# 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:

In this study, we utilized data from the City of Toronto's RentSafeTO program, accessed through the "opendatatoronto" package (Toronto 2023). 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).

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.

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 particularly useful for researchers and analysts looking to investigate temporal trends and the impact of the post-2023 enhancements on building safety and maintenance standards.

## 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.
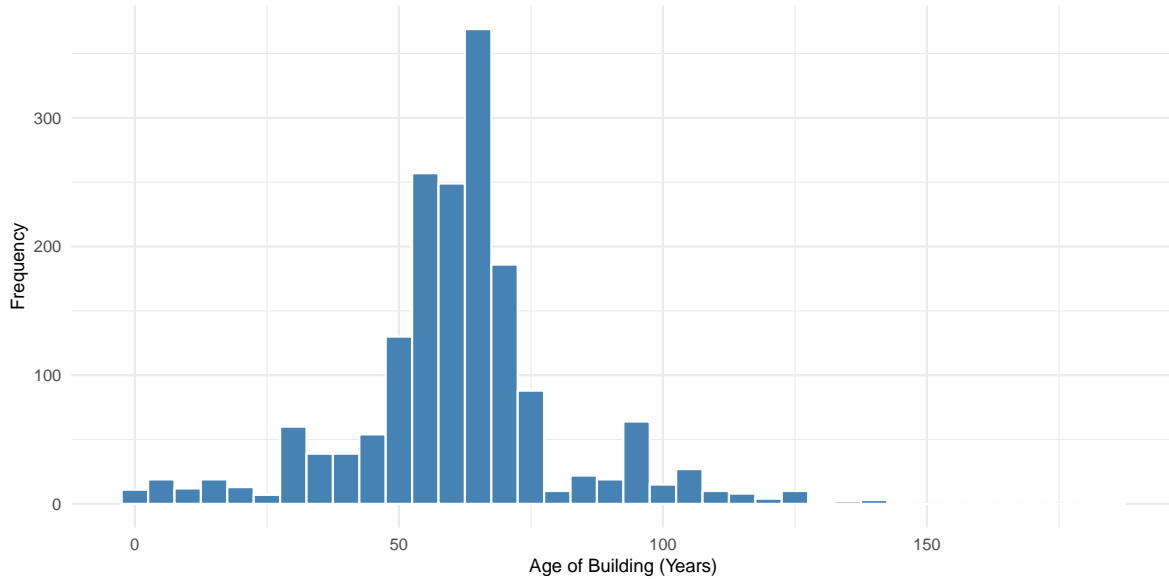
## 2.6.2 Age Distribution



Figure 1: 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 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, 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.
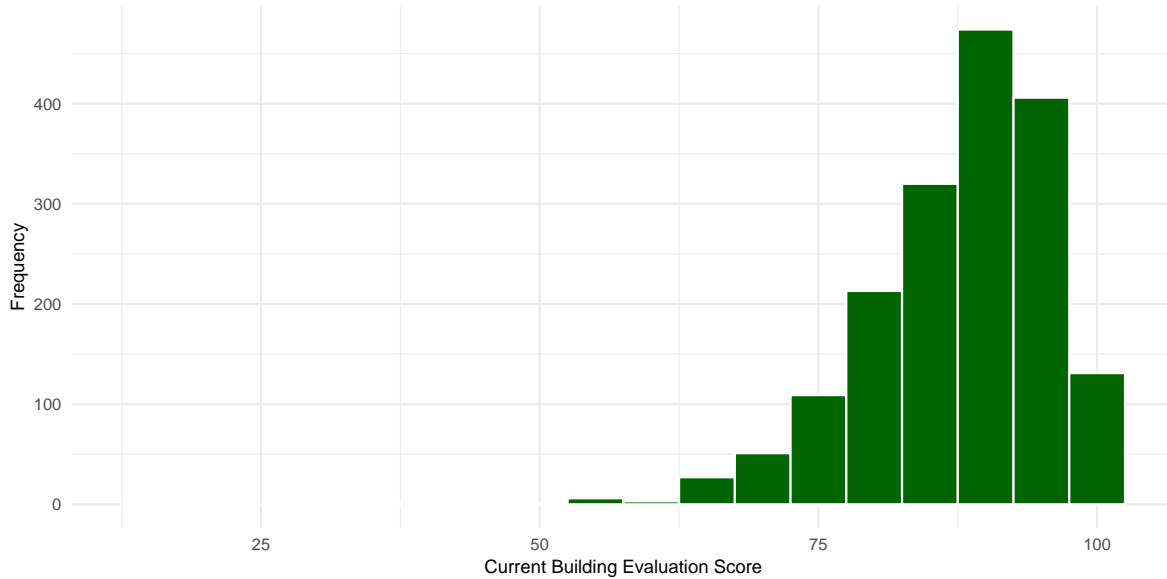
### 2.6.3 Score Distribution



Figure 2: 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, 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.

## 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:

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

$$\mu_i = \beta_0 + \beta_1 \times \text{AGE}_i \tag{2}$$

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

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

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 $\beta_0$ and slope $\beta_1$ , 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 $(\beta_1)$ 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 $(\beta_0)$, 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 $(\beta_1)$ 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** $(\beta_0)$:
The model's intercept, $\beta_0$, 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** $(\beta_1)$:
The slope parameter, $\beta_1$, 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

$$y_i \sim \text{Normal}(\mu_i, \sigma) \tag{5}$$
$$\mu_i = \beta_0 + \beta_1 \times x_i \tag{6}$$
$$\beta_0 = 93.364 \tag{7}$$
$$\beta_1 = -0.097 \tag{8}$$

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, $\mu_i$ is the mean of the normal distribution for the $i$-th observation,

$\beta_0$ is the intercept, and $\beta_1$ 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 |
| 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.
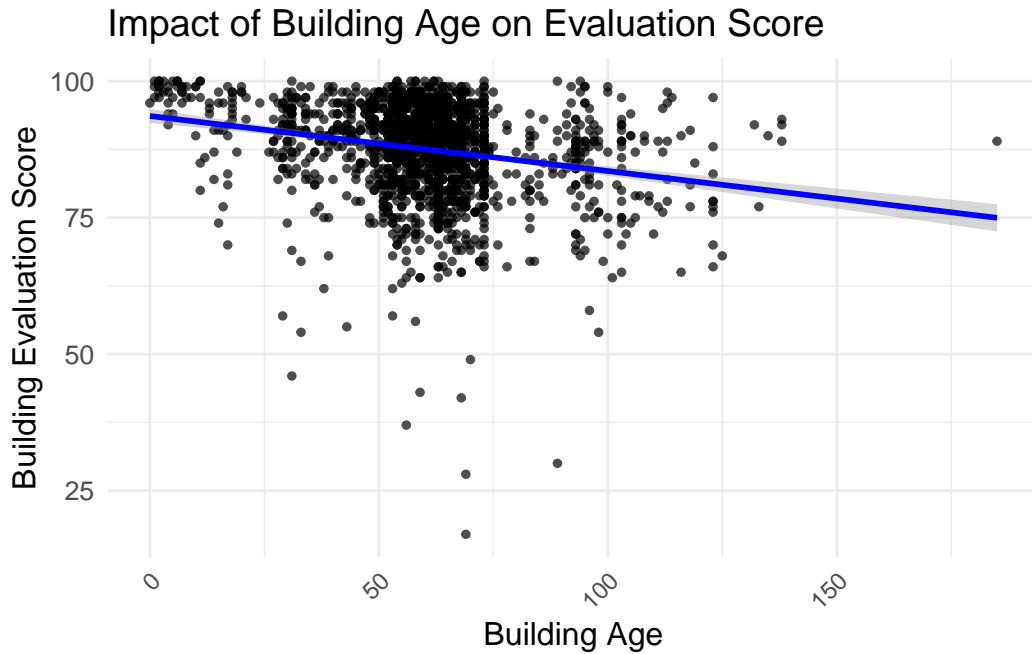
## 4.4 Plot for the linear model



Figure 3: 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 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 embarked on a journey to understand the relationship between the age of apartment buildings in Toronto and their safety evaluation scores. Leveraging a dataset of 3,435 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 literature on building safety and maintenance.

## 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 not 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.

## 5.5 Forward Look: 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 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.

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