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 has long been a critical focus for researchers and policymakers due to its significant impact on societal well-being and public safety. In Toronto, crime rates differ considerably across neighborhoods, often influenced by population density and socioeconomic factors. This study examines the relationship between population density and crime rates in Toronto neighborhoods from 2014 to 2023. By analyzing data from Toronto Police Services, we aim to understand how crime patterns are shaped by population distribution and to provide data-driven recommendations for more targeted crime prevention strategies. Through this analysis, we hope to shed light on the dynamics of urban crime in Toronto and contribute to more effective policies for mitigating crime in high-density areas. All of the analyses in the paper is conducted in R Core Team (2021).

2 Data

2.1 Raw Data

The Neighborhood Crime Rates dataset, obtained from Services (2024), spans from 2014 to 2023 and covers 158 Toronto neighborhoods. The dataset includes various crime types such as Assault, Auto Theft, Break and Enter, Robbery, and Homicide, expressed as rates per 100,000 people. Crime counts for per crime type per year are also shown in the data. 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 neighborhoods. Besides, lack of spatial attribute makes it hard to see the geography distribution of crimes in the subsequent sections of the paper. In Services (2024), another used variable population for 2023 year in each neighborhood is also included, enabling the analysis of the relationship between population density and crime frequency. Additionally, new variables, such as the average crime rate across Toronto from 2014 to 2023 and average neighborhood rankings based on crime counts, were constructed to analyze long-term trends

and identify high-risk areas. As for the measurement, crime rate is measured using population estimates from Environics Analytics, which is in line with the standard definition by Statistics Canada. The dataset records crimes that got Toronto Police intervention. This metric allows for fairer comparisons between neighborhoods with different population sizes. Also 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". Figure 1 gives us a glimpse about how the dataset looks. Each neighborhood is identified by their area name and a unique hood ID. Geometry data in the dataset is used to build up the Toronto city map to observe population density and crime distribution. The data is analyzed in R (R Core Team (2021)), using packages 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: A Lookup for the Raw Data

2.2 New Variable Constructure

Crime_Type and Crime_Count are constructed based on 2023 data. Crime_ 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 3 and Figure 4.

HOOD_ID	AREA_NAME	Crime_Type	Crime_Count
174	South Eglinton-Davisville	Assault	101
174	South Eglinton-Davisville	Robbery	3
174	South Eglinton-Davisville	Break and Enter	43
174	South Eglinton-Davisville	Theft Over	8
174	South Eglinton-Davisville	Auto Theft	21
174	South Eglinton-Davisville	Bike Theft	37
173	North Toronto	Assault	105
173	North Toronto	Robbery	14
173	North Toronto	Break and Enter	31
173	North Toronto	Theft Over	7

Figure 2: Summary Table for the Crime Count

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 3: 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 4: 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 5, 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 5 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 5 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. It is noticeable that 2020 is a turning point, when the pandemic begins. The crime rate experience a dramatic increase, expecially for Assault, increasing from 600 to 800 per 100,000 population.

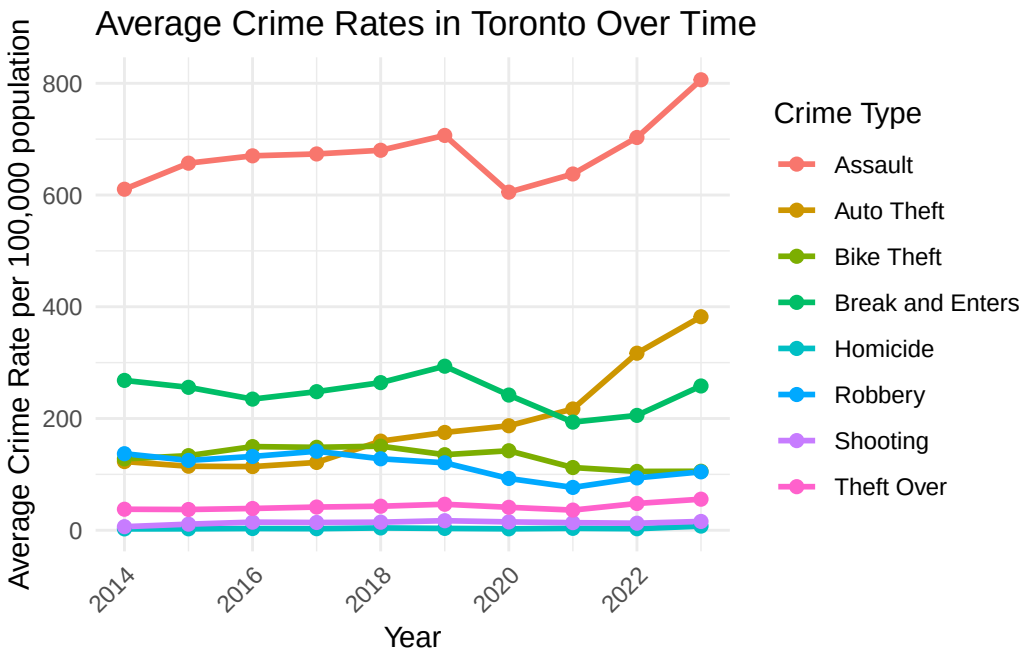

Figure 5: the crime rates for differnet crimes in Toronto over time

3.2 Toronto Population Distribution

Figure 6 shows the population distribution in Toronto, and help us to identify whether these crime frequency area is accordance with those high population density neighborhoods.

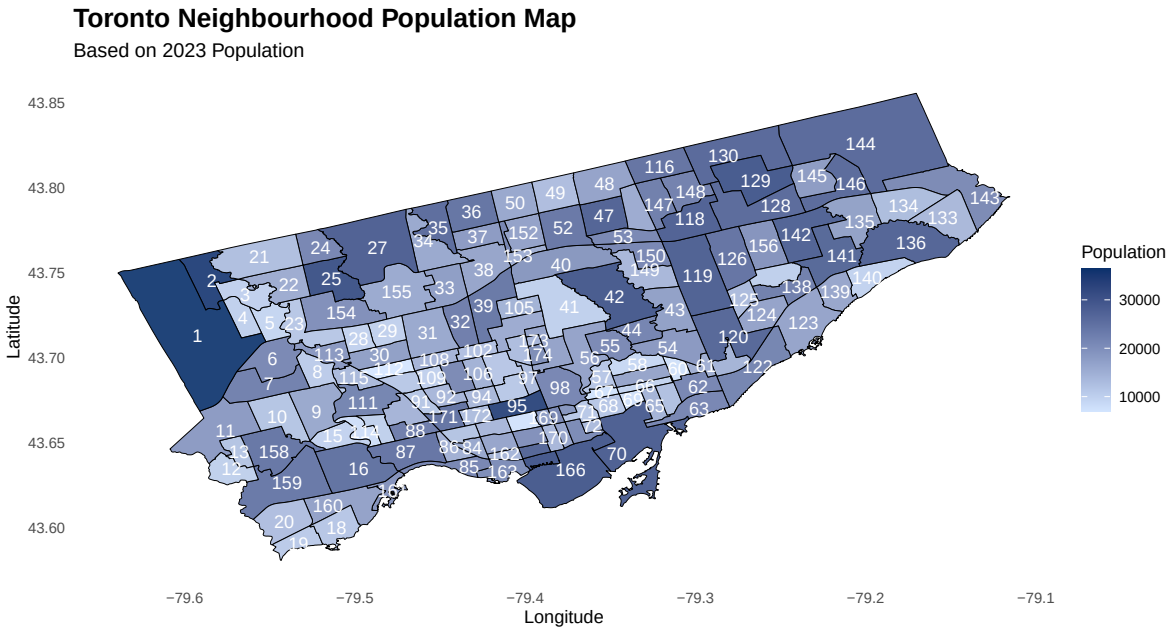

Figure 6: Population distribution in Toronto

3.3 Geographic Distribution of Crime

Based on Figure 6, Figure 7 represents a higher concentration of crimes in areas with higher population densities, particularly in economically disadvantaged neighborhoods. The black trend line here shows an Upward divergence in scatterplot for differnt crime types.

Such effects arise from nonlinear population effects that persist in rates due to the linear assumption. 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.

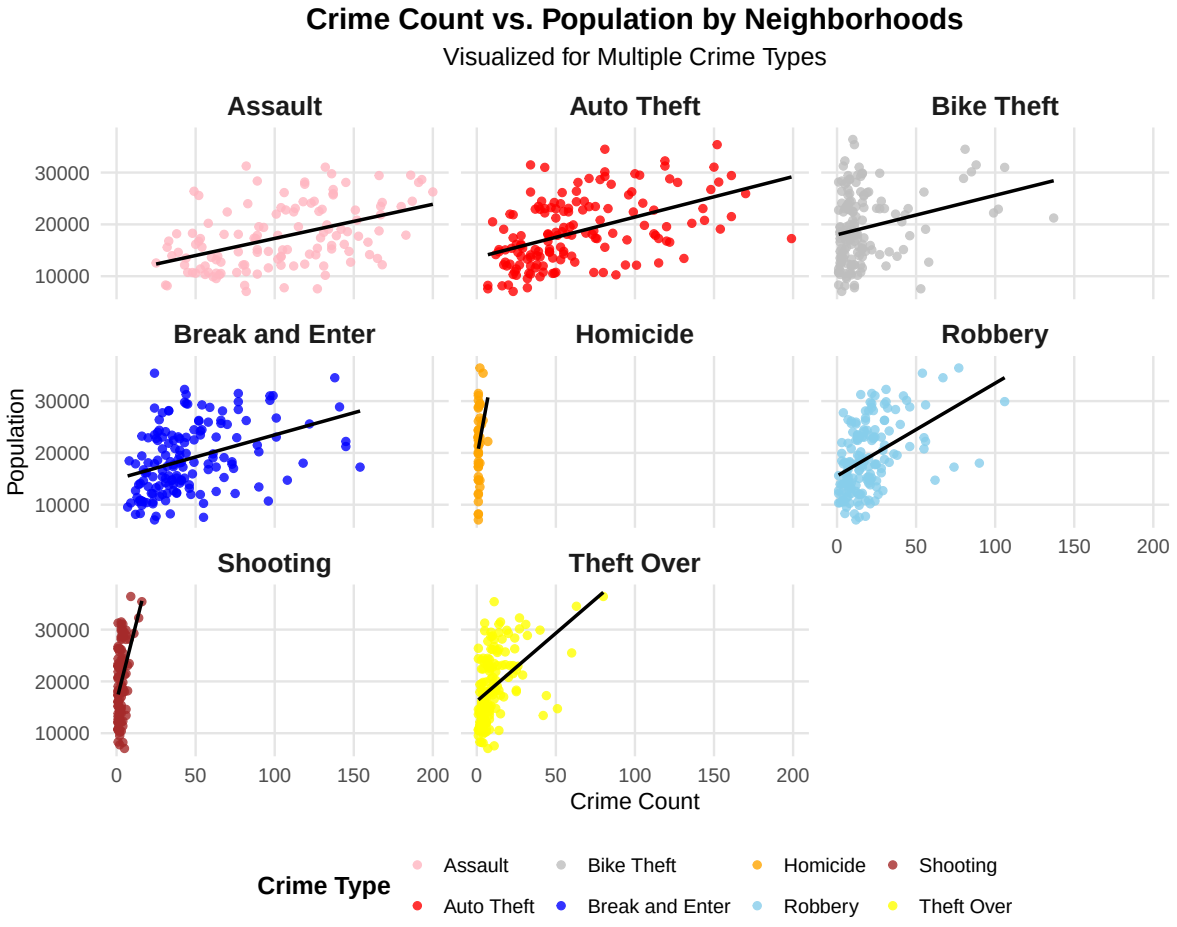

Figure 7: 2023 Crime Trend with Population

From Figure 7, these scatter plots represent upward trend between Crime Count and Population is shown. It seems that the lack of cases in **Shooting** and **Homicide** makes most

dots overlap together. So, the map for each crime is created respectively to help us see the distribution of these 2 particular crime types.

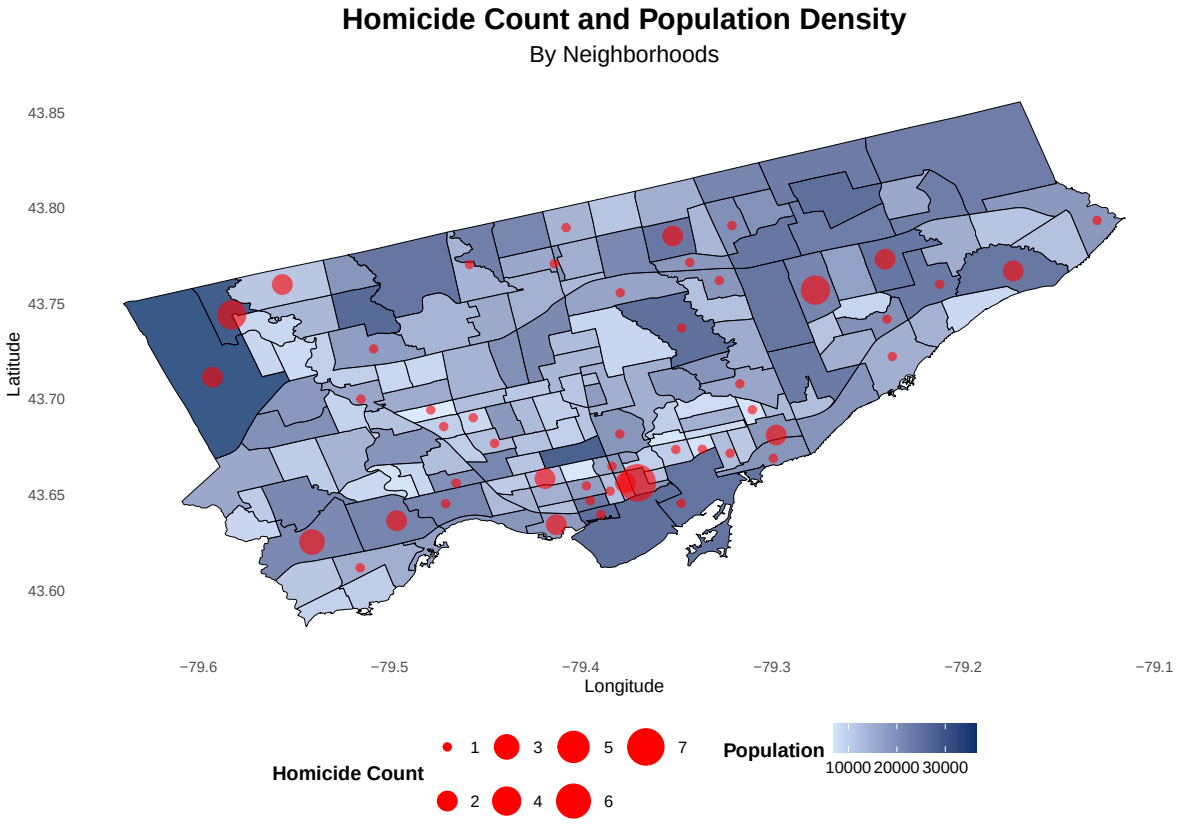

Figure 8: 2023 Homicide Distribution

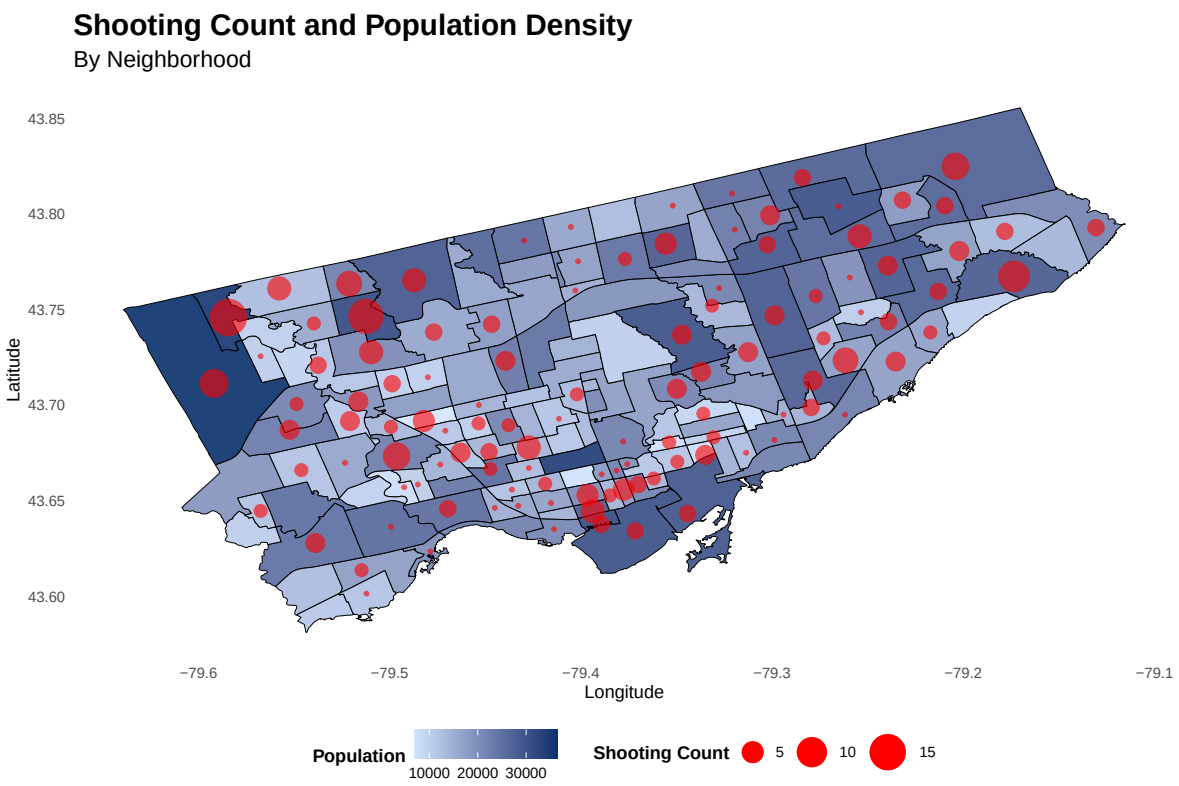

Figure 9: Shooting Count Distribution in 2023

3.4 Neighborhood Analysis

After looking at the trend of crimes in the whole Toronto, it is more important to take a look into those small neighborhoods. Top10 safest and Top10 Crime Prone neighborhoods are shown in the following content. It give police and security department to take different measures to differnt neighborhoods.

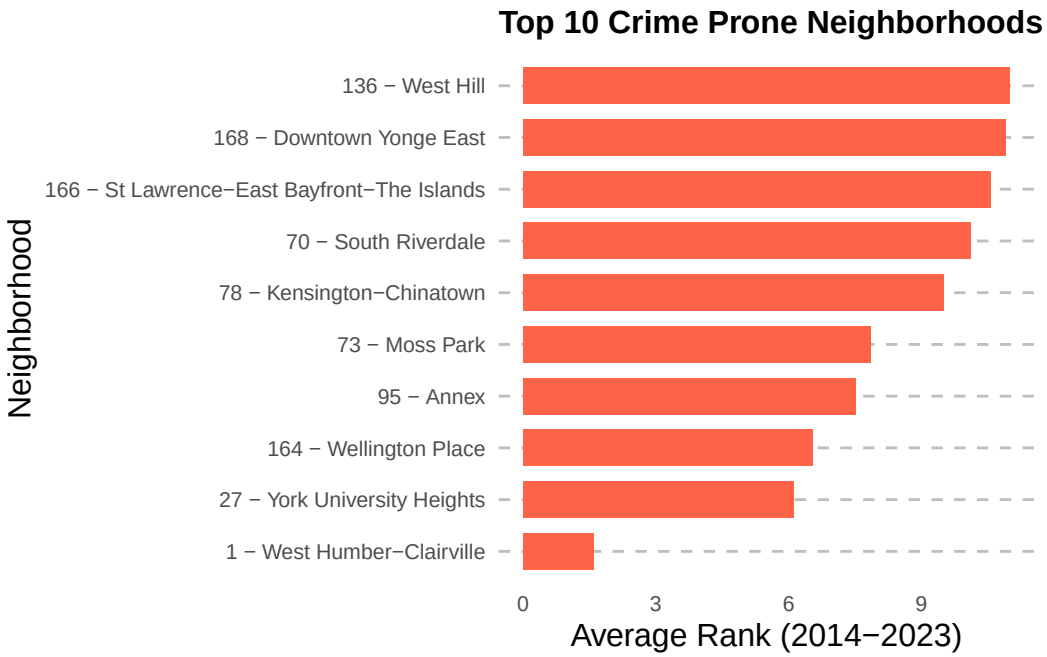

Figure 10: Top10 Ranked Crime Prone Neigborhoods Based on Crime Count

In Figure 10, 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 11 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.

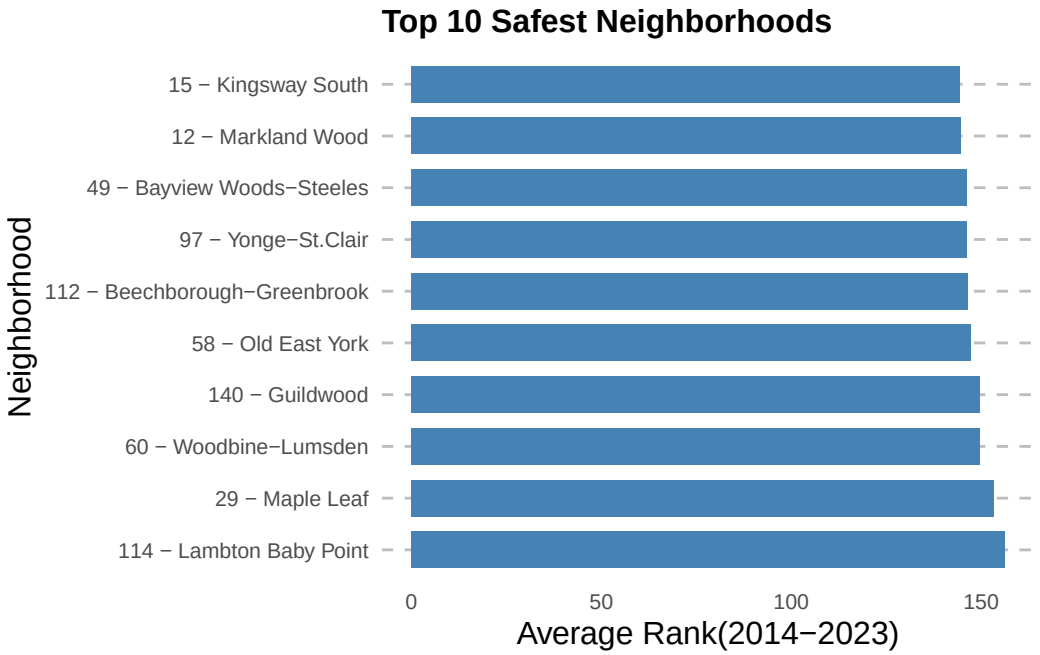

Figure 11: Top10 Ranked Safest Neigborhoods Based on Crime Count

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. The rise of urban centers brings both benefits and challenges. While urbanization can promote economic growth and innovation, it can also lead to social problems such as poverty, unemployment, and social isolation, which can lead to rising crime rates. Effective urban planning strategies that promote social cohesion, economic opportunity and access to resources are essential to mitigate these problems.

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. Crime rates vary widely across provinces and territories. Crime rates in densely populated urban areas are usually higher than in rural areas. This can be attributed to social anonymity, greater economic disparities, and a higher concentration of criminal opportunities in urban environments. In addition, remote areas with limited police resources face crime prevention and law enforcement challenges. 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 under-reported crimes such as domestic violence and cybercrime. Oliveira (2021)'s findings indicate that the assumption of linear crime growth is inaccurate. In over half of the analyzed data sets, we observed evidence of nonlinear crime growth, meaning that crime tends to increase with population size at a rate different from per capita expectations. This nonlinearity introduces

a population effect that impacts crime rates and alters city rankings. We showed that ranking cities based on crime rates alone yields significantly different results compared to rankings that account for population size. So, the further

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.

Besides, Lu, Lee, and Ian (2019) mentions the digital era has ushered in a new type of criminal activity: cybercrime and telecom crime. The Canadian Centre for Cyber Security (CCCS) reports a consistent rise in cybercrime incidents, which amounted to 74,073 police-reported cases as of recent data from Statista Lu, Lee, and Ian (2019). This kind of crime count is missing in our dataset.While obtaining a definitive national cybercrime rate is challenging due to underreporting, the CCCS highlights phishing scams, malware attacks, and ransomware as significant threats.

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.

5 Acknowledgements

We would like to express our appreciation to the City of Toronto and the Open Data Portal for granting access to the dataset via the Open Data Toronto package (Gelfand 2022). Besides, R codes from (**citerohan?**) are used to provide tables in this paper.The provision of high-quality, open-source data is essential for enabling precise research. Thanks to OpenAI (2023), which is used in this research paper.Code written in the scripts was checked and styled with lintr (**citelintr?**) and styler (**citestyler?**).

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