

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 3,435 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.git>

1 Introduction

The structural integrity of urban buildings is a paramount concern for city planners, policy-makers, and residents alike. The tragic collapse of a condominium in South Florida in June 2021, which resulted in 98 casualties, serves as a stark 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 that contribute to the safety and longevity of urban residential structures. In light of this, our study aims to investigate the relationship between building age and evaluation scores in the context of Toronto’s residential 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, which includes 3,435 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 the maintenance and inspection of 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, 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 coefficients of the linear model, 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 2023). The dataset encompasses 3,435 records, 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. 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.

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 modeling 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.

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:

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 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 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 to be unimodal with a peak around the 50-year mark, indicating that a substantial number of the buildings within this dataset were constructed around half a century ago. Following this peak, the frequency gradually decreases,

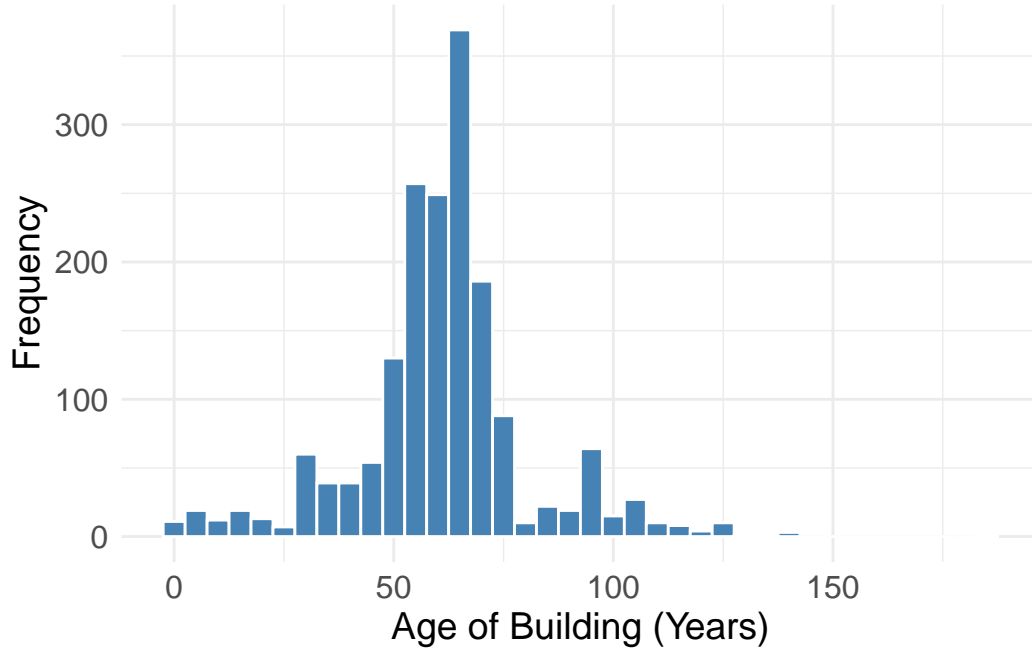


Figure 1: Distribution of building’s age for the cleaned data set

showing that fewer buildings have been in existence 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 showcases the distribution of building evaluation scores. The x-axis represents the scores assigned to buildings, which can range 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 being 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 spread of the scores and their frequency can offer insights into the overall health of the evaluated buildings, influencing urban planning and policy development.

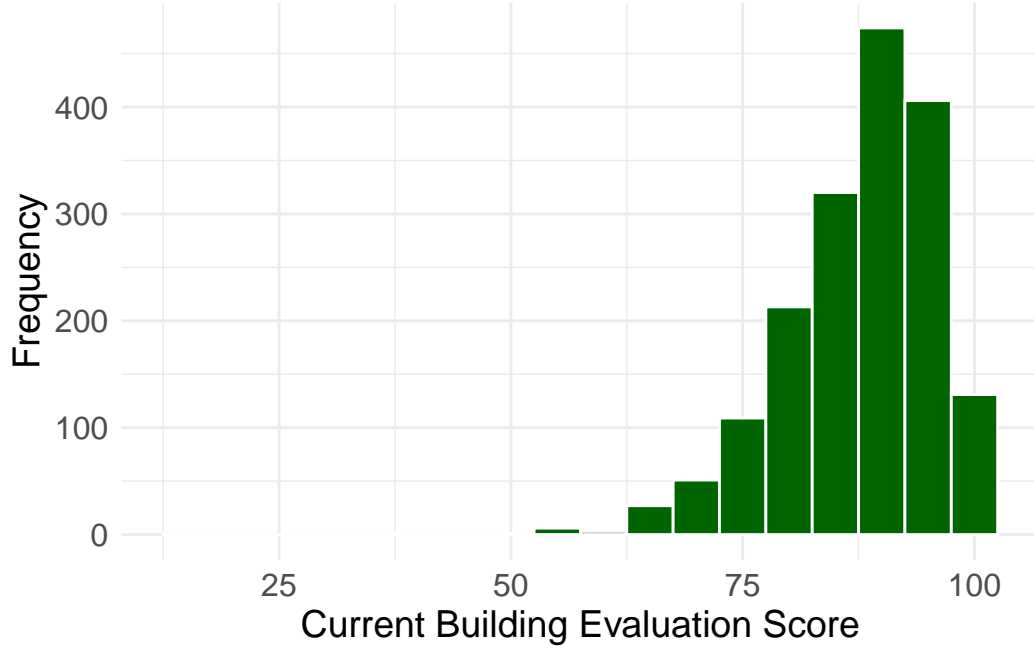


Figure 2: Distribution of building's evaluation score for the cleaned data set

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.

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:

$$y_i \sim \text{Normal}(\mu_i, \sigma) \quad (1)$$

$$\mu_i = \beta_0 + \beta_1 \times \text{AGE}_i \quad (2)$$

$$\beta_0 \sim \text{Normal}(85, 10) \quad (3)$$

$$\beta_1 \sim \text{Normal}(0, 0.05) \quad (4)$$

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. 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 around 90, with a wide spread 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 `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 therefore of particular interest, 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, thereby 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	93.364
Slope	-0.097

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 93.364. This represents the baseline evaluation score for a hypothetical newly constructed building. The intercept suggests that if a building were constructed in the current year, its expected evaluation score would be around 93.364, assuming all other factors remain constant.

Slope (β_1):

The slope parameter, β_1 , has an estimate of -0.097. This indicates that, on average, the evaluation score is expected to decrease by approximately 0.097 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

$$y_i \sim \text{Normal}(\mu_i, \sigma) \quad (5)$$

$$\mu_i = \beta_0 + \beta_1 \times x_i \quad (6)$$

$$\beta_0 = 93.364 \quad (7)$$

$$\beta_1 = -0.097 \quad (8)$$

In this model, y_i represents the predicted evaluation score for the i -th building, x_i represents the age for the i -th building, μ_i is the mean of the normal distribution for the i -th observation, β_0 is the intercept, and β_1 is the slope representing the change in evaluation score per year of building age.

4.3 Analysis of Residuals

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

Residual Statistics	Value
Min	-69.700
1st Qu.	-4.440
Median	1.687
Mean	-0.003
3rd Qu.	5.860

Residual Statistics	Value
Max	15.715

1. Minimum Residual: The minimum residual is -69.700, indicating that there is at least one building for which the model’s predicted evaluation score was lower than the actual score by approximately 69.700 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 -4.440, meaning that 25% of the buildings have evaluation scores that are less than 4.440 points below the model’s prediction for their age.

3. Median Residual: The median residual is 1.687, 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 5.860, indicating that 75% of the buildings have evaluation scores within 5.860 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 15.715, suggesting that there is at least one building for which the model’s predicted evaluation score was higher than the actual score by approximately 15.715 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 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 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.

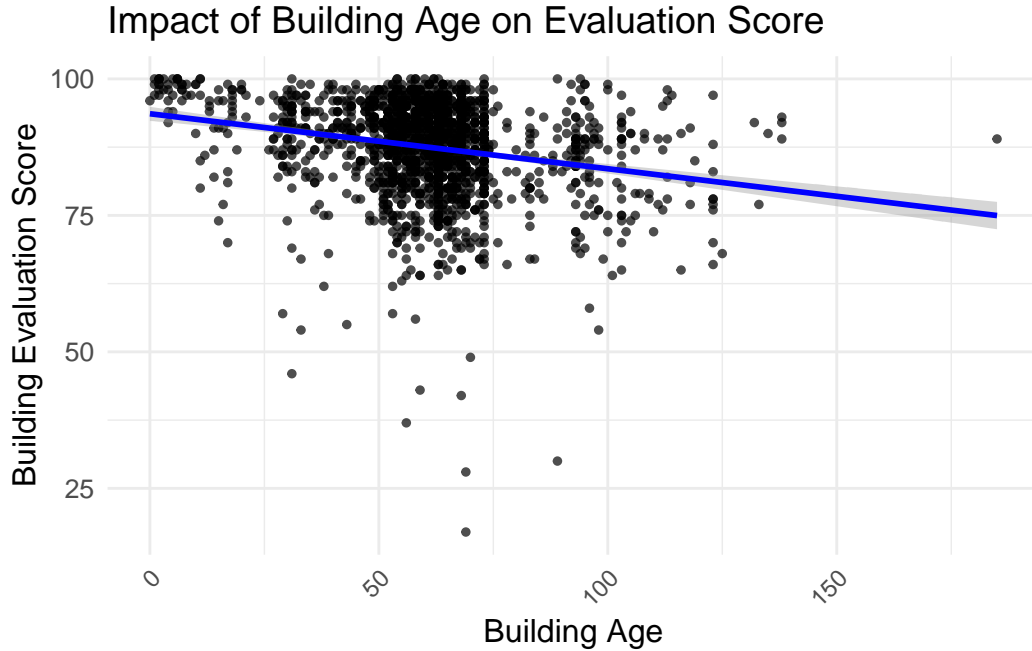


Figure 3: plot for the linear relationship between building age and evaluation score

In statistical analysis, the significance of this downward trend is supported by a p-value much lower than the conventional threshold of 0.05, confirming the relationship between building age and evaluation score is not due to random chance. However, 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 Overview of the Study

This paper presented a detailed analysis using simple linear regression to investigate the impact of building age on the evaluation scores assigned by the City of Toronto. By analyzing data from the Toronto Open Data portal, the study aimed to forecast evaluation scores for Toronto

residences in 2023. The analysis revealed a statistically significant inverse relationship between building age and evaluation score, suggesting that older buildings tend to have lower evaluation scores.

5.2 Insights into Urban Development and Maintenance

One key insight from this study is the importance of building age in the overall health and safety of urban residential environments. The findings underscore the potential risks associated with older buildings, which may not meet modern standards or may have deteriorated over time. This knowledge emphasizes the need for regular inspections, maintenance, and upgrades to older buildings to ensure they remain safe and habitable. Additionally, the study highlights the value of continuous monitoring and evaluation by urban authorities to maintain and improve housing standards across the city.

5.3 Policy Implications and Housing Quality

Another significant insight relates to the policy implications for housing quality and safety standards. The correlation between building age and lower evaluation scores may prompt policymakers to reconsider regulations surrounding building inspections, maintenance schedules, and renovation requirements. It suggests an opportunity for targeted interventions in older buildings to prevent potential hazards and improve living conditions for residents. Moreover, these findings could guide urban planning strategies, prioritizing the revitalization of aging housing stock and ensuring equitable access to safe and quality housing.

5.4 Limitations of the Study

Despite its contributions, this study has several limitations. Firstly, the model accounts for only a small fraction of the variability in evaluation scores, indicating that other factors besides building age significantly influence these scores. The exclusion of variables such as building materials, design, maintenance history, and location may limit the comprehensiveness of the findings. Additionally, the model's assumptions (e.g., linearity and homoscedasticity) and the presence of outliers suggest caution in generalizing the results without further investigation.

5.5 Future Directions

Given the limitations and the insights gained, future research should aim to incorporate additional variables that could affect building evaluation scores. A more comprehensive model including factors like renovation history, compliance with current building codes, and socio-economic characteristics of the neighborhood could provide a deeper understanding of what influences building evaluation scores. Longitudinal studies could also shed light on the trends

over time, offering insights into the effectiveness of policy interventions and maintenance practices. Moreover, comparative analyses across different cities or countries could highlight unique challenges and best practices in building maintenance and safety standards.

In conclusion, while this study has provided valuable insights into the impact of building age on evaluation scores, it also opens the door for further research to explore the multifaceted nature of building quality and safety. Addressing these questions is crucial for developing effective strategies to improve urban living conditions and ensure the longevity and safety of the housing stock.

6 Appendix

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