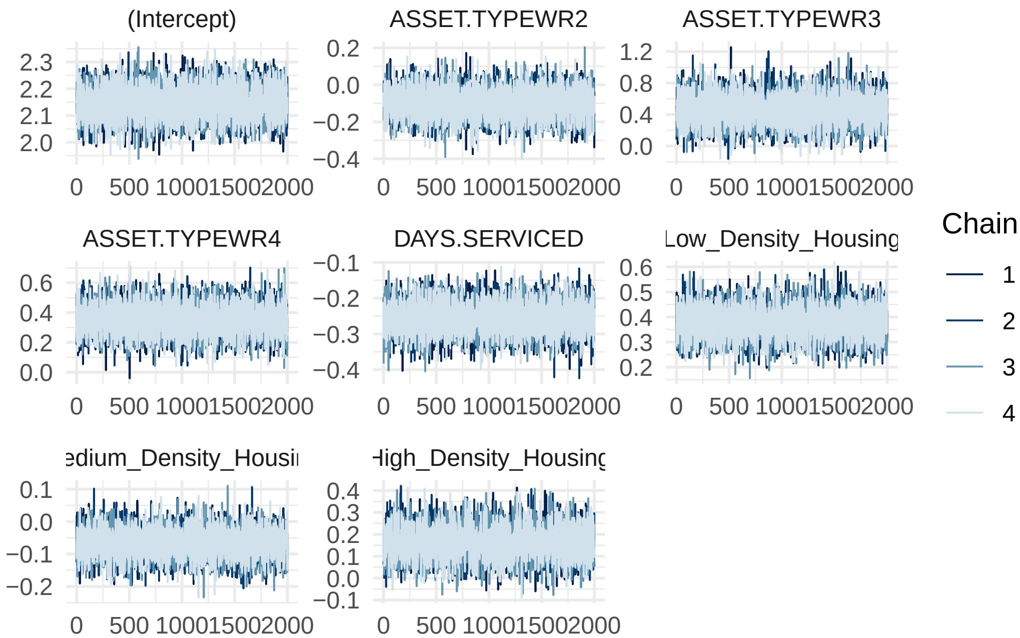

Figure 9: Checking the convergence of the MCMC algorithm - Trace

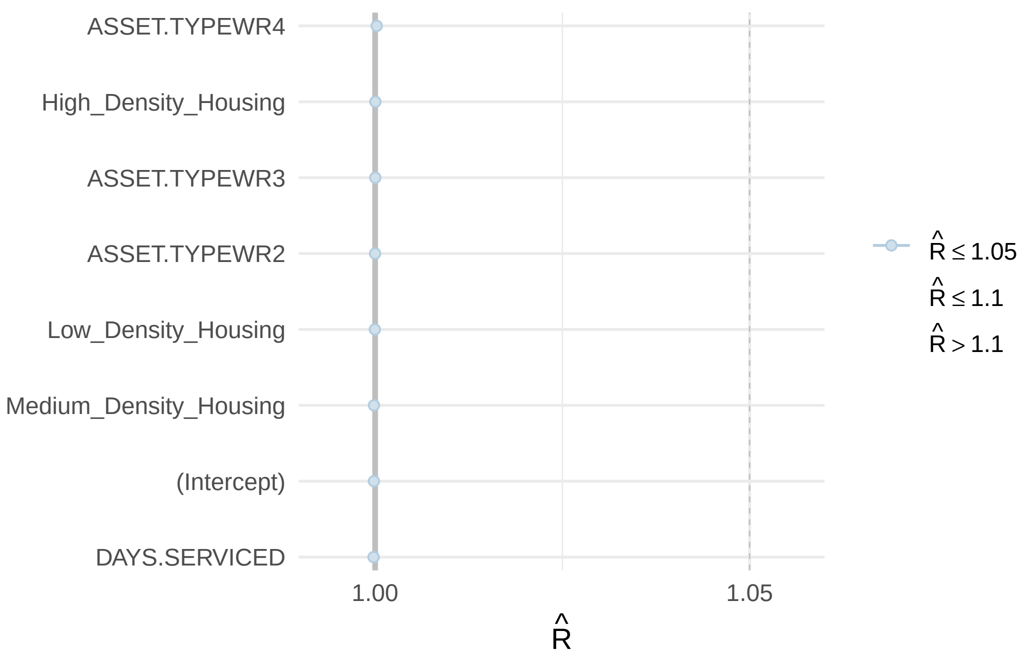

Figure 10: Checking the convergence of the MCMC algorithm - Rhat

A.2 Idealized Survey and Methodology

A.2.1 Survey Design

To thoroughly evaluate waste generation and collection patterns in Toronto, an ideal survey design would integrate primary data collection with observational methods to complement existing datasets. This approach addresses potential data gaps, including individual household contributions, temporal variations, and socio-economic factors. The survey's primary goals are to capture detailed waste generation behaviors across diverse demographic and dwelling groups and to evaluate the alignment of waste collection services with actual waste production.

The target population includes all 25 wards in Toronto, stratified by demographic characteristics (e.g., age distribution, household size) and dwelling types (e.g., low-density, medium-density, and high-density housing). To ensure adequate representation, a stratified random sampling framework will be employed, dividing the population into strata based on these attributes. A minimum of 500 households per ward will be sampled to achieve statistical power and enable detailed trend analysis.

A.2.2 Survey Instrument

The survey will collect data on key metrics, including the type of waste generated (recyclable, organic, landfill) and its weekly volume, alongside demographic variables such as age, household size, income bracket, and dwelling type. It will also gather feedback on current waste collection schedules and services. Furthermore, the survey will explore behavioral factors, such as recycling habits, composting practices, and waste reduction strategies. This approach is designed to provide a detailed understanding of waste management practices at the household level.

A.2.3 Observational Data Collection

To supplement survey data, direct observational methods will be utilized. Trained enumerators will conduct weekly assessments in sampled neighborhoods, recording waste bin fullness and instances of mismanagement. Additionally, pilot testing of IoT sensors in high-density wards will provide real-time data on bin utilization rates and waste segregation. This approach offers objective insights into waste collection and generation patterns, enhancing the analysis with precise, up-to-date information.

A.2.4 Simulation for Optimal Sampling

A simulation framework will be designed to assess the effectiveness of different sampling strategies, such as simple random sampling versus stratified sampling. The evaluation will focus on key metrics, including bias and variance in waste volume estimates, to determine the most reliable approach. The simulation will be implemented in R, utilizing the `survey` (Lumley 2023) and `sampling` (Tillé and Matei 2023) packages to ensure methodological rigor and accuracy.

A.2.5 Data Linkages and Validation

Survey data will be cross-validated with municipal records to ensure consistency and to address gaps, especially in wards with outdated or incomplete information. The findings will be contextualized within the framework of existing literature on urban waste management and demographic influences, ensuring that observed trends are consistent with established theoretical and empirical insights.

A.2.6 Anticipated Challenges

Two primary challenges are anticipated. First, non-response bias may occur if certain households, particularly in low-income areas, are less willing to participate, leading to demographic skewness in the data. Second, seasonal variations in waste generation could necessitate longitudinal follow-ups to capture trends throughout the year. These challenges will be mitigated through strategic planning, such as targeted outreach to increase participation in underrepresented areas, and adjustments to data collection protocols to ensure temporal coverage.

A.2.7 Contribution to Measurement Validity

This combined survey and observational framework strengthens the study by integrating detailed household-level insights with broader observational data. It creates a robust foundation for validating predictive models developed in the main analysis, ensuring alignment between theoretical estimates and real-world dynamics. By addressing gaps in the existing data, this approach offers a more accurate understanding of waste generation and collection patterns in Toronto.

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