Evaluating Modern vs. Older Buildings: Detailed Analysis on the Apartment Building Evaluation 2023*

Zhijun Zhong

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In this study, we dived into the Apartment Building Evaluation dataset from OpenDataToronto to understand what factors renters prioritize when choosing an apartment. Our focus is on how the year of construction influences rental decisions. By comparing various evaluation scores, such as window quality and building cleanliness, among buildings from different construction years, we discover trends in renter preferences. This research highlight on the significance of a building's age in the rental market, offering valuable insights for both renters and the housing industry.

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*Files, Codes and Paper are Availiable at https://github.com/JerrZzzz/ApartmentScoreAnalysis-2023.git

1 Introduction

Approximately 33.1% of Canadians are renters in today's society (Bush 2024). This statistic prompts an investigation into the factors influencing their housing choices. Youqin Huang's also did a similar study on renters' behavior in China, where housing decisions are deeply affected by socio-economic and institutional factors (HUANG 2003), it raises the question: What criteria do Canadian renters use when selecting a home? This paper seeks to explore how renters discern the value of a property based on limited information, such as online images. Key considerations might include the number of units, storeys, or the age of the building. Specifically, the paper examines whether newer buildings are more appealing to renters than older ones.

By our everyday logical reasoning, we might expect that buildings constructed a long time ago would pose numerous issues and require extensive maintenance. In Peng, Zhen and etc.'s paper *Retrofit or rebuild? The future of old residential buildings in urban areas of China based on the analysis of environmental benefits* (Peng et al. 2021), they talked about what issue senior building which constructed in 1970s till 1990s. They believed that there is a significant issue towards those building especially without sufficient insulation and ventilation. Moreover, these buildings are now approaching the end of their designed service life they also say (Peng et al. 2021). Therefore, we could hypothesize that older buildings would have lower scores, while modern buildings would score higher. Moreover, it is often challenging for older buildings to achieve standards in aspects like windows and building cleanliness compared to modern buildings. Thus, we can infer that there is a specific relationship between the year of construction and the evaluation score. In this paper, I will explore different aspects and inform future renters about the factors they need to consider before choosing an apartment in a specific building. However, before discussing the data and plotting graphs, we need to set aside our stereotypes.

This paper involved extensive coding. Utilizing ChatGPT was an efficient method for data cleaning and graph creation (OpenAI 2023). It means that all the code for the graphs in this paper, as well as the code for data cleaning and simulation, were generated by ChatGPT and reviewed and edited by the author (Zhijun Zhong).

To fully understand the relationship between the year of construction and the evaluation score, I have divided this paper into data, results, discussion, and conclusion sections. All data were obtained from the OpenDataToronto package (Gelfand 2023). In the data section, I will select relevant parts of my cleaned data to explain what each column represents. The results section will present all the graphs useful in analyzing the relationship. In the discussion section, I will interpret these graphs and offer my conclusions and suggestions based on the provided data which to give renters some valuable advise of which building is better to pick, old or new, high or low. Finally, the conclusion will summarize the entire paper and my main points.

2 Data

All data manipulated and presented in this paper were sourced from OpenDataToronto (Gelfand 2023). The code was generated by ChatGPT (OpenAI 2023). Data collection and analysis were conducted using the statistical programming software R (R Core Team 2023), with the following packages aiding in data collection, analysis, and graphing: opendatatoronto (Gelfand 2023), knitr (Xie 2023), janitor (Firke 2023), tidyverse (Wickham, Averick, et al. 2023), lubridate (Grolemund and Wickham 2023), ggplot2 (Wickham 2023), and dplyr (Wickham, François, et al. 2023).

The dataset obtained from OpenDataToronto, titled "Apartment Building Evaluations 2023," contains an extensive amount of information, making it challenging to present in a single table. In the following parts of the data section, I will showcase different columns and discuss their meanings.

2.1 Year and Score

Table 1: Sample of main columns

year	score
1970	97
1963	97
1968	93
1966	86
1965	85

We can get a glimpse of what the 'year' and 'score' columns look like in the dataset (see Table 1). The 'year' column indicates the year when the building was constructed. For instance, in the first row, the year 1990 means that the building was constructed in 1990, and as of 2023, it has achieved a score of 88. The 'score' is a scale ranging from 0 to 100, summarizing various aspects like windows, building cleanliness, etc., which I will elaborate on later. Essentially, in this dataset, the construction year and the score a building achieves are our primary focus.

2.2 Decade and Average_score

Table 2: Sample of secondary columns

Decade	Average_Score
1970	89.54190

Decade	Average_Score
1960	88.25347
1960	88.25347
1960	88.25347
1960	88.25347

As shown in this table (see Table 2), which consists of two columns named "decade" and "average_score", we address the dispersal of years in the 'year' column. The original year data is too scattered for effective graphical representation. Hence, I created a column named 'decade' based on the 'year' column, which indicates the decade of the original year. For example, a building constructed in 1943 would be listed under the 1940s decade. 'Average_score' means the average score of each decade. It represents the average score achieved by all buildings within that decade as of 2023.

2.3 Address, Storeys, Units and Criterion for different Category

Table 3: Sample of other columns

address	storeys	units	parkings	elevators	windows	cleanliness
5900 YONGE ST	13	233	2	3	3	3
6000 YONGE ST	18	265	2	3	3	3
6210 YONGE ST	7	83	2	3	3	3
90 YORK GATE BLVD	4	40	1	3	1	3
100 YORK GATE BLVD	11	133	2	3	3	3

In this table (see Table 3), 'address' refers to the building's address, such as 3179 Yonge St. 'storeys' and 'units' denote the number of storeys and units in the building, respectively. Meanwhile, 'parking', 'elevator', 'windows', and 'cleanliness' are four randomly chosen evaluation standards, each scaled from 0 to 3, with higher scores indicating better quality.

2.4 Frequency of full score on different category in 1950 and 2000

Table 4: Sample of Frequency vs Category

Year	Category	Value
2000	parking	0.6363636
2000	elevator	0.7272727
2000	window	0.9090909
2000	cleanliness	1.0000000
1950	parking	0.3263889

In the above table (see Table 4), 1950 and 2000 as two representative decades have the percentage of buildings achieving full marks in various categories for each decade. Each decade had four categories, followed by the probability of achieving full marks. For instance, for all buildings constructed in the 2000s, the probability of achieving full marks in building cleanliness is 82.76%.

This concludes the overview of the data we have cleaned from the OpenDataToronto package. The original data can be downloaded here: https://open.toronto.ca/dataset/apartment-building-evaluation/.

3 Results

Dividing the results into three parts is crucial to understanding the questions we raised at the beginning of the paper. I will analyze different aspects of my data using graphs and plots to answer these questions. In section 3.1, I will present the relationship between the built year and the score. Section 3.2 provides a detailed comparison between categories and the percentage of full scores achieved. Finally, in section 3.3, I will explore whether there is a connection between the number of units, the number of storeys, and the score.

To understand the relationship between the year a building was built and its score, it is beneficial to draw a graph examining whether the score depends on the year of construction. With assistance from ChatGPT (OpenAI 2023), I have developed a graph illustrating the score by year (See Figure 1). Although the pattern in the figure is not entirely clear, it is noticeable that there are a few data points from the 1950s achieving very low scores. However, throughout the 20th century, these older buildings do achieve very high scores, even surpassing those constructed in the 21st century.

Since we cannot draw definitive conclusions from the graph above, creating a graph that calculates the mean score for each decade can provide a much clearer understanding of the overall pattern or relationship between year and score. The following graph, which displays the relationship between decade and average score per decade (see Figure 2), reveals an obvious upward trend. Given the limited number of data points before 1900-possibly due to many older buildings being replaced with modern constructions-it is better to focus on data from

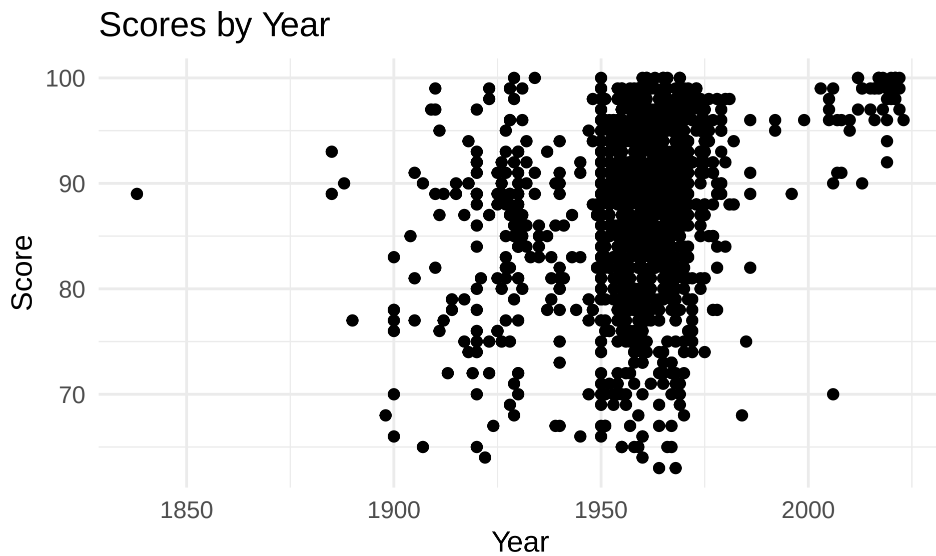

Figure 1: How Age can Effect a Building's Score

post-1900. I added a best fit line which will show the big trend of the point graph. I also calculated the y-intersection and slope for the line which is y = 0.13 x + -156.91. I think in this case the y-intersection is actually useless while slope is more useful. We can see from the slope k = 0.125 that in general for every 10 years of age for a building, it is going to lose 1.3 points which seems like not so much.

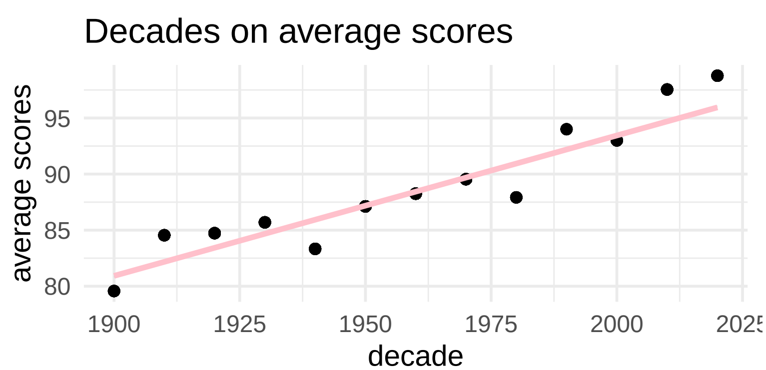

Figure 2: Average Score for each Decade which a building is built on

The data in Section 2.4 were specifically designed to suit the analysis in the following graph (see Figure 3). Here, the x-axis represents the category, while the y-axis shows the percentage of buildings achieving full marks. The "blue" bar represents data from the 2000s, and the "red" bar represents data from the 1950s. The graph clearly illustrates a significant difference between the two decades, with buildings constructed in the 2000s more likely to achieve full marks in all categories compared to those built in the 1950s.

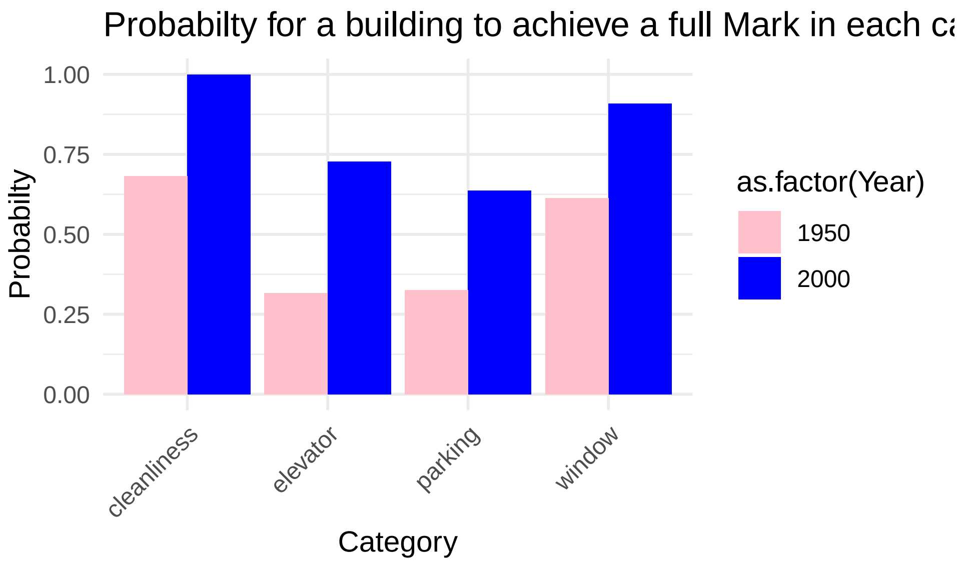

Figure 3: Probabilty for a building in different decade to achieve a full Mark in different category

Additionally, I was keen to explore the relationship of scores based on unit or storey numbers. After plotting graphs of scores against unit numbers (see Figure 4) and storey numbers (see Figure 5), a similar pattern emerges in both graphs. For buildings with a lower count of units (under 50) and storeys (under 10), scores vary widely, ranging from below 25 to 100. Conversely, buildings with a higher count of units (over 200) and storeys (above 20) tend to have scores consistently above 75. By adding a best fit line $y = 0.02\ x + 86.29$ for unit number and $y = 0.31\ x + 85.47$, we can see that it has a slope of $k = 0.018$ which we can say that it is almost a horizontal line. Also for the relationship between storey and score, even though that the slope is $k = 0.308$ which is not necessary horiziontal line, but it still does not provide us with a relationship.

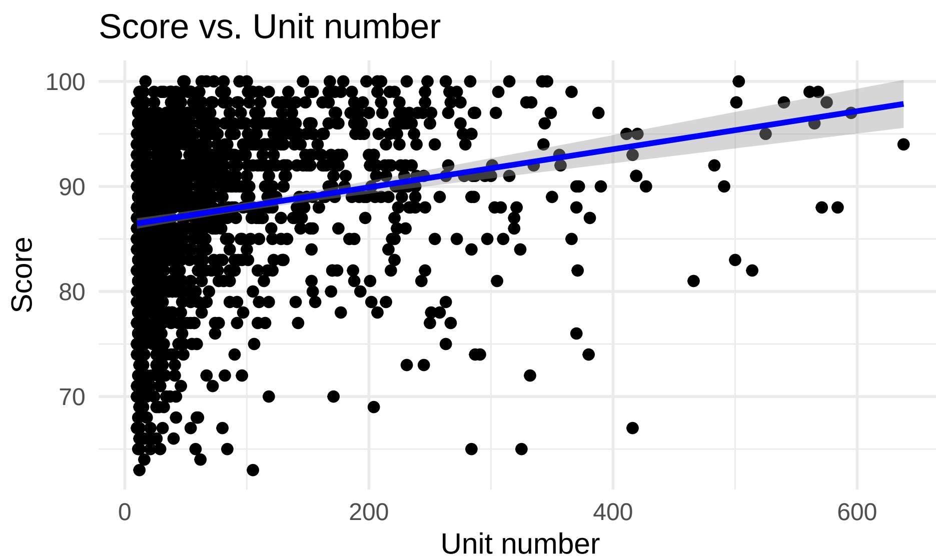

Figure 4: How number of Units Effect a Building's Score

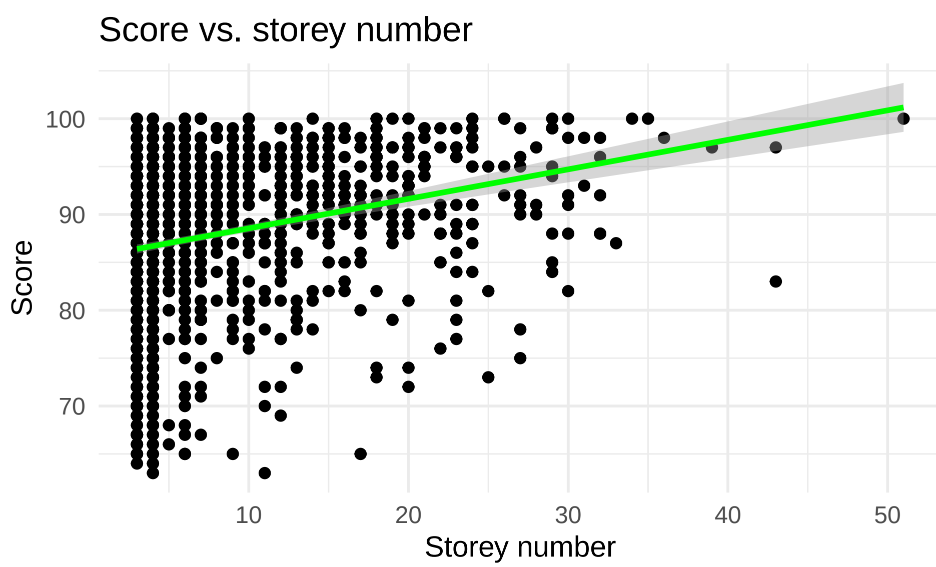

Figure 5: How Number of Storeys will Effect a Building's Score

4 Discussion

In order to answer the important question posed at the beginning of the paper – whether it is typically a better choice for renters to choose for buildings constructed more recently rather than older ones – we need to closely examine the data. By analyzing the 'score by year' graph (see Figure 1), we observe that not all older buildings score low. For instance, some buildings from the 1960s, such as one constructed in 1965 located at 24 Tyndall Ave, achieved a perfect score of 100. However, the 'decades vs. average scores' plot (see Figure 2) reveals a significant score difference of about 10 points between buildings constructed in 1900 and those in 2000. Although the data does not provide enough explanation to evaluate the significance of a 10-point difference, a trend is enough where newer buildings are more likely to achieve higher scores.

Before drawing conclusions, let's revisit Fig 1. Noticeable outliers[1], such as a building built in 1954 at 5 A Jasper Ave with a score of 17 out of 100, do bring the overall average down. Yet, denying the average score graph entirely would be hasty. A closer inspection of Fig 1 reveals that, excluding outliers, the score range for the 20th century (approximately 60 to 100) is still broader than that of the 21st century (about 82 to 100). Even with a 90% quantile or percentile adjustment, the pattern of increasing scores is unlikely to change significantly due to the dataset's size and score range [2].

Additionally, the detailed analysis of different categories further supports that newer buildings tend to score higher. As shown in figure 3 (see Figure 3), the likelihood of achieving full marks in categories like cleanliness, windows, and elevators is much higher for buildings from the 2000s compared to the 1950s. Focusing on cleanliness, since some older buildings lack elevators, we find that 82.76% of buildings from the 2000s achieve full marks in cleanliness, compared to 66.0% from the 1950s. This implies that out of 100 buildings constructed in the 1950s, about 66 would achieve full marks in cleanliness, while approximately 82 out of 100 buildings from the 2000s would.

Figures 4 (see Figure 4) and 5 (see Figure 5)explore the relationship between the number of units, the number of storeys, and scores. Contrary to the belief that a higher number of units or storeys hardened management and cleaning, the data does not show a specific pattern indicating a relationship. Buildings of varying unit and storey numbers have achieved high scores, suggesting that renters should not base their judgment solely on these factors.

[1] **Outlier**: Outliers in statistical analyzing are often refer to some certain data observations which are obviously outside of the common sense. For example, a column data set record the age of student going to STA302's class and there is one observation saying 80 which is an obvious special case. By Singh's paper(Singh and Upadhyaya 2012), we can say that our outlier here is a point outlier. He defines it as that if one of the data point can be considered as "anomalous", then it is a point outlier.

[2] **Note: After Peer Review, a friend commented my paper and said that outliers are serious issue and suggest that I take care of it. I redid my codes and removed 1% each side of my data on column score and I found that my conclusion stayed the same. The graph is still having a trend I talked about above. Thanks to @ zxc0707.

5 Conclusion

In conclusion, thanks to data from OpenDataToronto (Gelfand 2023), we were able to discuss and analyze the relationship between a building's year of construction and its achieved score. We found that older buildings might not score as high as newer ones on average. Therefore, this paper supports the notion of using the year of construction as a criterion, while not denying the quality of older buildings exclusively. However, we maintain the recommendation for renters not to use unit number and storey number as their primary judgment criteria.

6 Reference

**Reference From ref.bib:

Bush, Olivia. 2024. "Renting Statistics in Canada for 2024." https://madeinca.ca/renting-statistics-canada/.

Firke, Sam. 2023. *Janitor: Simple Tools for Examining and Cleaning Dirty Data*. https://CRAN.R-project.org/package=janitor.

Gelfand, Sharla. 2023. *Opendatatoronto: Access the City of Toronto Open Data Portal*. https://CRAN.R-project.org/package=opendatatoronto.

Grolemund, Garrett, and Hadley Wickham. 2023. *Lubridate: Make Dealing with Dates a Little Easier*. https://CRAN.R-project.org/package=lubridate.

HUANG, YOUQIN. 2003. "Renters' Housing Behaviour in Transitional Urban China." *Housing Studies* 18 (1): 103–26. https://doi.org/10.1080/0267303032000076867.

OpenAI. 2023. "ChatGPT: Optimizing Language Models for Dialogue." OpenAI.

Peng, Zhen, Sanjun Zhao, Luping Shen, Yuanli Ma, Qianxi Zhang, and Wu Deng. 2021. "Retrofit or rebuild? The future of old residential buildings in urban areas of China based on the analysis of environmental benefits." *International Journal of Low-Carbon Technologies* 16 (4): 1422–34. https://doi.org/10.1093/ijlct/ctab070.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Singh, Karanjit, and Shuchita Upadhyaya. 2012. "Outlier Detection: Applications and Techniques." *International Journal of Computer Science Issues (IJCSI)* 9 (1): 307.

Wickham, Hadley. 2023. *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. 2023. "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. 2023. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Xie, Yihui. 2023. *Knitr: A Comprehensive Tool for Reproducible Research in R*. Edited by Victoria Stodden, Friedrich Leisch, and Roger D. Peng. Chapman; Hall/CRC. http://www.crcpress.com/product/isbn/9781466561595.