Exploring the Impact of Population Density on Crime Distribution in Toronto Neighborhoods (2014–2023)*

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This paper examines the relationship between population density and crime frequency in Toronto neighborhoods from 2014 to 2023, using data from Toronto Police Services. It analyzes how crime patterns vary across the city and identifies the 10 safest neighborhoods. The study highlights the need for targeted, data-driven crime prevention strategies and offers policy recommendations for law enforcement and public officials. It also suggests future research directions to further explore crime dynamics in urban areas.

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*Code and data are available at:https://github.com/Cassieliu77/Crime-Frequency-and-Population-Density.git.

1 Introduction

Urban crime trends have long been studied due to their impact on social stability and policy-making. In Toronto, crime rates vary significantly across neighborhoods, often influenced by factors such as population density and economic disparity. This paper focuses on analyzing the trends in crime frequency across different types of crimes, using data from 2014 to 2023. The objective is to determine how crime patterns have changed over time and which neighborhoods are most affected. The result shows a increasing trend in crime rates. All the analysis in the paper is conducted in R Core Team (2021), OpenAI (2023) is used in this research paper to help simulate data. (Need to write more!)

2 Data

2.1 Raw Data

The Neighborhood Crime Rates dataset used in this study comes from Services (2024), which is downloaded on Gelfand (2022) and covers the period from 2014 to 2023. It records various crime types such as Assault, Auto Theft, Break and Enter, Robbery, Theft Over, Homicide, Shooting and so on. The data focuses on 158 neighborhoods in Toronto and provides crime rates per 100,000 population. Crime rate here is measured using population estimates from Environics Analytics, which is in line with the standard definition by Statistics Canada. This metric allows for fairer comparisons between neighborhoods with different population sizes. Unlike raw crime counts, crime rates offer a more balanced comparison over time as they account for population changes in the area. This explains why I do not choose to use Police Annual Statistical Report - Reported Crime as my dataset. It only contains the reported crime count for a certain year and a certain division, which lack a standard way to compare the crime frequency among different neigborhoods. Besides, lack of geometry attribute makes it hard to see the distribution of crimes in the subsequent sections of the paper. In Services (2024), population for 2023 year in each neighborhood is also included, enabling the analysis of the relationship between population density and crime frequency. Figure 1 gives us a glimpse about how the dataset looks. Note that this dataset incorporates data for the new structure of the 158 City of Toronto neighborhoods, enabling a more comprehensive geographic analysis, and it does not contain occurrences of crime which were deemed “unfounded”. Each neighborhood is identified by their area name and a unique hood ID. Geometry data in the dataset is useful to build up the Toronto city map to observe population and crime distribution. The data is analyzed in R (R Core Team (2021)), using packages such as Tidyverse (Wickham et al. (2019)), Dplyr(Wickham et al. (2023)), Geojsonsf(Cooley (2022)), Httr (Wickham (2023)), Knitr(Xie (2014)) and ggplot2 (Wickham (2016)) in order to visualize the data and communicate information intuitively.

HOOD_ID	POPULATION_2023	ASSAULT_2023	ASSAULT_RATE_2023
174	21987	101	459.3624
173	15077	105	696.4250
172	13837	104	751.6080
171	26240	229	872.7134
170	14731	543	3686.1042
169	19055	142	745.2112

Figure 1: the glimpse of the raw data

2.2 New Variable Constructure

Average Crime Rate in the whole Toronto is constructed to see the crime trend in the city. It is computed based on the average of 2014-2023 year data. Geometry column is transformed to the spatial data to help us make map visualizations in the Result sections. Average rank for each neighborhood is constructed based on the crime count for each year. Firstly, using the total count of crimes each year to rank 158 neighborhoods, and each neighborhood is able to get a rank for each year. Then, take average of it to get the average rank.The average rank of 2014-2023 is constructed based on the crime count for each year. The higher the crime count, the smaller the rank number. The summary for the top and bottom 10 ranked neighborhoods can be found in Figure 2 and Figure 3.

Neighborhood_ID_Name	Average_Rank
1 - West Humber-Clairville	1.60
27 - York University Heights	6.10
164 - Wellington Place	6.55
95 - Annex	7.50
73 - Moss Park	7.85
78 - Kensington-Chinatown	9.50
70 - South Riverdale	10.10
166 - St Lawrence-East Bayfront-The Islands	10.55
168 - Downtown Yonge East	10.90
136 - West Hill	11.00

Figure 2: Summary Table for Top10 Tanked Neighborhoods

Neighborhood_ID_Name	Average_Rank
15 - Kingsway South	144.50
12 - Markland Wood	144.60
49 - Bayview Woods-Steeles	146.20
97 - Yonge-St.Clair	146.25
112 - Beechborough-Greenbrook	146.65
58 - Old East York	147.30
140 - Guildwood	149.70
60 - Woodbine-Lumsden	149.80
29 - Maple Leaf	153.45
114 - Lambton Baby Point	156.20

Figure 3: Summary Rable for Bottom 10 Ranked Neighborhoods

3 Results

3.1 Crime Rates Over the Past Decade

In order to see the overall crime rate in Toronto. The average crime rate over the 158 neighbourhood is applied to visualize Figure 4, which presents a depiction of how various crime types have evolved from 2014 to 2023, particularly auto theft and break-and-enter offenses. Assault remains the most prevalent crime, while homicide and robbery rates have been relatively stable. Oliveira (2021) work suggests that theft often increases superlinearly with population size, and Toronto's recent surge in auto theft may reflect this pattern.The sharp increase in property-related crimes, such as break-and-enters, could also indicate broader economic and social shifts that align with similar trends observed in other cities globally Oliveira (2021).

The data reveals a marked increase in auto theft and break-and-enter crimes, while shooting and homicide rates have remained relatively low and stable. The rise in auto theft may be attributed to increased access to technology, while economic downturns might explain the surge in property-related crimes like break and enters. It highlights key trends in crimes such as **Assault, Auto Theft, Bike Theft, Break and Enters, Homicide, Robbery, Shooting,** and **Theft Over**, with each category visually represented by distinct colored lines. One of the most striking observations is the consistently high rate of **Assault** (represented by the red line), which has maintained its position as the most prevalent crime throughout the period. While the rate remained relatively stable between 2014 and 2020, it experienced a notable increase starting in 2022, reflecting a potentially alarming trend that may call for increased public safety measures or changes in law enforcement focus. In contrast, **Auto Theft** (brown line) shows one of the sharpest upward trajectories, particularly after 2020. This rise in auto-related crime could be indicative of broader societal or economic shifts, such as changes in vehicle accessibility, security measures, or even the impact of the COVID-19 pandemic, which has affected economic stability and possibly driven up theft-related crimes. The stark increase in auto theft from 2021 onward could suggest an emerging challenge for Toronto's law enforcement and policymakers as they respond to these shifts. Meanwhile, **Break and Enters** (green line) and **Bike Theft** (also green) exhibit moderate fluctuations over the years, with **Bike Theft** showing a noticeable increase post-2021. These fluctuations in property crimes could be influenced by a range of factors, including urban development, changes in housing density, and public awareness campaigns promoting better security practices. Other crime types like **Homicide, Robbery, Shooting,** and **Theft Over** display relatively low rates and less volatility, suggesting that these categories, while serious, have not seen significant recent surges. The data presented in Figure 4 provides an essential foundation for discussions around urban crime in Toronto. It allows us to visualize the persistence and emergence of specific crime types over time, highlighting areas where intervention may be most necessary. For instance, the increasing rates of **Auto Theft** and **Assault** should be a priority for policymakers and law enforcement agencies. The graph also reinforces the importance of data-driven decision-making in urban planning and crime prevention, as visualizing trends over time can reveal patterns and shifts that may not be immediately apparent in static data snapshots. Figure 4 serves as a powerful tool for understanding Toronto's crime landscape, emphasizing the need for continued monitoring and adaptive strategies in response to evolving crime dynamics.

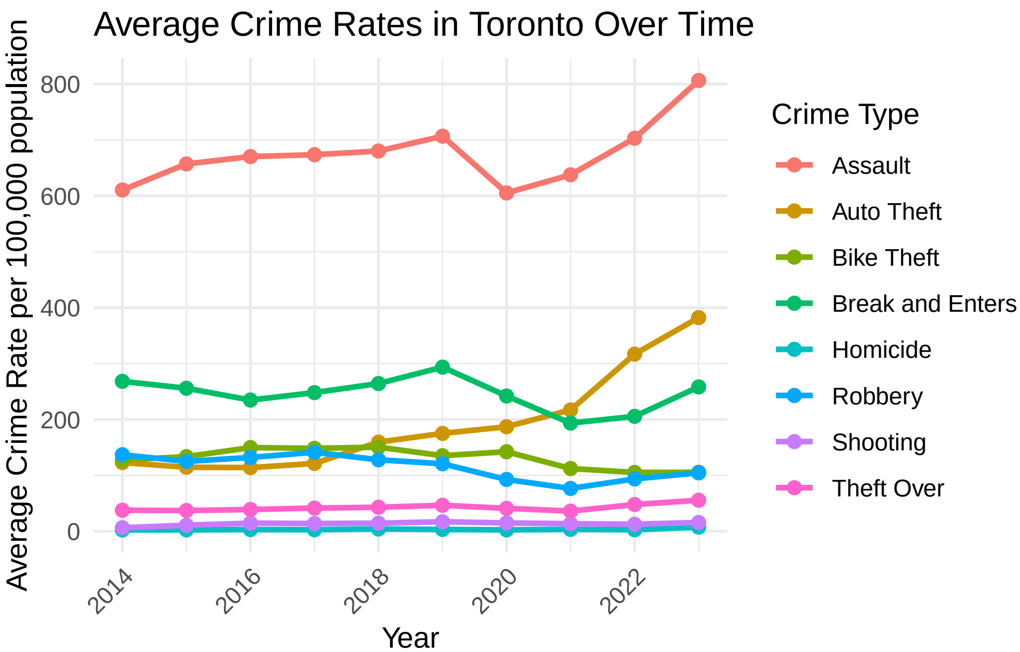

Figure 4: the crime rates for differnet crimes in Toronto over time

3.2 Toronto Population Distribution

Figure 5 shows the population distribution in Toronto, and help us to identify whether these crime frequency area is accordance with those high population density neighborhoods.

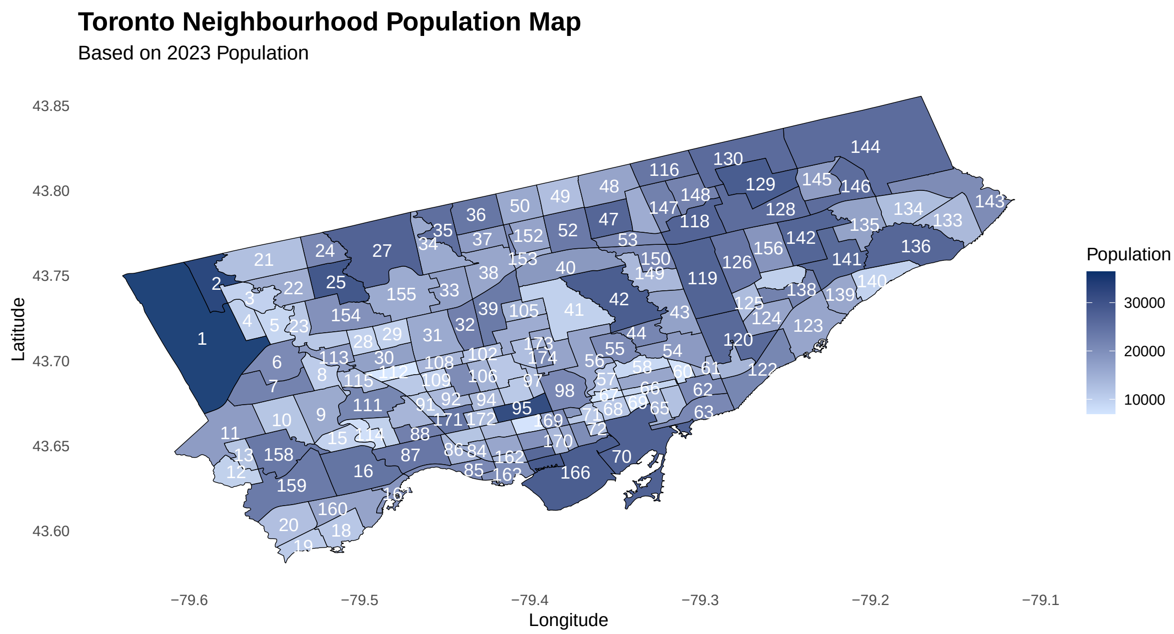

Figure 5: Population distribution in Toronto

3.3 Geographic Distribution of Crime

Based on Figure 5, Figure 7 represents a higher concentration of crimes in areas with higher population densities, particularly in economically disadvantaged neighborhoods. Those gray areas mean no crime was reported. From the map showing **Homicide**, it This finding shows that population size is a strong predictor of crime, with more densely populated areas experiencing higher crime rates. In Toronto, eastern neighborhoods report higher assault and robbery rates than western, more affluent areas.

Figure 6: 2023 Crime Trend with Population

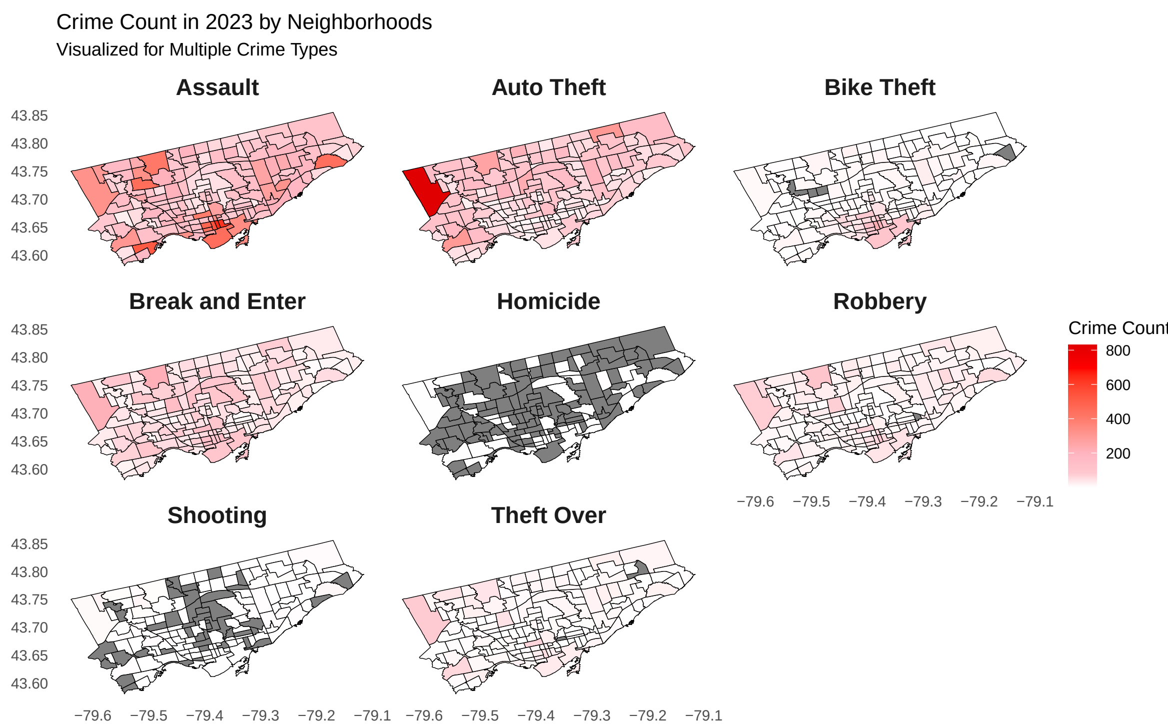

Figure 7: 2023 Crime Distribution in Toronto by Neighborhoods

3.4 Neighborhood Analysis

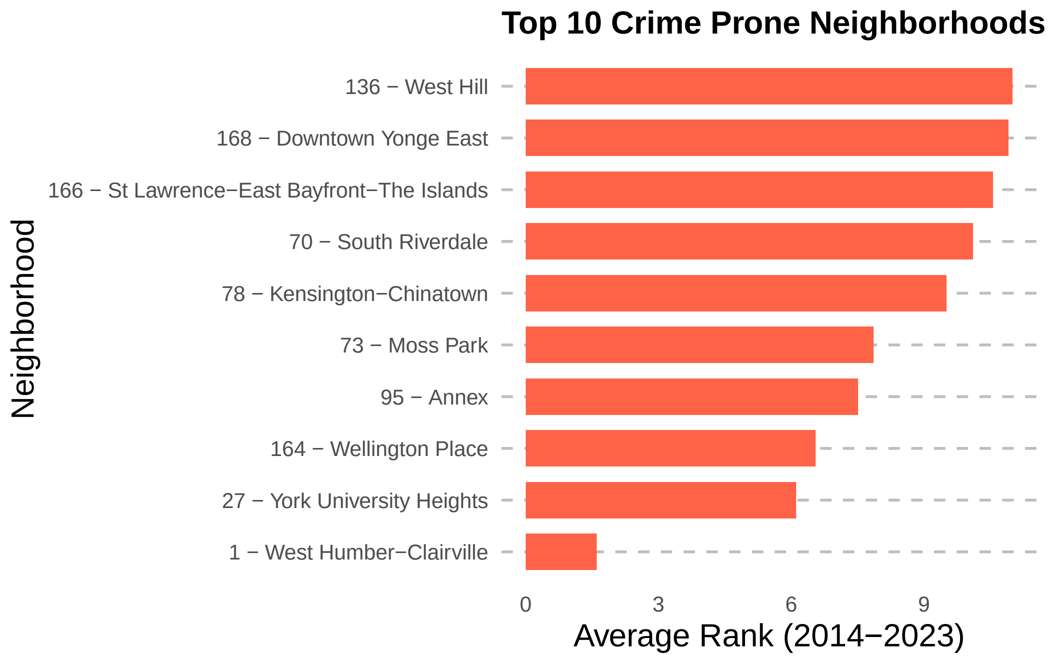

Figure 8: Top10 Ranked Crime Prone Neigborhoods Based on Crime Count

In Figure 8, neighborhoods such as West Humber-Clairville, York University Heights, and Wellington Place have consistently ranked among the top 10 crime-prone areas over the past decade. These neighborhoods are characterized by higher population densities and socioeconomic challenges, making them more vulnerable to crime. The increasing trend in auto theft and assault in these neighborhoods underscores the need for targeted interventions and enhanced security measures. In contrast,Figure 9 neighborhoods like Maple Leaf and Lambton Baby Point have consistently ranked as some of the safest areas in Toronto. These neighborhoods tend to have lower population densities and are more affluent, with better access to resources and community support. The stability of crime rates in these areas suggests that socioeconomic factors play a critical role in maintaining low crime levels.

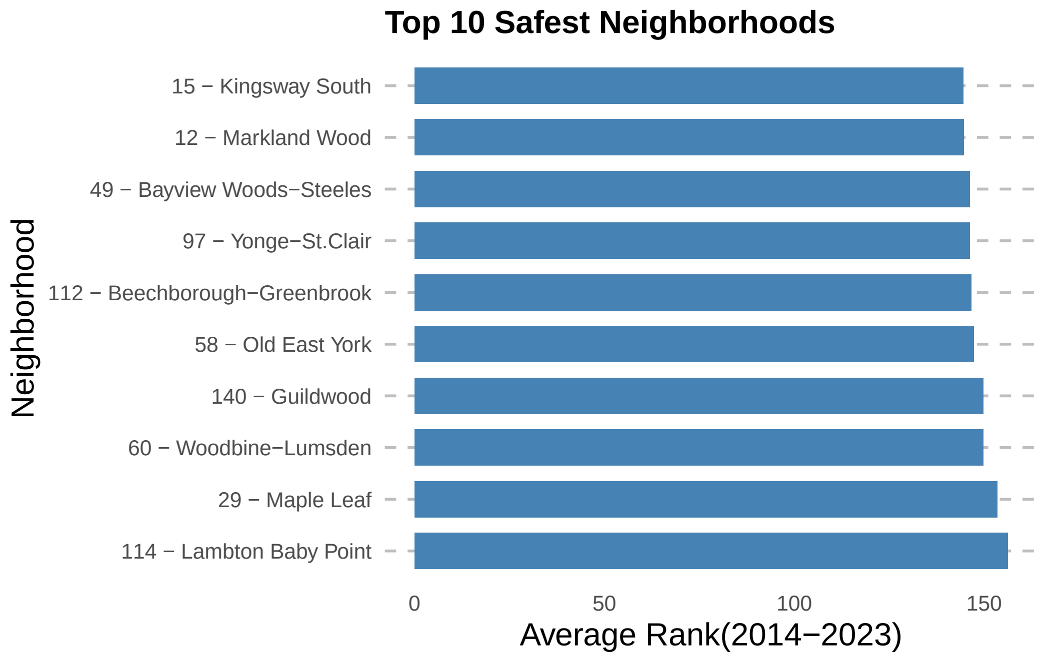

Figure 9: Top10 Ranked Safest Neigborhoods Based on Crime Count

4 Discussion

4.1 Summary of Findings

The study investigates the relationship between population density and crime frequency across Toronto neighborhoods from 2014 to 2023. The data reveals clear trends, particularly with crimes such as auto theft and assault, which are more prevalent in densely populated neighborhoods. The findings highlight how crime rates are not uniformly distributed but instead cluster in certain areas, often driven by socioeconomic factors.

4.2 Population Density as a Key Driver of Crime

The increasing trend in crimes like auto theft and assault calls for immediate attention from policymakers. As shown in the data, crime rates do not arise uniformly across all neighborhoods but are concentrated in specific areas. This concentration suggests that socioeconomic factors, along with population density, play a significant role in the prevalence of crime. The sharp increase in auto theft post-2020 highlights the need for enhanced security measures, while the stable yet high assault rates point to the need for sustained law enforcement efforts in vulnerable neighborhoods. The data clearly shows a significant correlation between population density and crime frequency in Toronto neighborhoods. Densely populated areas such as Moss Park, St. Lawrence-East Bayfront, and Kensington-Chinatown consistently rank among the highest in terms of crime rates. This supports existing criminological theories, such as Routine Activity Theory and Social Disorganization Theory, which suggest that increased population density leads to more opportunities for crime due to greater anonymity, social fragmentation, and limited community cohesion. The results from this study confirm that neighborhoods with more people living in close proximity are more likely to experience higher crime rates, especially property crimes like auto theft and break-and-enters.

The relationship between population density and crime suggests that urban planners and local governments should consider designing interventions that specifically address high-density environments. Strategies such as better lighting, increased public surveillance (e.g., CCTV), and more frequent police patrols can act as deterrents in areas where crime tends to cluster. Additionally, promoting community cohesion through events, neighborhood associations, and resident engagement initiatives can reduce the social disorganization that often accompanies densely populated urban settings.

4.3 Socioeconomic Disparities and Crime Hotspots

In addition to population density, socioeconomic factors significantly influence crime patterns. Neighborhoods with higher levels of economic disadvantage, such as Moss Park and York University Heights, experience higher crime rates. In contrast, affluent neighborhoods like Kingsway South report much lower crime rates. This suggests that addressing socioeconomic disparities is critical to reducing crime. Targeted social interventions, such as improving access to education, healthcare, and employment opportunities, could alleviate some of the underlying factors contributing to crime. Socioeconomic disparities shape crime dynamics by contributing to social strain and increasing the motivation for economic crimes such as theft, robbery, and property damage. Policymakers should focus on alleviating economic inequality through social programs that address poverty, unemployment, and access to education. For example, neighborhood revitalization programs that improve housing conditions, increase job opportunities, and provide better access to education and healthcare could reduce the social conditions that lead to higher crime rates.

4.4 Targeted Crime Prevention Strategies

The geographic concentration of crime in specific neighborhoods has significant implications for law enforcement and public policy. Policymakers and law enforcement agencies must recognize that crime prevention cannot be approached with a one-size-fits-all strategy. Instead, targeted interventions are necessary to address the unique challenges faced by high-risk neighborhoods. he data reinforces the idea that crime is not uniformly distributed across Toronto neighborhoods but is concentrated in specific high-risk areas. This suggests that a "one-size-fits-all" approach to crime prevention would be ineffective. Instead, law enforcement agencies should focus their efforts on areas where crime is most prevalent, such as Moss Park and Kensington-Chinatown, by deploying more officers and allocating more resources to these neighborhoods.

At the same time, the study highlights the importance of community-based crime prevention strategies. Engaging local residents in neighborhood watch programs, providing education on crime prevention techniques, and fostering collaboration between police and community organizations can empower communities to take ownership of their safety. This approach not only reduces crime rates but also builds trust between law enforcement and the communities they serve, which is essential for long-term success in crime reduction.

For neighborhoods like Moss Park and St. Lawrence-East Bayfront, which consistently rank among the highest neighborhodos in crimes, a multifaceted approach is required. This might include increased policing and community-based programs aimed at addressing the root causes of crime, such as poverty, unemployment, and lack of access to education and healthcare. Research suggests that addressing these underlying issues can have a significant impact on reducing crime rates, particularly in economically disadvantaged areas.

Furthermore, the rise in auto theft and break-and-enter incidents post-2020 suggests that law enforcement must adapt to changing crime patterns. Technological advancements, such as the increased use of vehicle tracking systems and smart security devices, could help curb the rising rates of property crime. In addition, public awareness campaigns aimed at promoting better security practices, particularly in high-risk neighborhoods, may also prove effective in preventing crime.

4.5 Limitations and Future Research

While this study represents the relationship between population density and crime frequency in Toronto, several limitations must be acknowledged. Firstly, the analysis relies on reported crime data, which may not fully capture the extent of criminal activity, particularly for underreported crimes such as domestic violence and cybercrime.

Secondly, the study focuses primarily on the relationship between population density and crime rates, without accounting for other factors that may also influence crime, such as the presence of law enforcement, urban infrastructure, and even social events. Future research could incorporate these variables to provide a more nuanced understanding of crime dynamics in urban areas.

Finally, the analysis spans a relatively short period (2014–2023), which may not capture long-term trends or shifts in crime patterns. Expanding the dataset to include earlier years or incorporating data from other cities could offer a broader perspective on crime dynamics in Toronto and beyond. Future research should expand on these findings by incorporating additional data sources to capture a broader range of criminal activity. It would also be useful to explore how different types of urban infrastructure, such as public transportation or lighting, influence crime rates. Finally, comparative studies with other major cities could provide a more comprehensive understanding of urban crime dynamics, enabling better-targeted interventions for crime prevention.

References

Cooley, David. 2022. *Geojsonsf: GeoJSON to Simple Feature Converter*. https://CRAN.R-project.org/package=geojsonsf.

Gelfand, Sharla. 2022. *Opendatatoronto: Access the City of Toronto Open Data Portal*. https://CRAN.R-project.org/package=opendatatoronto.

Oliveira, M. 2021. "More Crime in Cities? On the Scaling Laws of Crime and the Inadequacy of Per Capita Rankings—a Cross-Country Study." *Crime Science* 10 (7). https://doi.org/10.1186/s40163-021-00155-8.

OpenAI. 2023. "ChatGPT: GPT-4 Model." https://openai.com/chatgpt.

R Core Team. 2021. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Services, Toronto Police. 2024. "Neighbourhood Crime Rates." https://open.toronto.ca/dataset/neighbourhood-crime-rates/.

Wickham, Hadley. 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org.

———. 2023. *Httr: Tools for Working with URLs and HTTP*. https://CRAN.R-project.org/package=httr.

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, Kirill Müller, and Davis Vaughan. 2023. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

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.