Structural Insights 2023: A Linear Analysis of Apartment Age and Safety Scores in Toronto*

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This study harnesses a dataset from the Toronto Open Data portal, comprising 1,758 records of apartment evaluations, to analyze the correlation between building age and safety scores. Employing a linear regression model, we discovered a significant inverse relationship, highlighting that older buildings tend to have lower safety evaluations. The findings suggest a need for policy reform, particularly in the maintenance and inspection of Toronto's aging residential infrastructure. Despite the study's focus on building age, further research considering additional variables could offer a more comprehensive understanding of factors influencing building safety.

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*Code and data supporting this analysis are available at https://github.com/TEJMaster/Toronto-Building-Safety-Analysis-2023

1 Introduction

The structural integrity of urban buildings is always the topmost concern for city planners, policymakers, and residents alike. The tragic collapse of a condominium in South Florida in June 2021, which resulted in 98 casualties, serves as a reminder of the potential consequences of neglecting building maintenance and inspections (Anderson 2021). This event highlights a critical gap in our understanding of the factors contributing to urban residential structures' safety and lifespan. In light of this, our study aims to investigate the relationship between building age and evaluation scores in the context of Toronto's apartment buildings.

Our study's estimand is the effect of building age on evaluation scores in Toronto. We investigate how the age of buildings influences their assigned evaluation scores, reflecting their compliance with safety standards and overall condition. Utilizing a dataset from the Toronto Open Data portal (Toronto 2023a), which includes 1,758 records, we apply a simple linear regression model to forecast evaluation scores for Toronto residences in 2023. By conducting this analysis, we aim to quantify the impact of building age on evaluation scores and understand its implications for urban housing safety and maintenance.

The analysis reveals a statistically significant inverse relationship between building age and evaluation score, indicating that older buildings tend to receive lower evaluation scores. This finding highlights the critical need for regular inspections and maintenance to preserve the safety and habitability of aging buildings. It also suggests that policies should prioritize maintaining and inspecting older structures to prevent potential safety hazards.

Moreover, our study offers insights into urban development and maintenance, suggesting that policymakers might need to revisit regulations surrounding building inspections and maintenance schedules. It further emphasizes the importance of continuous monitoring and evaluation by urban authorities to maintain and enhance housing standards across the city. These insights carry substantial implications for urban planning and public safety, underscoring the necessity of proactive measures to mitigate risks associated with aging infrastructure. In conclusion, this paper significantly advances our understanding of the relationship between building age and evaluation scores, underlining the importance of proactive strategies to ensure the safety and integrity of the urban housing stock.

The remainder of this paper is structured as follows: Section 2 (Data) details the raw data and the cleaning process and provides an overview of the data distribution. Section 3 (Model) describes the linear model employed to predict the building evaluation score based on the building's age. Section 4 (Results) presents the linear model coefficients, analyses the residuals, and includes a plot illustrating the linear model applied to the analysis dataset. Finally, Section 5 (Discussion) discusses the limitations of the analysis and suggests potential insights for future research.

2 Data

2.1 Raw Data

In this research, we examine apartment data sourced using the opendatatoronto package (Toronto 2023a). The dataset encompasses 1,758 records (1,748 records after cleaning), focusing on specific variables: the ward of each apartment, its evaluation score, and the construction year. The data covers evaluations across Toronto's 25 wards, with scores varying between a minimum of 0 and some achieving the maximum score of 100. The study includes apartments that are over three stories in height and contain at least 10 units. These apartments span a wide range of construction years, from as early as 1805 to as recent as 2023. For the description of the data cleaning process and data validation checks performed, please refer to Section 6 (Appendix).

All the apartments in this dataset adhere to the City's Apartment Building Standards bylaw, which is designed to safeguard the interests and safety of both landlords and tenants by mandating these evaluations. Although we have access to the building evaluation datasets from previous years, we chose to analyze the most recent data to ensure our study reflects the current state of apartment building scores in Toronto. This approach allows us to provide up-to-date insights into the relationship between building age and evaluation scores, which is critical for informing policy and maintenance practices in the city.

2.2 Data Analysis Tools

The data analysis was performed using R (R Core Team 2022), a powerful open-source statistical programming language. A suite of packages from the tidyverse (Wickham et al. 2019), an assemblage of R packages designed for data science, was harnessed to enhance the efficiency of our data operations. The `ggplot2` package (Wickham 2016) facilitated the creation of sophisticated visualizations, while `dplyr` (Wickham et al. 2022) provided a grammar of data manipulation, offering a coherent set of verbs that help in filtering, summarizing, and arranging the dataset. The `readr` package (Wickham, Hester, and Bryan 2022) was utilized for its fast and friendly data reading capabilities. Navigation and file path management were streamlined using the `here` package (Müller 2020), simplifying the process of file referencing within the project's directory structure. Report generation was dynamically handled by knitr (Xie 2014), enabling the integration of R code within this document. Additionally, `kableExtra`(Zhu 2021) was employed to produce aesthetically pleasing and customizable tables, enriching the presentation of our results. For the Bayesian analysis, rstanarm (Goodrich et al. 2020) was utilized to create a linear model, providing an elegant interface to Stan, a state-of-the-art platform for statistical modelling and high-performance statistical computation. This package enabled us to estimate the relationship between building age and safety evaluation scores using a Bayesian framework.

2.3 Variable Description

CURRENT BUILDING EVAL SCORE: The Current Building Evaluation Score represents a measure of a building's adherence to property standards. This score is derived by summing two components: the current reactive score, which reflects the compliance based on any outstanding Orders and Notices of Violations, and the proactive building score, which is based on the most recent comprehensive evaluation of the building (Toronto 2023b).

YEAR BUILT: This indicates the year when the building was initially constructed, sourced from Building Owners/Managers.

YEAR EVALUATED: This denotes the year in which the building underwent evaluation, reflecting its condition and performance.

AGE: In this research, neither YEAR BUILT nor YEAR EVALUATED was used directly, we have generated a new variable called AGE which use YEAR EVALUATED minus YEAR BUILT.

2.4 Sample of Cleaned Building Evaluation Data

Table 1: Sample of Building Evaluation Data

Building ID	Age (Years)	Evaluation Score
1	62	86
2	44	94
3	54	78
4	73	89
5	54	99
6	53	99

Table 1 represents a subset of the larger building evaluation data. Each row corresponds to a unique building identified by X_id. The AGE column indicates the age of the building in years, while the CURRENT.BUILDING.EVAL.SCORE column shows the building's current evaluation score on a scale from 0 to 100, with higher scores indicating better compliance with safety standards.

2.5 Measurement:

In this study, we utilized data from the City of Toronto's RentSafeTO program, accessed through the "opendatatoronto" package (Toronto 2023a). The RentSafeTO program, initiated in 2017, aims to ensure that apartment buildings with at least three stories or 10 units meet essential safety and maintenance standards. This program is crucial for enhancing resident living conditions and extending the longevity of buildings in Toronto (Toronto 2024).

The RentSafeTO program involves regular evaluations conducted by Bylaw Enforcement Officers, who assess various aspects of buildings, including common areas, mechanical and security systems, and exteriors. In 2023, the evaluation process was updated to require biennial evaluations, expand the assessment categories to 50, and introduce a scoring system ranging from zero to three. This updated process addresses previous challenges in evaluations and non-applicabilities, providing a more comprehensive and nuanced understanding of building conditions.

The dataset resulting from these evaluations offers valuable insights into the dynamics of building aging within Toronto's regulatory and maintenance framework. It is beneficial for researchers and analysts looking to investigate temporal trends and the impact of the post-2023 enhancements on building safety and maintenance standards.

To prepare the dataset for analysis, we made several adjustments, including the introduction of a new variable, "AGE," which represents the age of the building and serves as the sole predictor in our simple linear regression analysis. We also excluded observations with missing values to ensure the completeness of our dataset. Detailed variable descriptions can be found at Section 2.3.

2.6 Data Exploration:

2.6.1 Data Summary

Table 2: Summary Statistics for the Cleaned Dataset

Count	Mean Age (Years)	SD of Age (Years)	Mean Score	SD of Score
1748	60.644	19.939	87.504	8.693

Table 2 presents a concise overview of the key descriptive metrics for the age of buildings and their evaluation scores within the dataset:

- **Count**: The analysis dataset encompasses a total of 1,748 buildings, indicating a robust sample size for statistical analysis.
- **Mean Age**: The average age of the buildings is approximately 60.644 years, suggesting that the dataset primarily includes buildings that have been standing for over half a century.
- **Standard Deviation of Age**: With a standard deviation of about 19.939 years, there is considerable variability in the ages of the buildings. This range implies a diverse sample, encompassing both relatively new constructions and much older structures.

- **Mean Score**: The average building evaluation score is approximately 87.504 on a scale from 0 to 100. A higher score corresponds to better adherence to safety and maintenance standards, suggesting that the buildings in this dataset are generally well-maintained.
- **Standard Deviation of Score**: The standard deviation of approximately 8.693 for the evaluation scores indicates that while scores are clustered around a high mean, there is still notable variability, reflecting differences in the condition or compliance of the buildings.

These statistics offer a snapshot of the dataset's characteristics, providing foundational insights for further analysis regarding the state of building safety and integrity in the population studied.

2.6.2 Age Distribution

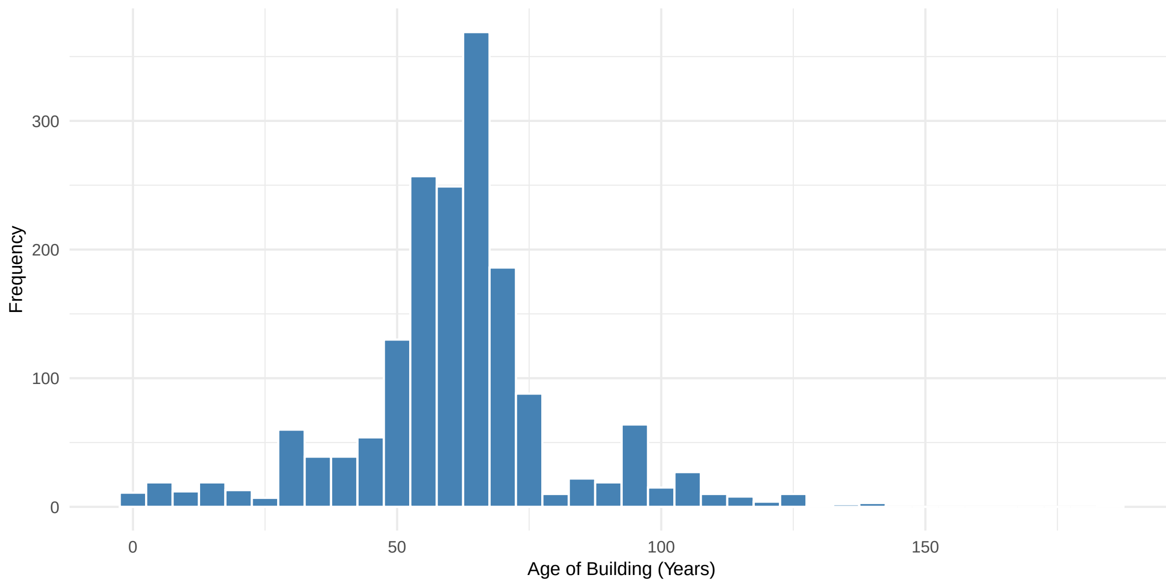

Figure 1: Distribution of building's age for the cleaned data set

Figure 1 illustrates the frequency distribution of the ages of buildings within the dataset. The x-axis represents the age of the buildings in years, while the y-axis shows the frequency of buildings within each age range. The distribution appears unimodal, with a peak around the 60-year mark, indicating that a substantial number of the buildings within this dataset were constructed more than half a century ago. Following this peak, the frequency gradually decreases, showing that fewer and fewer buildings exist beyond this age. The distribution suggests a relatively young building population, with ages concentrated below 100 years and very few buildings reaching beyond 120 years of age. This visualization aids in understanding the age profile of buildings under consideration for safety evaluation scoring.

2.6.3 Score Distribution

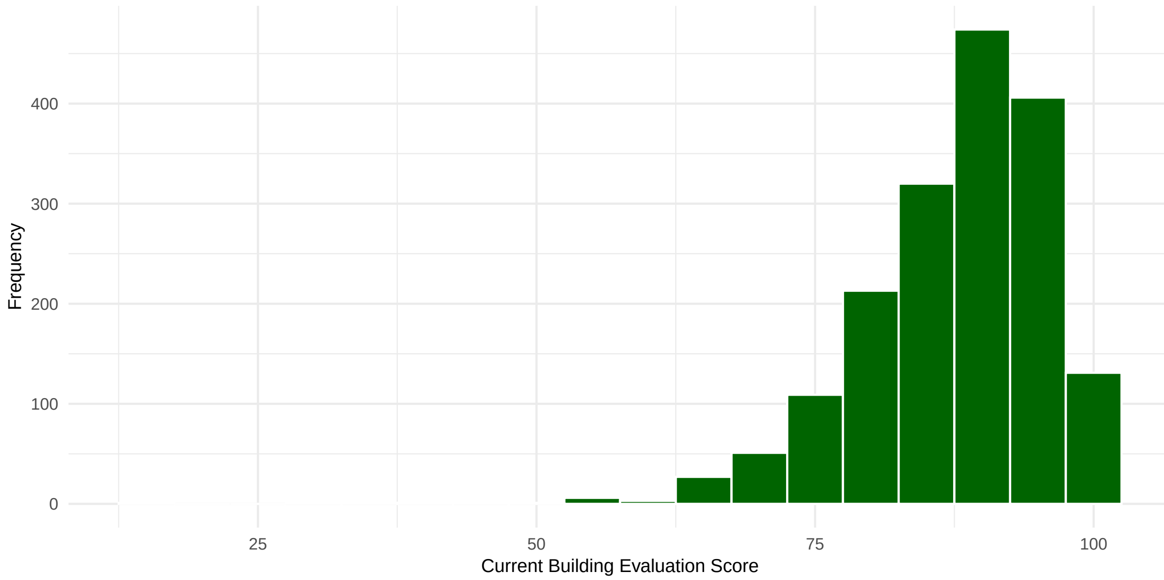

Figure 2: Distribution of building's evaluation score for the cleaned data set

Figure 2 showcases the distribution of building evaluation scores. The x-axis represents the scores assigned to buildings, ranging from 0 to 100, with the y-axis displaying the frequency of buildings for each score interval. The chart reveals a concentration of high evaluation scores, suggesting that many of the buildings in the dataset are rated as in good or excellent condition according to the evaluation criteria. The tallest bars are clustered towards the higher end of the score range, indicating that buildings with scores close to 100 are prevalent. This positive skew in the distribution might reflect effective building standards and maintenance practices in place. The scores' spread and frequency can offer insights into the overall health of the evaluated buildings, influencing urban planning and policy development.

3 Model

The objective of our model is dual: to discern the relationship between building age and safety evaluation scores and to quantify this relationship's strength and direction. The study utilizes a simple linear regression model to analyze the dataset obtained from the Toronto Open Data portal. Additional details and diagnostics for this model are included in Section 6.3.

3.1 Model set-up

Let y_i represent the safety evaluation score for each building. The building's age is denoted by x_i.The model is defined as follows:

$$y_i|\mu_i, \sigma \sim \text{Normal}(\mu_i, \sigma) \tag{1}$$
$$\mu_i = \beta_0 + \beta_1 \times x_i \tag{2}$$
$$\beta_0 \sim \text{Normal}(90, 10) \tag{3}$$
$$\beta_1 \sim \text{Normal}(-0.1, 0.05) \tag{4}$$
$$\sigma \sim \text{Exponential}(1) \tag{5}$$

The model is implemented in R using the `rstanarm` package, which allows us to incorporate prior beliefs about the parameters and to estimate the posterior distributions. For the intercept β_0 and slope β_1, we choose normal prior distributions centered around our initial estimates based on exploratory data analysis (Section 2.6). The `stan_glm` function from `rstanarm` is utilized to carry out the Bayesian regression, providing a framework for inference that incorporates both the data and our prior knowledge.

The priors are chosen to reflect reasonable beliefs about the parameters before observing the data. The intercept prior reflects an expectation that a new building will have a high safety score of around 90, with a widespread to accommodate uncertainty. Similarly, the slope prior indicates an expected small negative impact of age on the safety score, acknowledging some uncertainty in the precise effect. The standard deviation σ is given an exponential prior with a rate of 1, reflecting a belief in the likelihood of smaller variability in evaluation scores. The `stan_glm` function combines these priors with the data to estimate the posterior distributions of the model parameters.

3.2 Model justification

We hypothesize that the coefficient for building age (β_1) will be negative, reflecting the tendency for older buildings to exhibit lower safety scores. This expectation is rooted in the general understanding that buildings can deteriorate over time due to wear, aging materials, and possible obsolescence in older construction methods. The intercept (β_0), representing the baseline evaluation score for a new building, is presumed to be relatively high, indicating the score a building would receive if it were built in the current period with modern standards. The slope (β_1) is particularly interesting, as it encapsulates the average annual decline in evaluation score attributable to aging. The Bayesian framework allows us to incorporate these hypotheses as priors in our model, aligning the analysis with our substantive expectations and providing a more nuanced interpretation of the data.

4 Result

4.1 Model Coefficients Interpretation

Table 3: Summary Statistics for the Coefficients of the Linear Model

Term	Estimate
Intercept	93.607
Slope	-0.100

Table 3 provides two key coefficients to understand the relationship between building age and the evaluation score:

Intercept (β_0):
The model's intercept, β_0, has an estimate of 93.607. This represents the baseline evaluation score for a hypothetical newly constructed building. The intercept suggests that if a building were constructed in the year for evaluation, its expected evaluation score would be around 93.607, assuming all other factors remain constant.

Slope (β_1):
The slope parameter, β_1, has an estimate of -0.100. This indicates that, on average, the evaluation score is expected to decrease by approximately 0.100 points for each additional year of a building's age. This negative value suggests a trend where older buildings tend to have lower evaluation scores compared to newer ones.

Interpretation: The analysis suggests a negative relationship between building age and evaluation score. The estimates indicate that newer buildings tend to have higher evaluation scores, which decrease as buildings age. This trend highlights the importance of age as a factor in building evaluations and underscores the need for ongoing maintenance and updates to preserve building safety and integrity over time.

4.2 Model Equation

$$y_i = 93.607 - 0.100x_i + \varepsilon_i \tag{6}$$

The above model equation serves as a predictive tool, estimating a building's evaluation score based on its age. In this equation, y_i is the estimated evaluation score, x_i represents the age of the building, and ε_i captures the residual effect—factors influencing the score that is not explained by the building's age. This implies that scores can differ among buildings of similar ages based on variables like maintenance quality, renovations, or compliance with updated building codes. The equation recognizes that while age is a significant predictor, the complexity of real-world conditions means there's always an element of variability unexplained by age alone.

4.3 Analysis of Residuals

Table 4: Summary Statistics for the Residuals of the Bayesian Linear Model

Residual Statistics	Value
Min	-69.676
1st Qu.	-4.377
Median	1.705
Mean	-0.012
3rd Qu.	5.821
Max	15.835

1. Minimum Residual: The minimum residual is approximately -69.676, indicating that there is at least one building for which the model's predicted evaluation score was lower than the actual score by approximately 69.676 points. This could be an outlier or a building with exceptional characteristics not captured by the model.

2. First Quartile Residual: The first quartile (Q1) of the residuals is approximately -4.377, meaning that 25% of the buildings have evaluation scores that are less than 4.377 points below the model's prediction for their age.

3. Median Residual: The median residual is approximately 1.705, suggesting a slight positive bias in the model's predictions, as the median of the error distribution is above zero. This indicates that, on average, the model tends to slightly overestimate the evaluation scores.

4. Third Quartile Residual: The third quartile (Q3) is approximately 5.821, indicating that 75% of the buildings have evaluation scores within 5.821 points of the model's predictions or better. This shows that the model provides reasonably accurate predictions for the majority of buildings.

5. Maximum Residual: The maximum residual is approximately 15.835, suggesting that there is at least one building for which the model's predicted evaluation score was higher than the actual score by approximately 15.835 points. This could be another outlier or a building that performed exceptionally well.

Interpretation: The residuals provide insights into the model's fit and the distribution of errors. The presence of outliers and the distribution's slight asymmetry warrant further investigation. It's crucial to assess the model's assumptions, such as linearity, homoscedasticity, and normality of residuals, to ensure the validity of the statistical inferences made from the model. Understanding the reasons behind significant deviations can help improve the model and provide more accurate predictions.

4.4 Plot for the linear model

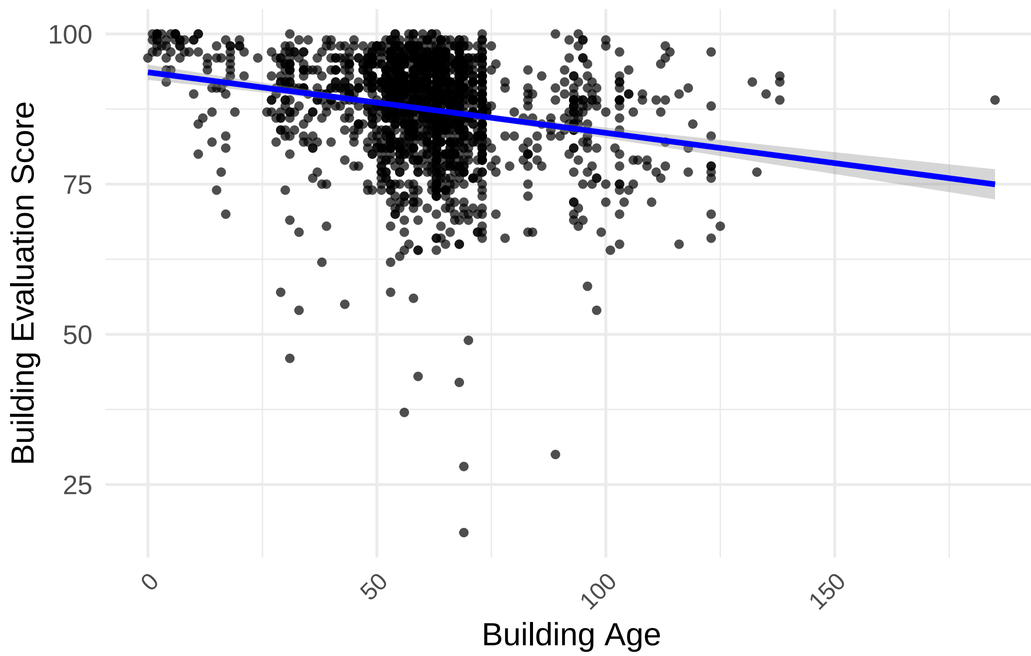

Figure 3: plot for the linear relationship between building age and evaluation score

Figure 3 provides a clear visual relationship between the age of buildings and their evaluation scores. Displayed with building age on the x-axis and evaluation score on the y-axis, the data points represent individual apartment buildings. The blue line running through the cluster of points represents the linear regression line, which captures the average effect of age on the evaluation score. Noticeably, the slope of the line is downward, suggesting a negative correlation; as the buildings get older, their evaluation scores tend to decrease. This trend is consistent across the dataset, indicating a general decline in scores as building age increases, a reflection of the typical effects of wear and time on building integrity.

The plot also reveals that while younger buildings cluster more densely around higher evaluation scores, older buildings exhibit a wider spread of scores. This variation suggests that other factors may influence the condition and safety of older buildings, which are not captured solely by age. The plot does not show any clear pattern or funnel shape in the residuals, indicating that the variance of the evaluation scores is fairly consistent across the range of building ages, and the assumption of homoscedasticity is not visibly violated. Nonetheless, the model's findings imply the importance of consistent maintenance and updates to older buildings to ensure safety standards are upheld over time.

5 Discussion

5.1 Summary of Findings

This study aimed to understand the relationship between the age of apartment buildings in Toronto and their safety evaluation scores. Leveraging a dataset of 1,758 records from the Toronto Open Data portal, we employed simple linear regression analysis to unearth a significant inverse correlation between building age and safety scores. Specifically, our findings indicate that older buildings in Toronto tend to receive lower safety evaluation scores. This observation underscores the potential risks associated with aging infrastructure, aligning with the broader building safety and maintenance literature.

5.2 Insights into Building Safety

Our analysis brings to light a critical insight into the urban infrastructure landscape: the aging of buildings could be a ticking time bomb if not properly managed. The negative correlation between building age and evaluation scores signals that older buildings may need to meet current safety and maintenance standards compared to newer constructions. This poses a significant challenge for city planners, policymakers, and building owners alike, emphasizing the need for regular inspections, maintenance, and renovations to ensure that these structures remain safe for occupancy.

5.3 Policy Implications

The findings of this study have profound implications for public policy and regulatory frameworks. They suggest a need for revisiting and possibly tightening regulations concerning building inspections and maintenance, especially for older structures. Moreover, the results could inform the development of targeted policies that prioritize interventions in older buildings, potentially including incentives for owners to upgrade and maintain their properties to meet current safety standards. Implementing such policies could significantly reduce the risks associated with structural failures, thereby enhancing urban safety and resilience.

5.4 Limitations and Areas for Improvement

While our study provides valuable insights, it is not without limitations. The primary focus on building age as the sole predictor of safety scores overlooks other potential factors that might influence these scores, such as the materials used in construction, the building's design, and the history of renovations and repairs. Additionally, the linear regression model, though powerful in detecting linear relationships, may not capture non-linear dynamics that could be present between building age and safety scores.

Future research should consider incorporating more variables into the analysis to capture a broader spectrum of factors influencing building safety. Moreover, employing more complex models, such as multivariate regression or machine learning algorithms, could unveil more nuanced relationships and provide a more comprehensive understanding of what determines building safety scores.

In addition to the previously mentioned limitations, the study examining the correlation between the age of apartment buildings in Toronto and their safety evaluation scores may face further constraints due to various factors. One significant issue is sampling bias, where the dataset might not uniformly represent all building types, particularly if it disproportionately includes certain structures (such as residential over commercial) or concentrates on specific locales within Toronto, potentially leading to skewed outcomes. Another concern is data quality issues stemming from the Toronto Open Data portal, which could feature outdated records, missing details, or errors in data recording, thereby affecting the analysis's accuracy and dependability. The voluntary nature of surveys or reporting mechanisms used to collect data on building safety evaluations could also introduce bias, as buildings with higher safety scores might be more inclined to report than those with lower scores, possibly distorting the results.

5.5 Sources of Bias

One potential source of bias in our analysis stems from the nature of the evaluation scores. These scores are determined by human evaluators, which introduces a subjective element to the assessment. Consequently, the scores might not accurately reflect the actual condition of a building. Factors such as the evaluator's experience, training, and mood on the day of the evaluation can influence the scores assigned. Furthermore, inconsistencies in evaluation criteria or their application across different evaluators or buildings could lead to variability in scores unrelated to the actual condition of the buildings. This subjectivity and potential for inconsistency can introduce bias into our analysis, as the evaluation scores may not perfectly represent a building's safety and maintenance standards. It is essential to consider these limitations when interpreting the results of our study and to approach the findings with caution.

5.6 Comparion with Similar Studies

To compare our results with similar studies, we looked at the findings from a study conducted by Matthew Wankiewicz titled "Apartment Age is a Strong Predictor for Overall Quality" Wankiewicz, 2020 (Wankiewicz 2020). In this study, Wankiewicz explored the impact of apartment age on the scores assigned by the City of Toronto. Similar to our findings, Wankiewicz's analysis revealed a strong and linear relationship between the age of apartments and their evaluation scores, with older apartments tending to score lower. This supports our conclusion that the age of a building is a significant predictor of its evaluation score.

5.7 Looking Forward: Beyond Age

This study marks a starting point in the exploration of factors influencing building safety in Toronto. As we move forward, it is crucial to broaden our analytical lens to include a wider array of variables that could affect building safety. Investigating the role of renovation histories, compliance with evolving building codes, and the impact of environmental factors such as climate change could enrich our understanding. Additionally, comparative studies across different cities or countries could reveal interesting insights into how various regulatory frameworks and building practices impact safety outcomes.

Ultimately, enhancing building safety is a complex challenge that requires a multifaceted approach, combining rigorous research, policy innovation, and community engagement. Our study contributes to this ongoing conversation, highlighting the urgency of addressing the risks associated with aging urban infrastructures. As we look to the future, let us draw upon the lessons learned from this research to build safer, more resilient communities for all.

6 Appendix

6.1 Data Cleaning

The data cleaning process involved several key steps to prepare the building evaluation dataset for analysis. Initially, the dataset was loaded into a data frame, and entries with missing values in the YEAR.BUILT and YEAR.EVALUATED columns were removed to ensure the accuracy of subsequent calculations. This step was essential to maintain the integrity of the dataset. Next, the age of each building was calculated by subtracting the year it was built from the year it was evaluated, and this information was added to the dataset as a new column, AGE. The cleaned (analysis) dataset, now free of missing values and containing the calculated ages, was saved as a CSV file in the 'analysis_data' directory for further analysis. This thorough cleaning process was crucial for ensuring the reliability of the study's findings and laying a solid foundation for the statistical modeling that followed.

6.2 Data Validation

Following the data cleaning process, a series of data integrity tests were conducted on the cleaned building evaluation dataset to ensure its accuracy and reliability for analysis. The first test verified that there were no negative values in the AGE column, as negative building ages would be illogical. The second test confirmed the absence of missing values (NA) in the critical columns YEAR.BUILT, YEAR.EVALUATED, and CURRENT.BUILDING.EVAL.SCORE, which are essential for the analysis. The third test checked that all evaluation scores fell within the expected range of 0 to 100, a necessary condition for valid score data. Lastly, the fourth test ensured that all buildings were evaluated in the year 2023, aligning with the study's focus on contemporary building evaluations. These validation checks were crucial for maintaining the dataset's integrity and provided confidence in the subsequent statistical modeling and analysis.

6.3 Posterior Predictive Check

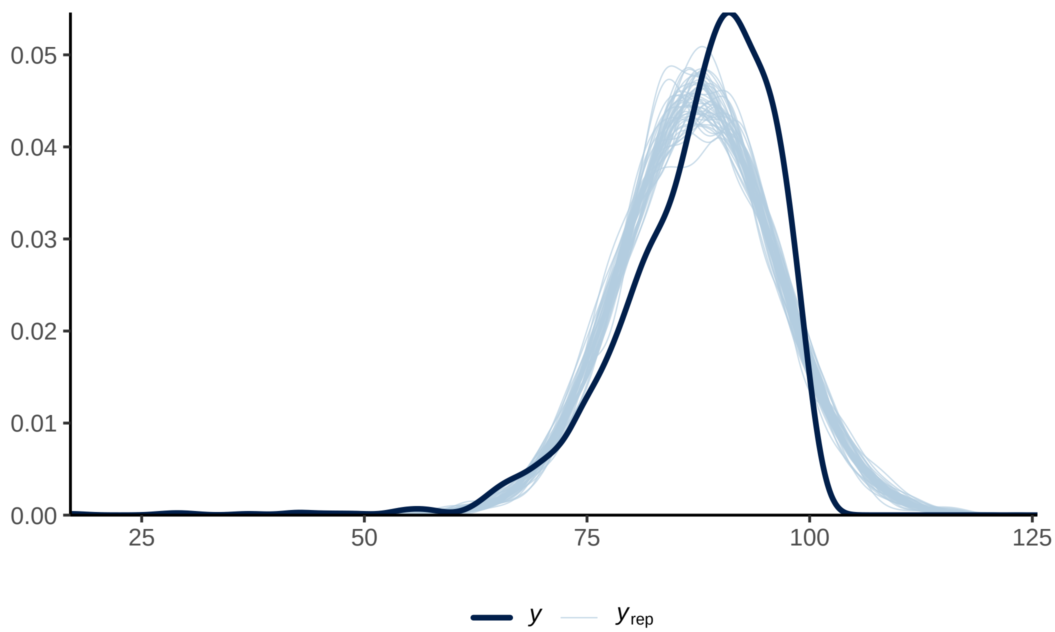

Figure 4: comparison between observed evaluation scores with those generated by our Bayesian model

From Figure 4, we observe that the simulated data from the posterior distribution (represented by the lighter lines) closely match the distribution of the observed data (depicted by the solid line). This suggests that our model is a good fit for the observed data and that the chosen priors and model structure can reasonably replicate the variations in evaluation scores across buildings. The spread of the lighter lines around the solid line also highlights the degree of uncertainty in our predictions, which is a natural aspect of modelling real-world phenomena.

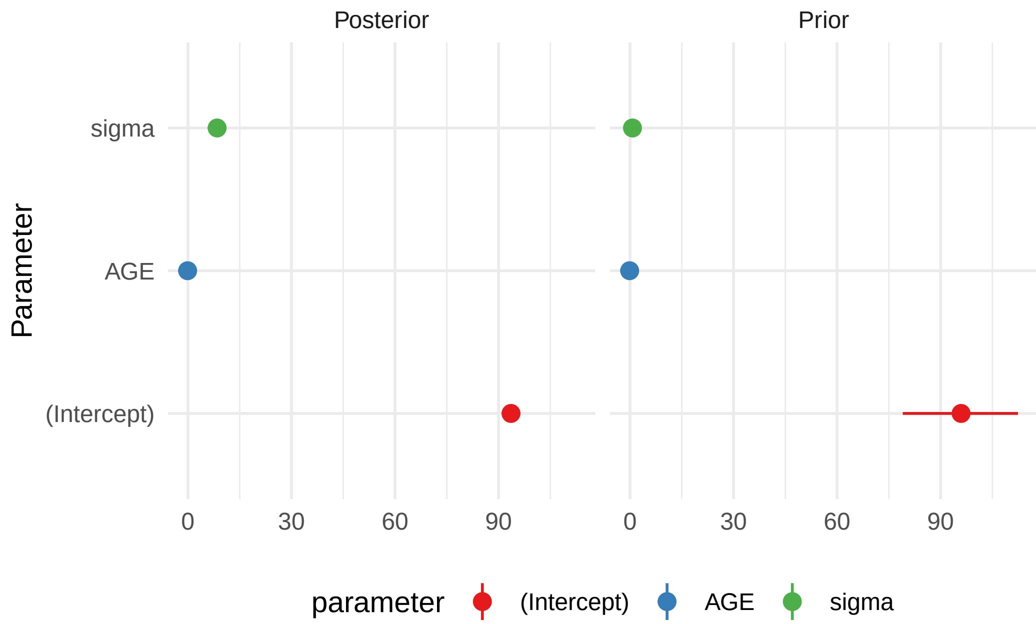

Figure 5: Comparison of posterior and prior distributions for model parameters

Figure 5 displays the median and spread of prior and posterior distributions for our model's parameters. It shows the posterior for the slope, related to the building's age, is quite similar to the prior, meaning our initial guess was on target. For the intercept and sigma, the data has slightly adjusted our estimates, reflecting its informative value. Overall, the data confirmed our prior thoughts about the effect of age on the building's evaluation score without much alteration.

References

Anderson, Curt. 2021. "Lawsuit Claims Surfside Condo Collapse Triggered by Building Work." *NBC 6 South Florida*. NBC 6 South Florida. http://www.nbcmiami.com/news/local/lawsuit-claims-surfside-condo-collapse-triggered-by-building-w ork/2622574/.

Goodrich, Ben, Jonah Gabry, Imad Ali, and Sam Brilleman. 2020. *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. 2022. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Toronto, City of. 2023a. "Open Data." *City of Toronto*. https://open.toronto.ca/dataset/apartment-building-evaluation/.

———. 2023b. "Rentsafeto: Get to Know Your Building Score." *City of Toronto*. https://www.toronto.ca/community-people/housing-shelter/rental-housing-tenant-information/rental-housing-standards/apartment-building-standards/rentsafeto-for-building-owners/rentsafeto-building-evaluations-and-audits/.

———. 2024. "Rentsafeto: Apartment Building Standards." *City of Toronto*. https://www.toronto.ca/community-people/housing-shelter/rental-housing-tenant-information/rental-housing-standards/apartment-building-standards/.

Wankiewicz, Matthew. 2020. "Apartment Age Is a Strong Predictor for Overall Quality." *Apartment Age Is a Strong Predictor for Overall Quality*. https://www.matthewwankiewicz.com/post/2020-09-26-apartment-age-is-a-strong-predictor-for-overall-quality/.

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, and Kirill Müller. 2022. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Wickham, Hadley, Jim Hester, and Jennifer Bryan. 2022. *Readr: Read Rectangular Text Data*. https://CRAN.R-project.org/package=readr.

Xie, Yihui. 2014. "Knitr: A Comprehensive Tool for Reproducible Research in R." In *Implementing Reproducible Computational Research*, edited by Victoria Stodden, Friedrich Leisch, and Roger D. Peng. Chapman; Hall/CRC. http://www.crcpress.com/product/isbn/9781466561595.

Zhu, Hao. 2021. *kableExtra: Construct Complex Table with 'Kable' and Pipe Syntax*. https://CRAN.R-project.org/package=kableExtra.