Assessing Population Density and Crime Patterns in Toronto Neighborhoods (2014–2023)*

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This study examines the relationship between population density and crime distribution across Toronto neighborhoods from 2014 to 2023. The analysis reveals that high-density areas experience higher crime rates, particularly for auto theft and assault, with socioeconomic factors further influencing crime patterns. Based on these findings, we propose targeted interventions, such as improved public surveillance and increased community engagement, to address crime in high-risk areas. This research offers valuable insights for policymakers and urban planners to enhance crime prevention strategies in Toronto.

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

1 Introduction

Urban crime is a pressing issue for policymakers and researchers, especially in rapidly growing cities like Toronto. Population density plays a significant role in shaping the spatial distribution of crime, as high-density environments often create more opportunities for criminal activity. This study examines the correlation between population density and crime patterns in Toronto neighborhoods from 2014 to 2023, with a focus on identifying key crime hotspots.

Toronto's urban landscape is diverse, with neighborhoods varying widely in terms of socioeconomic status and population density. Previous research has established that densely populated areas tend to experience higher crime rates, particularly for property crimes such as auto theft and break-and-enter offenses. Moreover, socioeconomic factors such as poverty and residential instability further contribute to crime concentration in certain neighborhoods. This study aims to explore these relationships by analyzing data on crime occurrences across 158 neighborhoods.

By examining crime trends over a decade, this research seeks to inform policymakers about the specific challenges faced by high-density neighborhoods. The study's findings will guide the development of targeted crime prevention strategies, emphasizing the importance of urban planning and community engagement in reducing criminal activity. Through this approach, we aim to offer data-driven suggestions that contribute to safer, more resilient urban environments in Toronto.

2 Data

2.1 Data Overview

The Neighborhood Crime Rates dataset, obtained from Gelfand (2022), spans from 2014 to 2023 and covers 158 Toronto neighborhoods.It is designed to offer communities more information about public safety and awareness. The data provided to the Toronto Police Service by reporting parties is preliminary and may not have undergone full verification at the time of publication. The dataset includes various crime types such as Assault, Auto Theft, Robbery, Break and Enter, Bike Theft, Shooting, and Homicide. According to the standard definition by Statistics Canada, the crime rate is calculated as the number of crimes per 100,000 people each year. Besides, crime counts per crime type per year are also shown in the data. In Gelfand (2022), another variable of interest *Population 2023* refers to the population in the 2023 year in each neighborhood, enabling the analysis of the relationship between population density and crime frequency. Geometry column is transformed into spatial data to build up the Toronto city map to observe population density and crime distribution. Table 1 gives us a glimpse of how the dataset looks. Each neighborhood is identified by its *Area Name* and a unique *Hood ID*.

The average crime rates represent the mean crime rate across 158 neighborhoods from 2014 to 2023, and were calculated to analyze long-term trends and highlight crime types that have seen significant increases. The variables *Crime Type* and *Crime Count* are based on 2023 data (Table 2).Each neighborhood's average rank was determined by ranking all 158 neighborhoods based on their total annual crime count. A rank is assigned for each year, and the average rank over the past decade (2014–2023) is calculated by averaging these yearly ranks. A lower rank indicates a higher crime count. Summaries of the top 10 and bottom 10 ranked neighborhoods are provided in Table 3 and Table 5.

Table 1: A Lookup for the Raw Data

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

Table 2: Summary Table for the Crime Count in 2023

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

Table 2: Summary Table for the Crime Count in 2023

Hood ID	Area Name	Crime Type	Crime Count
173	North Toronto	Theft Over	7

Table 3: Summary Table for Top10 Crime-Prone Neighborhoods (2014-2023)

Neighborhood ID and 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

2.2 Measurement

As for the measurement, the 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 that were deemed "unfounded". The term "unfounded," as defined by Statistics Canada, refers to cases where a police investigation concludes that the reported offense did not happen and was not attempted. Fields have also been updated to reflect the new structure of the 158 City of Toronto neighborhoods. Population figures only account for the resident population in each region and do not include temporary populations like commuters or business patrons. To protect the privacy of those involved, the locations of crime incidents have been intentionally shifted to the nearest road intersection node. As a result, all location data should be regarded as approximate.

Crime rates offer a more balanced comparison over time as they account for population changes in the area and give us a fairer way to see the crime trends in the past decade, which explains why a similar dataset called "Police Annual Statistical Report - Reported Crimes" is not be chosen as my dataset, which only contains the reported crime count for a certain year and a certain division. It lack a standard way to show the crime trends and spatial attribute to see the geography distribution and it also includes reported crimes deemed as unfounded.

3 Results

3.1 Crime Rates Over the Past Decade

Figure 1 uses the variable *Average Crime Rate* (Table 4) to show the crime rate trend between 2014 and 2023 and demonstrate the evolution of different crime types in the city of Toronto. It can be seen that the visualization reveals certain patterns in some specific crime types.

Table 4: Average Crime Rate in Toronto

Area Name	Year	Crime Type	Average Crime Rate
Toronto Average	2014	Assault	610.4018
Toronto Average	2015	Assault	656.9970
Toronto Average	2016	Assault	670.1699
Toronto Average	2017	Assault	673.5303
Toronto Average	2018	Assault	680.1286
Toronto Average	2019	Assault	706.7088
Toronto Average	2020	Assault	605.1265
Toronto Average	2021	Assault	637.6509
Toronto Average	2022	Assault	703.0305
Toronto Average	2023	Assault	806.3105

Figure 1 reveals a significant upward trend in **Auto Theft** and **Assault**, particularly after 2020. The crime rate for **Assault** consistently remained the highest across all crime types, starting at around 600 per 100,000 population in 2014 and reaching a peak of approximately 800 per 100,000 population in 2023. This consistent rise suggests that assault has been a persistent issue in Toronto, with an even sharper increase following the onset of the COVID-19 pandemic.**Break and Enter**,**Robbery** and **Theft Over** all experienced increases after 2021. This rise suggests a sharp increase in private property related crimes, possibly influenced by socioeconomic factors or changes in law enforcement or technology. In contrast, **Homicide** and **Shooting** had relatively lower crime rates and displayed more stability over time, with little significant change compared to **Assault** and **Auto Theft**.

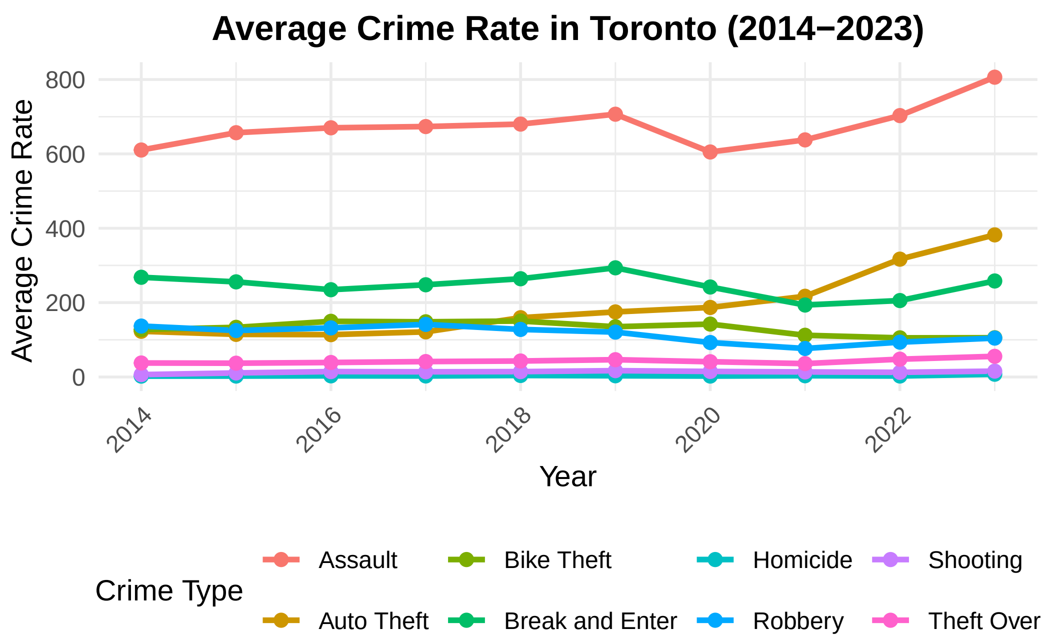

Figure 1: Average Crime Rates per 100,000 population in Toronto (2014-2023)

3.2 Toronto Population Density

Figure 2 shows the population density in Toronto, constructed by using variable *Population 2023* and geometry data. Higher saturation represents higher population density in 2023. Neighborhoods with lighter shading have smaller populations, such as neighborhood 12 and 13. Notably, neighborhoods 1 and 95 exhibit the darkest saturation, indicating the highest population density. In the following sections, we will explore whether these high-density neighborhoods correspond to areas that are more prone to crime.

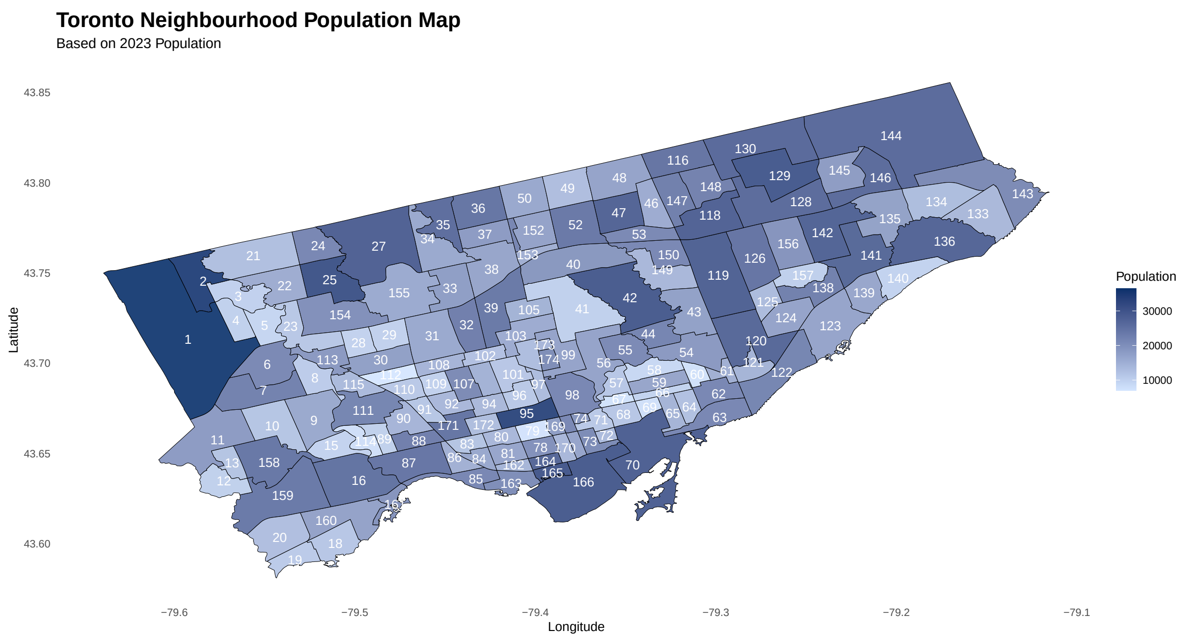

Figure 2: Toronto Population Density (2023)

3.3 Relationship between Crime Count and Population

The scatterplots in Figure 3 illustrate the relationship between crime count and population for various crime types across Toronto neighborhoods in 2023. Each crime type is represented by a separate plot, and a trendline has been added to demonstrate the relationship between crime count and population size.

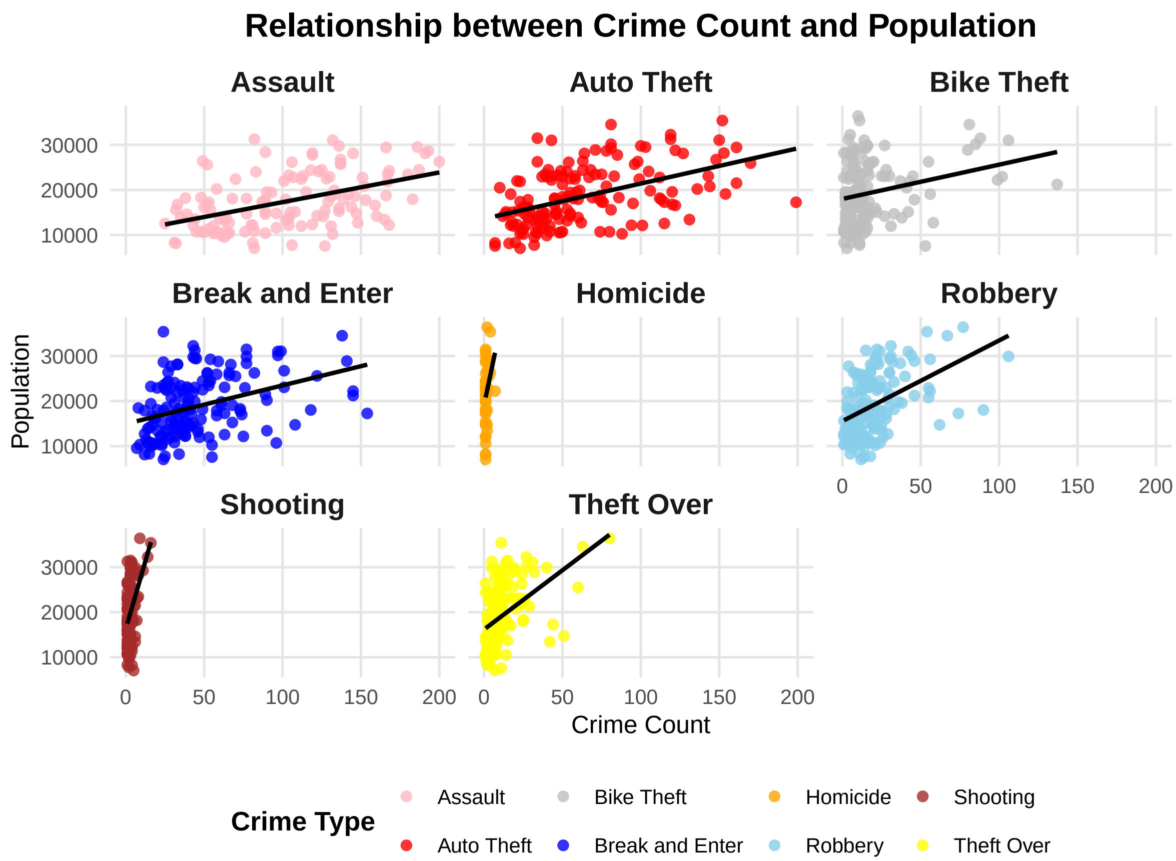

Figure 3: Scatterplots for Crime Count and Population in 2023

Assault and **Auto Theft** exhibit strong positive correlations with population, as indicated by the upward slope of the trendlines. This suggests that as the population of a neighborhood increases, the number of assaults and auto theft incidents tends to rise as well. **Break and Enter** shows a similar trend, with higher crime counts in neighborhoods with larger populations. **Robbery** and **Theft Over** also show a positive relationship with population, although the correlation is not as strong as it is for Assault or Auto Theft. **Bike Theft**, while showing an upward trend, appears more dispersed, indicating a weaker correlation between population size and the number of incidents.

Overall, the graph highlights that property crimes, such as **Auto Theft**, and **Break and Enter**, are more likely to increase with population density, whereas violent crimes like **Homicide** and **Shooting** remain relatively low in Toronto regardless of neighborhood size.

From Figure 3, most of 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. These crimes are less frequent, and the relationship between population and crime count is less pronounced compared to property crimes.

Consequently, extra maps are shown in Figure 4 and Figure 5 to display these two relatively rare crime types' occurrence in particular neighborhoods. The size of red dot represents for the crime count and is marked on the area they occur. It can be observed that most larger size dots appear in the neighborhoods with darker shading, and most of neighborhoods with lowest saturation blue does not have a reported homicide or shooting case.

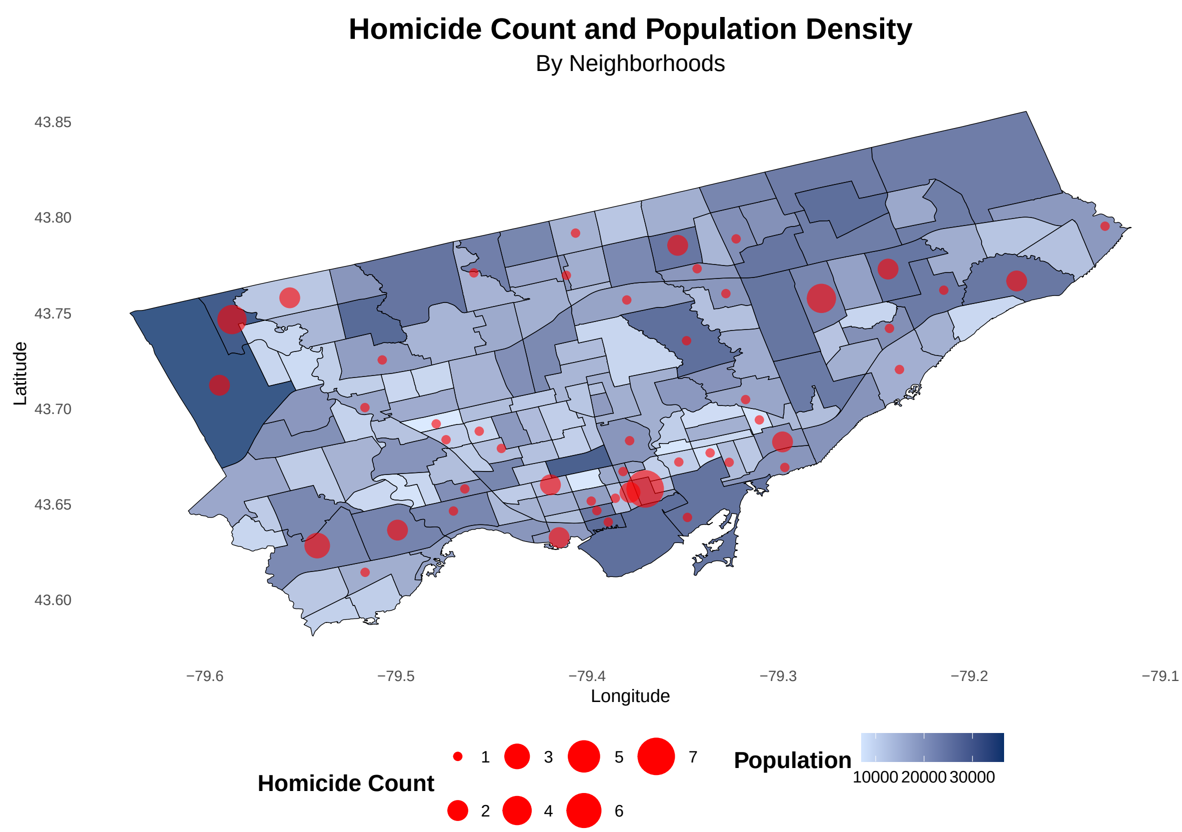

Figure 4: Homicide Count Distribution (2023)

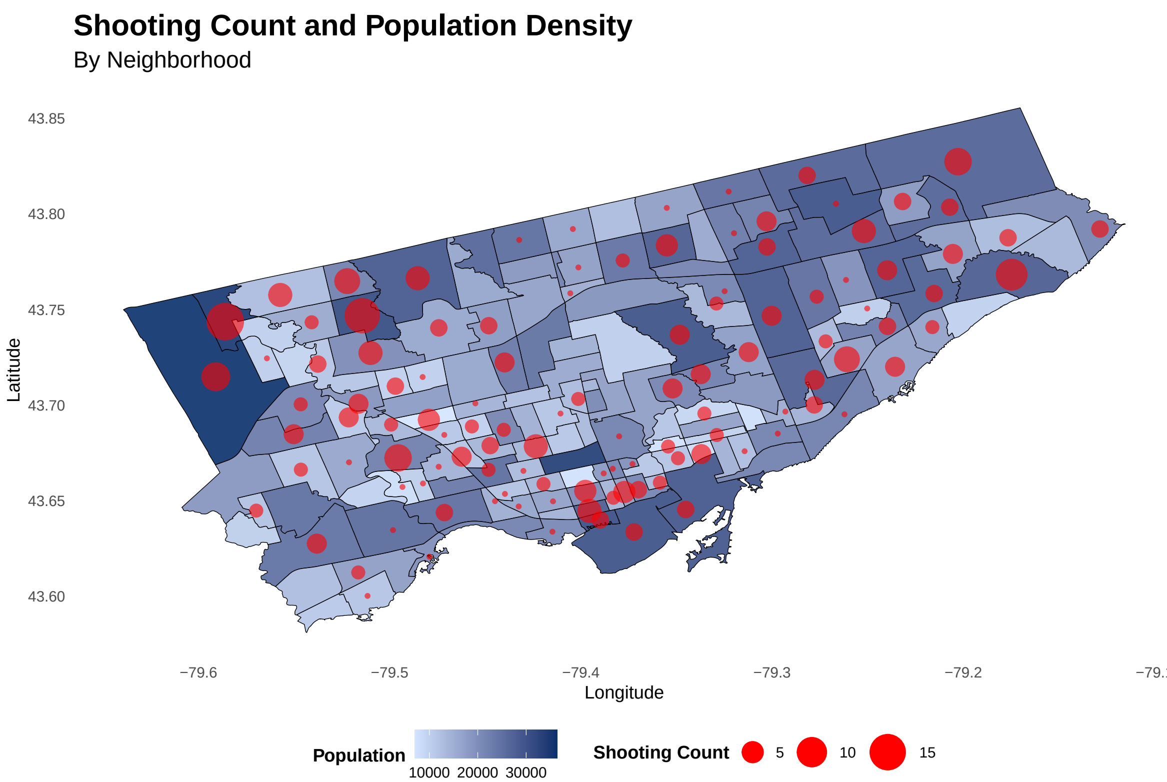

Figure 5: Shooting Count Distribution (2023)

3.4 Neighborhood Analysis

After looking at the pattern of crimes in the whole Toronto, it is more important to take a look into those small neighborhoods. The rank here is counted based on the total crime count for each neighborhood each year. Higher rank implies higher crime count on average. Top 10 safest and Top 10 Crime-Prone neighborhoods are drawn from the average rank in past 10 years. Neighborhoods like West Humber-Clairville and York University Heights ranked among the most crime-prone areas, likely due to their high population density (around 30,000 population) and busy commercial districts. This supports existing criminological theories that link high-density environments with increased opportunities for crime. Besides, as we noted in Figure 2, both of the most density neighborhoods 1 (West Humber-Clairville) and 95 (Annex) show in the Top 10 crime-prone ranked neighborhoods. In addition to West Humber-Clairville and Annex, Wellington Place, Kensington-Chinatown, and Moss Park also ranked among these most 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.

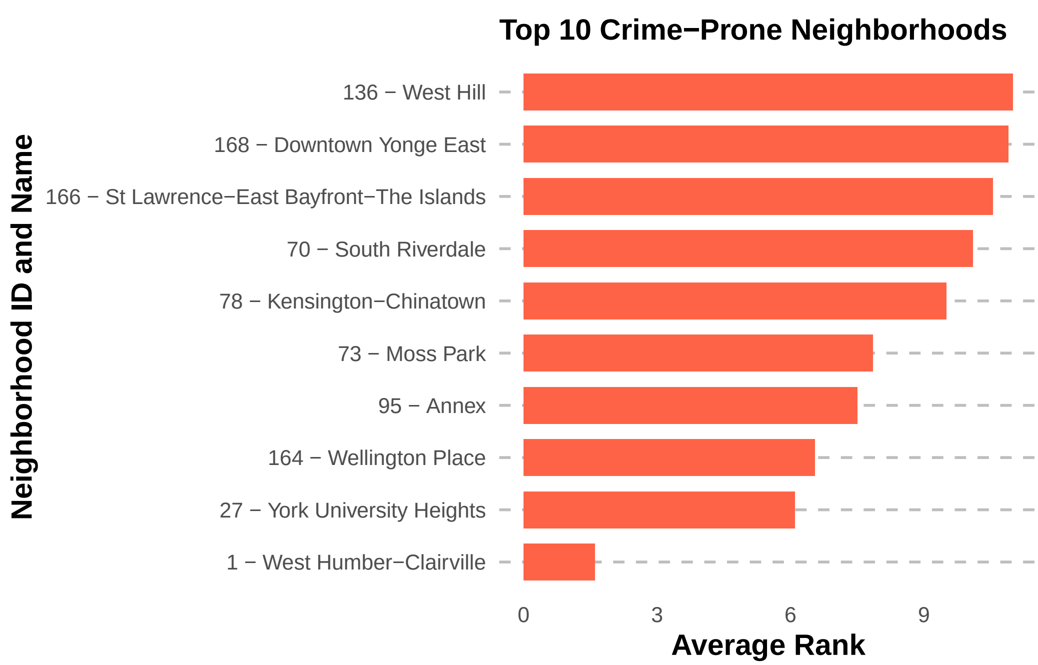

Figure 6: Top10 Ranked Crime-Prone Neigborhoods (2014-2023)

Table 5: Top10 Ranked Safest Neigborhoods (2014-2023)

Neighborhood ID and 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

In contrast, Table 5 shows the neighborhoods with least crime occurrences in past 10 years. Neighborhoods such as 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 all of them just have a population around 10,000 in 2023. This significant difference is likely due to their suburban residential character, lower population densities, and enhanced social cohesion."

4 Discussion

4.1 Summary of Findings

The analysis reveals notable fluctuations in crime rates over time, with significant increases in property crimes like Auto Theft and Break and Enter. Assault has remained the most prevalent crime over the past decade. A marked rise in crime rates, particularly in Assault and Auto Theft, was observed after 2020, suggesting a potential link between population density and heightened criminal activity, especially in the post-pandemic period.

High-crime neighborhoods often have greater population densities, which can create more opportunities for crime due to increased anonymity and weakened social cohesion. These areas are frequently economic hubs or feature mixed-use development, which may elevate the risk of crimes such as theft or assault.

Conversely, safer neighborhoods tend to have lower population densities and greater residential stability. The reduced anonymity and slower pace of life may contribute to lower crime rates. Additionally, these areas often benefit from stronger community engagement and better surveillance infrastructure, further deterring criminal activity.

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. 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.

Crime is not randomly distributed but tends to cluster in specific neighborhoods with particular socioeconomic characteristics. High concentrations of both property and violent crime are observed in the downtown core, the northeast (North York), and the northwest (Etobicoke), while lower crime rates are observed in central and west Toronto. Neighborhoods with high levels of marginalization tend to see higher crime rates, reinforcing theories of social disorganization and relative deprivation (Lu, Lee, and Ian 2019). The findings also support criminological theories that increased population density creates more opportunities for crime due to social fragmentation and anonymity.

Urban planners and policymakers must consider interventions such as improved public surveillance and community engagement initiatives to reduce crime in high-density areas. They should focus on strategies designed specifically for high-density areas. Solutions such as improved public lighting, increased surveillance by CCTV and more frequent police patrols can help deter criminal activity in these hotspots. Furthermore, fostering community engagement through neighborhood associations, local events, and resident-driven initiatives can reduce social disorganization and strengthen neighborhood resilience.

4.3 Socioeconomic Disparities and Crime Hotspots

Lu, Lee, and Ian (2019)'s study highlights the significant role of socioeconomic deprivation, residential instability, and ethnic concentration in explaining the spatial distribution of crime. Neighborhoods marked by high levels of deprivation and instability tend to experience more violent crime, while property crimes, though more widespread, are still linked to similar socioeconomic factors.

Socioeconomic factors, together with population density, play a key role in shaping crime patterns. Economically disadvantaged areas, such as Moss Park and York University Heights, tend to have higher crime rates. This underscores the importance of addressing socioeconomic disparities to reduce crime. Targeted social interventions—such as improving access to education, healthcare, and employment—could help tackle the root causes of crime.

Mohammadi et al. (2022)'s research reinforces this view, suggesting that neighborhoods with high levels of marginalization often see elevated crime rates, supporting theories of social disorganization and relative deprivation. The presence of commercial establishments and large buildings is also positively associated with homicide rates, likely due to increased social interactions and conflicts in these busier, more economically active areas.

Socioeconomic inequality fuels crime dynamics by creating social strain and increasing the likelihood of economic crimes like theft, robbery, and property damage. Policymakers should focus on reducing economic inequality through programs that target poverty, unemployment, and lack of access to education. Revitalizing disadvantaged neighborhoods by improving housing, creating job opportunities, and enhancing access to essential services like education and healthcare could help address the underlying causes of crime and reduce its incidence in these areas.

4.4 Targeted Crime Prevention Strategies

A pattern has been verified in Toronto is that persistently high crime rates often draw additional criminal activity, leading to what is known as the "law of crime concentrations at places" (Mohammadi et al. 2022). It means crimes tend to recur in some areas with specific features, thus these features can be found out to take crime prevention strategies. Property and violent crime hotspots are concentrated in the downtown core, northwest, and eastern parts of the city (Lu, Lee, and Ian 2019). This geographic concentration has significant implications for law enforcement and public policy. Policymakers and law enforcement agencies must recognize that crime prevention strategies cannot be one-size-fits-all. Instead, interventions need to be tailored to address the unique challenges faced by high-risk neighborhoods.

This study underscores the importance of community-based crime prevention strategies. Engaging local residents through neighborhood watch programs, educating the public on crime prevention techniques, and fostering collaboration between the police and community organizations can empower communities to take charge of their safety. Such an approach not only helps reduce crime frequency but also strengthens the relationship between law enforcement and the communities they serve—an essential element for long-term success in crime reduction.

Lu, Lee, and Ian (2019) propose that neighborhoods with higher levels of socioeconomic disadvantage—marked by unemployment, poverty, and lower education levels tend to experience higher crime rates. This aligns with social disorganization theory, which links socioeconomic disadvantages to an increase in crime. For neighborhoods like Moss Park and St. Lawrence-East Bayfront, which consistently rank among the areas with the highest crime rates, a multifaceted approach is necessary. This could include increased policing along with community programs that address the root causes of crime, such as poverty, unemployment, and lack of access to education and healthcare. Tackling these underlying issues can significantly reduce crime rates, particularly in economically disadvantaged areas.

Additionally, the rise in auto theft and break-and-enter incidents in recent years indicates that law enforcement must adapt to evolving crime patterns. The information era has introduced new types of crime, such as cybercrime and telecom crime. These types of crimes are missing from our dataset. Technological advancements, like vehicle tracking systems and smart security devices, can help curb these rising property crime rates. Public awareness campaigns promoting better security practices, especially in high-risk neighborhoods, could also be effective in preventing crime.

4.5 Limitations and Future Research

While this study provides a strong foundation for assessing population density and crime patterns in Toronto neighborhoods, some limitations must be acknowledged. Firstly, the analysis relies on reported crime data, which may not fully reflect the actual scope of criminal activity, especially for underreported crimes like domestic violence and cybercrime. Information era has led to some new types of criminal activities like cybercrime and telecom crime. Obtaining a definitive national cybercrime rate or count is still a challenging task because of underreporting.

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

Future research could expand on these findings by incorporating additional data sources and other potential influences to capture a wider range of criminal activity. It would also be valuable to explore how different aspects of urban infrastructure and development of new technology affect crime patterns.

5 Acknowledgements

All data analysis was performed in R (R Core Team 2021), utilizing a range of packages including Tidyverse (Wickham et al. 2019), Dplyr (Wickham et al. 2023), Geojsonsf (Cooley 2022), Knitr (Xie 2014), ggplot2 (Wickham 2016), sf (Pebesma 2018), gt (Iannone et al. 2024), and lintr (Hester et al. 2024). These tools facilitated both data visualization and the clear communication of findings.

We extend our gratitude to the City of Toronto and the Open Data Portal for providing access to the dataset via the Open Data Toronto package (Gelfand 2022). Additionally, R code from Alexander (2023) was utilized to generate tables in this paper. We also acknowledge the use of ChatGPT by OpenAI (OpenAI 2023). Finally, the code was reviewed and formatted using lintr (Hester et al. 2024) and styler (Müller and Walthert 2024).

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