Neighbourhood Crime in Toronto: A Socioeconomic Perspective*

Analyzing Crime Trends in Low, Medium, and High Opportunity Areas (2019–2024)

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This study examines how neighbourhood-level crime trajectories in Toronto evolved from 2019 through 2024, using socioeconomic clustering to identify crime rate divergence across 159 Toronto neighbourhoods. Drawing upon Canadian census and Toronto Police crime data, we applied K-means clustering to group neighbourhoods into three socioeconomic categories reflecting relative socioeconomic advantage (High-, Medium-, and Low- Opportunity) and compared crime rates across these clusters over time. Policy implications include targeted interventions in low-opportunity neighbourhoods and continued support for equity-driven community policing and economic opportunity programs.

1 Introduction

The COVID-19 pandemic profoundly disrupted social and economic systems worldwide—and crime trends were no exception. In Canada, police-reported incidents plummeted in 2020 before rebounding sharply in 2021 (Canada (2021)), with violent crime surging 5% above pre-pandemic levels while property crime fell to historic lows.

However, these national trends obscure local disparities; crime clusters unevenly across urban spaces, concentrated in areas marked by structural inequities—e.g., income inequality, educational disparities, and labour market marginalization ((Mohammadi et al. 2022; Wang, Lee, and Williams 2019)). This spatial unevenness is particularly pronounced in Toronto, Canada's largest city, where neighbourhoods diverge sharply in socioeconomic conditions—from affluent enclaves to zones of concentrated disadvantage ((Jargowsky and Tursi 2015)). A plethora of research confirms that these inequalities stratify crime patterns, making city-wide or national

*Code and data are available at: [https://github.com/mcowan38/tswd_toronto_crime].

averages poor proxies for local realities ((**wamg_2019_the?**; **uesugi_2024?**; Yu and Fang 2025)).

Building on this established research, this paper examines how Toronto's neighbourhood-level crime patterns evolved during the pandemic and its aftermath. We analyze official crime counts for Toronto's neighbourhoods from 2019 through 2024, assessing how pre-existing social and economic inequalities—often termed "opportunity" or "advantage" differences ((Yu and Fang 2025))—relate to diverging crime trends. Specifically, we classify Toronto neighbourhoods into Low-, Medium-, and High-Opportunity clusters via K-means clustering on socioeconomic variables and compare the crime trajectories of these clusters over time.

This paper proceeds as follows: First, we ground our analysis in criminological frameworks—i.e., social disorganization and strain—which help explain how neighbourhood opportunity structures (e.g., income, education, employment) may condition crime trends. Next, we describe our data and methodological approach, justifying our construction of neighbourhood opportunity clusters via K-means socioeconomic variables—analyzing their distinct crime trajectories from 2019-2024. Practically, we consider what our neighbourhood-level results suggest for urban policy—particularly targeting policing resources and economic opportunity programs. Finally, we identify directions for future research on urban crime patterns during periods of social disruption.

2 Literature Review

2.1 Criminological Theory

Criminological theory and empirical evidence converge on two insights in urban crime literature: (1) neighbourhood-level structural conditions fundamentally shape crime, and (2) spatial inequalities between neighbourhoods amplify these effects.

Social disorganization theory suggests that poverty, residential instability, ethnic heterogeneity, and family disruption erode collective efficacy—the capacity of communities to enforce informal social controls; the resulting conditions create criminogenic environments where crime flourishes due to weakened guardianship and institutional neglect (Frevel and Schulze 2021; Antunes and Manasse 2021). Strain theory complements this perspective, arguing that material deprivation and relative disadvantage generate frustration that may motivate criminal coping strategies (Antunes and Manasse 2021), particularly during systemic crises—such as the COVID-19 pandemic.

Contemporary research extends these theories by emphasizing the study of spatial inequality—the juxtaposition of affluence and deprivation across proximate neighbourhoods. For example, Kang (2016) demonstrates that inter-neighbourhood income disparities, rather than city-wide inequality alone, predict localized violence, suggesting that proximity to wealth exacerbates perceptions of exclusion and strain. This finding aligns with Yu and Fang (2025) findings in Paterson, NJ, where median household income exerted the strongest neighbourhood-level influence on crime patterns, underscoring the need to analyze socioeconomic factors at granular spatial scales.

Unsurprisingly, decades of evidence confirm that concentrated disadvantage—marked by poverty, unemployment, and single-parent households—correlates strongly with elevated crime rates (Jargowsky and Tursi 2015; Frevel and Schulze 2021). Toronto exemplifies this dynamic: neighbourhoods with higher marginalization indices exhibit disproportionately high rates of violent and property crime (Wang, Lee, and Williams 2019), while areas with entrenched poverty report elevated homicide incidence (Mohammadi et al. 2022). However, spatial heterogeneity of these relationships is also critical. Geographically weighted regression studies in Chicago (Arnio and Baumer 2012) and Tokyo (Uesugi and Hino 2024) reveal that the strength—and even the direction—of socioeconomic predictors of burglary or robbery vary across neighbourhoods, calling for local (rather than purely global) models of crime.

The COVID-19 pandemic undoubtedly exposed and amplified these spatial inequities. Initial lockdowns reduced city-wide crime through diminished routine activities, but declines in some cities were uneven (Andresen and Hodgkinson 2022). For instance, while property crime in Vancouver decreased in wealthy neighbourhoods with robust security infrastructure, violent crime surged in disadvantaged areas strained by disrupted social services and weakened guardianship.

These disparities underscore three critical lessons: first, structural disadvantage predicts vulnerability to crime spikes during crises, aligning with social disorganization theory's emphasis on resource-deprived communities. Second, inter-neighbourhood inequality magnifies criminogenic risks, as strain theory posits when relative deprivation fuels frustration. Third, opportunity structures—access to security, institutional support, and economic stability—are spatially stratified, privileging affluent areas with systemic advantages.

Building on these insights, we operationalize "opportunity" as the structured availability of socioeconomic resources that mediate crime risks, focusing on Toronto's neighbourhoods. Our analysis extends prior work in two ways: first, we expand the temporal scope to 2019–2024, assessing whether pandemic-era disparities persisted into the recovery phase. Second, we apply K-means clustering to classify neighbourhoods into High-, Medium-, and Low-Opportunity clusters using variables (income, education, employment) empirically shown to influence crime patterns (Yu and Fang 2025). If social disorganization and strain theories hold, Low-Opportunity clusters should exhibit both higher baseline crime rates and greater volatility during disruptions, reflecting their structural precarity.

3 Data

We use the programming language Python (Python Core Team 2019) alongside polars (Vink and Polars Contributors 2025) and sci-kit-learn (Pedregosa et al. 2011) for all subsequent data cleaning and analysis.

3.0.1 Neighbourhood Crime Data

We sourced crime data from the Open Data Toronto Portal (The City of Toronto 2025), which includes assaults, break-and-enters, robberies, and shootings—the types of crime we chose to analyze between 2019 and 2024. Each entry includes incident years and total counts by neighbourhood (see Table 1).

Table 1: "Toronto Crime Data (2014-2024)"

_id	AREA_NAME	HOOD_ID	ASSAULT_2014	BREAKENTER_2014	...
1	"South Eglinton-D"	174	55	27	""
2	"North Toronto"	173	53	25	""
3	"Dovercourt Villa"	172	62	38	""
4	"Junction-Wallace"	171	164	37	""
5	"Yonge-Bay Corrid"	170	387	69	""
...	...	...	...	...	...
154	"West Humber-Clai"	1	289	148	""
155	"Black Creek"	24	222	26	""
156	"Pelmo Park-Humbe"	23	58	30	""
157	"Humbermede"	22	105	35	""
158	"Humber Summit"	21	90	54	""

Table 1 Previews crime variables across Toronto neighbourhoods, including assault and break-and-enter incidents. Values are cleaned and truncated for display.

3.0.2 Neighbourhood Census Profiles

2021 Toronto Census Profile data was obtained from the Open Data Toronto Portal (The City of Toronto 2025). This data was transformed to align with neighbourhood identifiers used in the crime dataset (see Table 2).

Table 2: "Toronto Neighbourhood Census Data (2021)"

Neighbourhood Name	West Humber	Mt. Olive	Thistletown	Elms-Old	...
"Neighbourhood Number"	"1"	"2"	"3"	"5"	""
"Total - Age groups of th"	"33300"	"31345"	"9850"	"9355"	""
" 0 to 14 years"	"4295"	"5690"	"1495"	"1610"	""
" 0 to 4 years"	"1460"	"1650"	"505"	"440"	""

Table 2: "Toronto Neighbourhood Census Data (2021)"

Neighbourhood Name	West Humber	Mt. Olive	Thistletown	Elms-Old	...
" 5 to 9 years"	"1345"	"1860"	"540"	"480"	""
...	...	...	...	...	...
"Total - Eligibility and "	"3875"	"5540"	"1325"	"1520"	""
" Children eligible for "	"335"	"395"	"120"	"70"	""
" Eligible children wh"	"255"	"245"	"75"	"60"	""
" Eligible children wh"	"75"	"145"	"45"	"10"	""
" Children not eligible "	"3540"	"5145"	"1205"	"1445"	""

Table 2 Census-derived socioeconomic variables (e.g., education, income) by neighbourhood, used as clustering inputs. Values are cleaned and truncated for display.

3.1 Measurement

Transforming the lived realities of Toronto's neighbourhoods into data suitable for our analysis required two steps: (1) constructing a composite socioeconomic profile for every neighbourhood and (2) aggregating police-reported crime counts to rate units.

From the Census data, we extracted four attributes that decades of criminological research identify as correlates of neighbourhood crime: median household income, share of adults with a bachelor's degree or higher, unemployment rate, and proportion of single-parent families (cite).

From the crime dataset, we aggregated annual counts of assaults, break-and-enters, robberies and shootings (2019–2024) and transformed them into rates per 100,000 persons using neighbourhood-level population denominators.

These two sources were paired by Toronto's 159 neighbourhoods, yielding socioeconomic features and crime rates from the early pre- to post-COVID-19 pandemic.

4 Model

Mirroring prior spatial criminological studies—which have employed diverse spatial statistics to characterize neighbourhood heterogeneity in crime and socio-economic conditions (Mohammadi et al. 2022; Uesugi and Hino 2024; Wang, Lee, and Williams 2019; Yu and Fang 2025)—we apply K-means clustering to the four standardized indicators—education rate, single-parent households, unemployment rate, and median household income—to uncover latent socio-economic typologies.

Let $\mathbf{x}_i = (x_{i1}, x_{i2}, x_{i3}, x_{i4})$ denote the four-dimensional vector of z-scored socioeconomic features for neighbourhood i, $i = 1, \dots, N = 159$. The features are defined as:

- x_{i1}: education rate (proportion with bachelor's degree or higher)
- x_{i2}: proportion of single-parent households
- x_{i3}: unemployment rate
- x_{i4}: median household income

We standardize each raw feature via

$$x_{ij}^{\text{scaled}} = \frac{x_{ij} - \overline{x}_j}{s_j},$$

where $\overline{x}_j$ and s_j are the sample mean and standard deviation of feature j.

We then partition $\{\mathbf{x}_i\}_{i=1}^N$ into $K = 3$ clusters using the K-means algorithm, minimizing the within-cluster sum of squares:

$$\{\mu_k\}_{k=1}^3 = \arg\min_{\{\mu_k\}} \sum_{i=1}^N \left\| \mathbf{x}_i - \mu_{z_i} \right\|^2,$$

where μ_{z_i} is the centroid of neighbourhood i's assigned cluster.

We tested $K = 2, \dots, 5$ and selected $K = 3$ based on silhouette and Davies–Bouldin diagnostics (see Appendix{sec-}), and because a three-fold typology (High-, Medium-, Low-Opportunity) aligns with established frameworks of urban socioeconomic stratification. A preliminary Principal Components Analysis—conducted as a diagnostic check—showed that the first two components explain ~89% of total variance, confirming a strong low-dimensional socioeconomic gradient underlying the four indicators.

The resulting clusters are labeled as:

Table 3: "Descriptive Statistics by SES Cluster (2019–2024)"

Cluster	Neighbourhoods (n)	Avg. Median Income ($)	Single-Parent Proportion	Education Rate	Unem
0	19	132368.421053	0.12	0.7	9.67
1	72	88775.0	0.15	0.58	12.75
2	67	76870.149254	0.25	0.34	16.37

Table 3 Presents the average socioeconomic features by cluster for Toronto neighbourhoods over 2019–2024. Clusters were derived via K-means clustering on standardized education rate,

proportion of single-parent households, unemployment rate, and median household income. High-Opportunity (Cluster 0) neighbourhoods exhibit high educational attainment and median income alongside low unemployment and single-parent household rates. Medium-Opportunity (Cluster 1) neighbourhoods display a mixed socioeconomic profile. Low-Opportunity (Cluster 2) neighbourhoods are characterized by lower education and income, and higher unemployment and single-parent household rates. All values represent means of each indicator across the study period.

Although we also explored Gaussian Mixture Models (GMM)\footnote{GMM models the data as a mixture of K multivariate normal distributions, estimating for each component a mean vector and covariance matrix both methods yielded similar groupings (Pedregosa et al. 2011). We retained K-means for its interpretability and marginally better cluster evaluation scores (see Section A)

5 Results

Our results are summarized in Figure 1

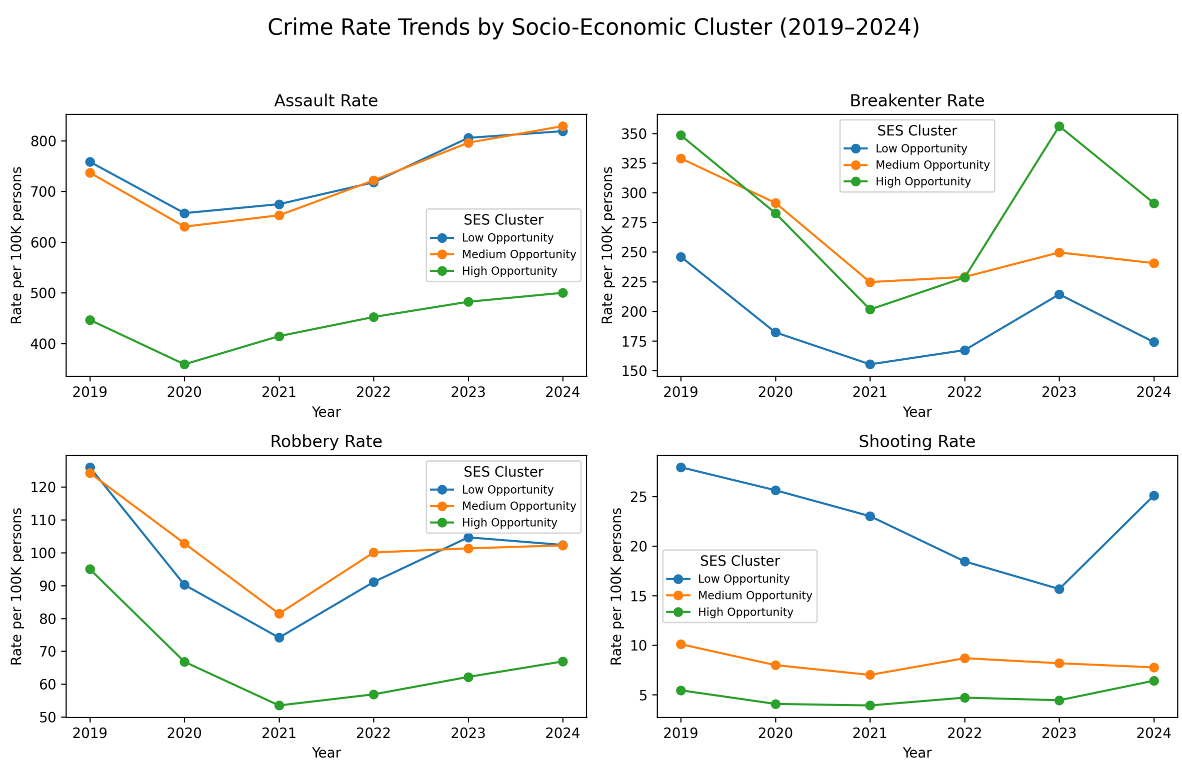

Figure 1: Assault

Average Crime Rate Trends (2019–2024) by Socio-Economic Cluster

Figure 1 Plots...

6 Discussion

6.1 Neighbourhood Crime Rates

- ETA: May 28

6.2 Theoretical Implications

- ETA: May 28

6.3 Policy Relevance

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6.4 Limitations

- ETA: May 28

A Appendix

A.1 Model Evaluation

- ETA: May 28

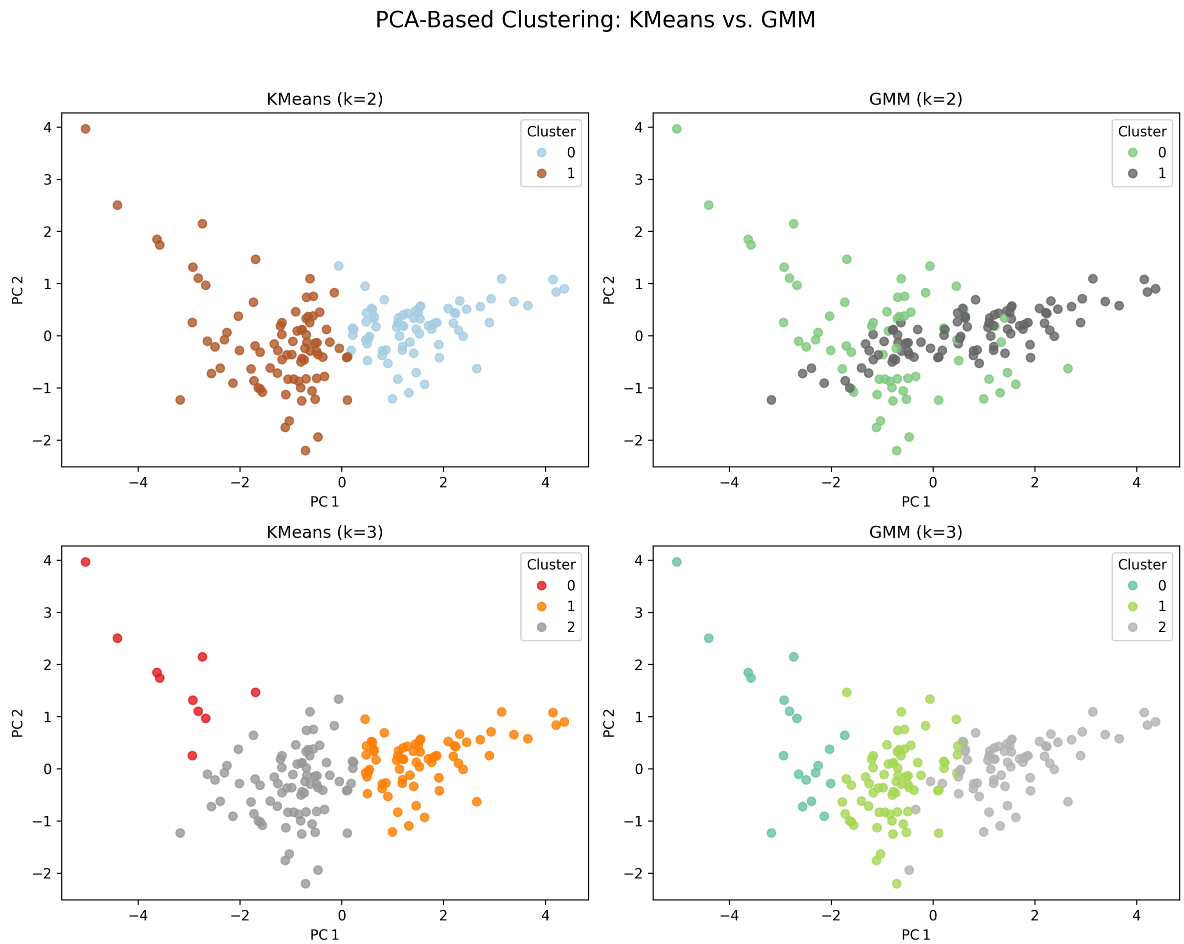

Figure 2: KMeans (k=2)

Dimensionality-Reduced Clustering Comparisons (2019–2024 SES)

Figure 2 Displays...

Further, [ETA: May 28]

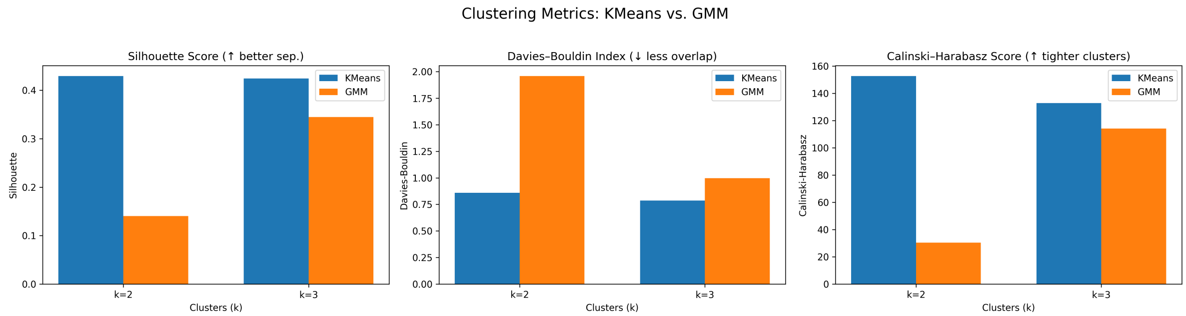

Figure 3: Silhouette Score

Clustering Evaluation Metrics by Model and k

Figure 3

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