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SPECIAL SECTION ON COVID-19: QUANTITATIVE RESEARCH

COVID-19 case rates, spatial mobility, and neighbourhood socioeconomic characteristics in Toronto: a spatial–temporal analysis

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Abstract

Objectives This study has two primary research objectives: (1) to investigate the spatial clustering pattern of mobility reductions and COVID-19 cases in Toronto and their relationships with marginalized populations, and (2) to identify the most relevant socioeconomic characteristics that relate to human mobility and COVID-19 case rates in Toronto's neighbourhoods during five distinct time periods of the pandemic.

Methods Using a spatial-quantitative approach, we combined hot spot analyses, Pearson correlation analyses, and Wilcoxon two-sample tests to analyze datasets including COVID-19 cases, a mobile device–derived indicator measuring neighbourhood-level time away from home (i.e., mobility), and socioeconomic data from 2016 census and Ontario Marginalization Index. Temporal variations among pandemic phases were examined as well.

Results The paper identified important spatial clustering patterns of mobility reductions and COVID-19 cases in Toronto, as well as their relationships with marginalized populations. COVID-19 hot spots were in more materially deprived neighbourhood clusters that had more essential workers and people who spent more time away from home. While the spatial pattern of clusters of COVID-19 cases and mobility shifted slightly over time, the group socioeconomic characteristics that clusters shared remained similar in all but the first time period. A series of maps and visualizations were created to highlight the dynamic spatiotemporal patterns.

Conclusion Toronto's neighbourhoods have experienced the COVID-19 pandemic in significantly different ways, with hot spots of COVID-19 cases occurring in more materially and racially marginalized communities that are less likely to reduce their mobility. The study provides solid evidence in a Canadian context to enhance policy making and provide a deeper understanding of the social determinants of health in Toronto during the COVID-19 pandemic.

Résumé

Objectifs Cette étude a deux grands objectifs de recherche : 1) examiner les schémas d'agrégation spatiale des baisses de mobilité et des cas de COVID-19 à Toronto et leurs liens avec les populations marginalisées; et 2) cerner les caractéristiques socioéconomiques les plus pertinentes liées à la mobilité humaine et aux taux de cas de COVID-19 dans les quartiers de Toronto au cours de cinq périodes distinctes de la pandémie.

Méthode À l'aide d'une approche spatio-quantitative, nous avons combiné des analyses de points chauds, des analyses de corrélation de Pearson et des tests de Wilcoxon à deux échantillons pour analyser des ensembles de données incluant : les cas de COVID-19, un indicateur dérivé d'appareils mobiles pour mesurer le temps passé à l'extérieur du domicile au niveau du quartier (c.-à-d. la mobilité), ainsi que les données socioéconomiques du recensement de 2016 et de l'indice de marginalisation ontarien. Nous avons aussi examiné les variations temporelles entre les phases de la pandémie.

Résultats Nous avons repéré d'importants schémas d'agrégation spatiale des baisses de mobilité et des cas de COVID-19 à Toronto, ainsi que leurs liens avec les populations marginalisées. Les points chauds de la COVID-19 se trouvaient dans des grappes de quartiers plus défavorisés sur le plan matériel, où il y avait davantage de travailleurs essentiels et de personnes

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passant du temps à l'extérieur de leur domicile. La structure spatiale des grappes de cas de COVID-19 et de la mobilité a légèrement changé au fil du temps, mais les caractéristiques des groupes socioéconomiques communes à toutes les grappes sont restées semblables durant toutes les périodes sauf la première. Nous avons créé une série de cartes et de visualisations pour faire ressortir les schémas spatio-temporels dynamiques.

Conclusion Les quartiers de Toronto ont vécu la pandémie de COVID-19 de façons très différentes : les points chauds des cas de COVID-19 sont survenus dans des communautés plus marginalisées sur le plan matériel et racial et moins susceptibles de réduire leur mobilité. L'étude fournit des preuves solides dans un contexte canadien pour améliorer l'élaboration des politiques et approfondir la compréhension des déterminants sociaux de la santé à Toronto pendant la pandémie de COVID-19.

Keywords Mobility · COVID-19 · Hot spot analysis · Marginalization · Neighbourhood health · Toronto

Mots-clés Mobilité · COVID-19 · analyse de points chauds · marginalisation · santé du quartier · Toronto

Introduction

The unprecedented scale of health, social, and economic repercussions caused by the COVID-19 pandemic has had an extraordinary impact on global cities like Toronto, the most populous urban centre in Canada. Canada's first documented case of the virus occurred on January 21, 2020, in Toronto and in the ensuing months public health officials implemented various non-pharmaceutical interventions (NPIs) to limit the strain on the healthcare system and "flatten the curve" of the epidemic (CTV News, 2020). Although NPIs have been shown to be effective, communities' ability to adhere to these policies can range greatly due to socioeconomic realities (Kavanagh et al., 2020). Since the outset of the pandemic, spatial analysis techniques powered by novel data, such as device-level mobility indicators, paired with socioeconomic data have provided researchers an additional lens with which to investigate the geographic distributions of COVID-19 hotspots and changes to mobility patterns (Badr et al., 2020; Huang et al., 2021; Lou et al., 2020). However, to date, limited research has been conducted in Canada on the spatiotemporal variations in mobility reductions and their corresponding relationship with COVID-19 case rates, in particular, in urban centres that consist of neighbourhoods of very diverse socioeconomic characteristics.

This study aims to develop an understanding of how COVID-19 case rates and reductions in mobility transpired in Toronto's neighbourhoods and the corresponding socioeconomic characteristics at various phases of the pandemic from January 21, 2020, to April 24, 2021. The two primary research objectives include (1) to investigate the spatial clustering pattern of mobility reductions and COVID-19 cases in Toronto and their relationships with marginalized populations, and (2) to identify the most relevant socioeconomic characteristics that relate to human mobility and COVID-19 case rates in Toronto's neighbourhoods during different phases of the pandemic. This study provides solid evidence on the spatial and social patterning of COVID-19 cases and mobility in a Canadian context to enhance policy making and provide a deeper understanding of the social determinants of health in Toronto during the COVID-19 pandemic.

Background

A fast-growing body of literature has investigated how NPIs, such as encouraging physical distancing, closing non-essential businesses, enacting stay-at-home orders, and regional lockdowns, have influenced population-level movement patterns by using mobile device–derived mobility indicators (Ferguson et al., 2020; Oliver et al., 2020). Population-level movement data on behavioural change are effective at modelling outbreak trajectories by incorporating data on disease characteristics, public health policies, and estimates based on census and survey data collected in previous years (Price & van Holm, 2020; Flaxman et al., 2020; Kim & Kwan, 2021a; Leung et al., 2021; Maroko et al., 2020). Movement data derived from mobile devices from technology companies like Apple (Apple, 2021) and Google (Google, 2021) have made it possible to quantify population-level mobility changes and directly compare its effects on case counts in near real-time by measuring time spent away from home, routing requests, or visits to specific points of interest such as parks or grocery stores. These kinds of data have also been successfully applied to modelling data-driven COVID-19 reproductive rates I values, an epidemiological metric used to indicate the transmissibility of the virus for improving disease forecasting and policy intervention (Sharkey & Wood, 2020; Vegvari et al., 2022; Vollmer et al., 2020). The most common forms of mobility data are proxies for time spent away from home, but other applications such as origin–destination matrices can supplement or replace traditional commuting data that would typically be used in modelling the relationships between cities during periods with substantial travel disruptions (Tizzoni et al., 2014).

The ability to follow public health guidance to stay home is highly reliant on sociodemographic characteristics

(Winskill et al., 2020). Low-income populations have a higher probability of death compared to their higher-income counterparts and are often unable to follow mobility reduction policies due to employment in jobs that require their physical attendance (Hawkins et al., 2020; Huang et al., 2022). Individuals' perception of risk has also been found to strongly correlate with reducing their mobility away from home and varies greatly based on their culture, values, age, and prior personal exposure to the virus (Dryhurst et al., 2020). Since risk perception is rooted in culture and lived experience, traits which often cluster and vary by location, there is an inherent spatial component to how different regions follow various NPIs. In addition, a higher risk perception is found associated with reduced spatial mobility of urban residents during the COVID-19 pandemic (Hotle et al., 2020; Parady et al., 2020; Wang et al., 2021). These findings add a new dimension to the well-studied fundamental connection between health outcomes and the local geographic context of places (Awuor & Melles, 2019; Diez Roux & Mair, 2010; Wang, 2014). A neighbourhood-based understanding of health helps to explain spatial variability in health outcomes, and incorporates multiple risk factors, including individual characteristics and neighbourhood contexts, such as the local built and natural environment and collective socioeconomic conditions to which residents are exposed (Diez Roux & Mair, 2010). Neighbourhood-level spatial demographic analysis is a powerful tool to help target public health campaigns, estimate neighbourhood-level disease burden, describe variations in access to health services, and develop targeted interventions in vulnerable communities (Abbas et al., 2008; Harris et al., 2005; Kimura et al., 2011; Wang & Ramroop, 2018).

To date, limited research has been conducted in Canada that connects mobility, social determinants of COVID-19, and neighbourhood variations. Studies have found areas with lower socioeconomic status to have higher rates of COVID-19 for a variety of reasons (Choi et al., 2021; Sung, 2021). In a United States context, mobility reductions have been shown to be practiced differently between neighbourhoods (Huang et al., 2021b). Communities may (or may not) adhere to stay-home guidelines for reasons including work, skepticism about the efficacy of physical distancing or the severity of COVID-19, or political beliefs (Lou et al., 2020). Essential workers are often more vulnerable due to insufficient workplace safety measures and limited paid sick leave or unemployment benefits. Given these contexts, this Canada-based study fills a significant gap in the literature by incorporating a novel form of data—aggregated device level mobility data—in examining the role of mobility reductions and neighbourhood demographics in COVID-19 outcomes.

Data and methods

Data

We combined COVID-19 case counts, a mobile device–derived mobility indicator, and Census-based socioeconomic data to investigate neighbourhoods that were disproportionately impacted by COVID-19 in the city of Toronto (Table 1). Toronto is Canada's largest city, with a 2021 population of 2,794,356. It is deeply multicultural, with 46.5% of the population being immigrants. It is the core of the Greater Toronto Area metropolitan area and is composed of an amalgamation of six former municipalities: Toronto, Etobicoke, York, North York, East York, and Scarborough. Toronto consists of 140 social planning neighbourhoods designated by the City of Toronto, each consisting of a number of census tracts sharing similar socioeconomic characteristics. Neighbourhoods represent an additional geography to the existing Census administrative boundaries. They have been used in various health-based geographic studies of Toronto (Awuor & Melles, 2019; Kolpak & Wang, 2017), and were selected as the unit of spatial analysis for this study (City of Toronto, 2021a). While the number of neighbourhoods in Toronto has increased from 140 to 158

Table 1 Data table

Dataset	Data source	Key metrics	Temporal range	Last updated	Spatial resolution
COVID-19 case counts	Toronto Public Health	Cases, cases per 1000 population	Daily, Jan 21, 2020, to Apr 24, 2021	Jun 2, 2021	Toronto neighbourhood
Census data	City of Toronto	Average income, household size, population density, essential workers	Static, 2016	2016	Toronto neighbourhood
ON-Marg	Ministry of Health Ontario	Material deprivation, ethnic concentration, dependency, residential instability	Static, 2016	2018	Toronto neighbourhood
Mobility indicator	BlueDot	"Time away" indicator	Daily, Jan 1, 2020, to Apr 24, 2021	Apr 24, 2021	Toronto neighbourhood

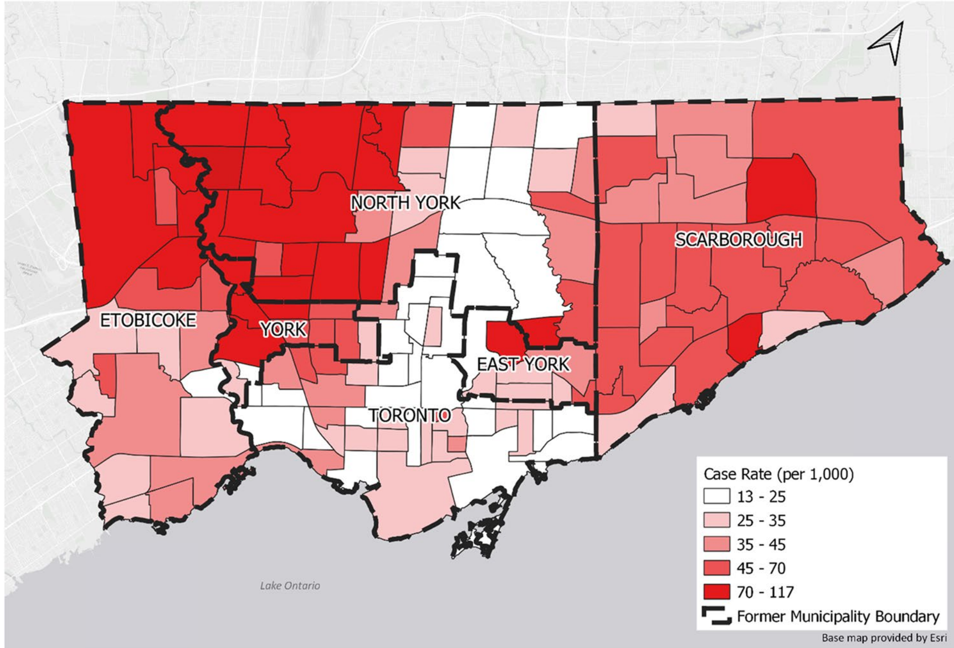

Fig. 1 COVID-19 rates (per 1000) in Toronto neighbourhoods over the full study period

since March 2022 due to population increase and splitting of several neighbourhoods, the study used the 140 neighbourhoods to be consistent with the study period.

As summarized in Table 1, line-listed data for each COVID-19 case in Toronto was retrieved from the City of Toronto Open Data portal (City of Toronto, 2021b) and filtered to include cases with episode dates (the best estimate date when the disease was acquired) between January 21, 2020, and April 24, 2021, to align the case data with the full temporal range of available mobility data. Case data contained limited supplemental information on age, gender, or other individual characteristics for each case. Cases without spatial information (i.e., a known home neighbourhood) (2429) were removed; those with source of infection as congregate (shelter) settings ($n=2090$) and healthcare settings ($n=11{,}224$) were also removed, resulting in 130,484 cases for further analysis (Fig. 1).

Five distinct time periods from January 21, 2020, to April 24, 2021, were selected based on major changes in public health recommendations by the government of Ontario (Table 2). COVID-19 case rates in neighbourhoods were calculated independently for each of the five time periods, as well as the full study period. The temporal dimension of the case data allows the study to explore within-period spatial patterns regardless of their prior or subsequent caseloads at various segments of the pandemic.

This study integrated an anonymized, aggregated device-level movement indicator provided by BlueDot, a Toronto-based health technology company that has partnered with mobile location data providers (Veraset, 2021). Aggregated mobile phone data have been used to investigate measures of mobility throughout the COVID-19 pandemic (Badr et al., 2020; Sharkey & Wood, 2020; Watts et al., 2020). The movement indicator, which approximates each neighbourhood's amount of time spent away from home, was provided at the neighbourhood level and powered by smartphone app-based GPS location data from a mobility panel of roughly 85,000 monthly active users within the city. The time away indicator was calculated by first determining each device's home location based on where it spent the majority of its

Table 2 Study time periods for COVID-19 incidence and mobility indicator groupings

Time period	Time period start and end	Rationale	# cases	% total cases
1	January 21, 2020 – March 16, 2020	First case in Toronto, early pandemic	440	0.3
2	March 17, 2020 – June 21, 2020	Initial lockdown, first wave	8070	6.2
3	June 22, 2020 – October 9, 2020	Reduced restrictions, summer	8524	6.5
4	October 10, 2020 – December 25, 2020	Rising second wave	34,021	26.1
5	December 26, 2020 – April 24, 2021	Beginning of province-wide shelter-in-place, 3rd wave	79,429	60.9

time between midnight and 9 AM each day. Next, the proportion of time that each device was observed more than 200 m from its respective assigned home was calculated. Device-level data were aggregated to daily neighbourhood-level indicator values by calculating the mean proportion of time away across all devices that spent the previous night in a neighbourhood. All data provided for this research were only available as daily indicator values at the neighbourhood level and no device-level data were accessible. To assign a single mobility value to each neighbourhood per time period, the mean daily time away from home was used for the days within the time period. As device data are recorded at varying frequencies depending on device, time away values are best interpreted as relative proxies of movement rather than literal hours away from home. For example, a 0.5 time away value indicates approximately 50% of the time (when the devices included in the sample were in use) the devices in a neighbourhood spent time 200 m from home on average. It does not necessarily mean the neighbourhood was away from their home for 12 h (half of) a day. Instead, the time away measure provides information for use to understand the general movement patterns of neighbourhoods.

Socioeconomic data were sourced from the Ontario Marginalization Index (ON-Marg) and Toronto's Neighbourhood Profiles. The relationship between marginalization and COVID-19 has been well documented (Hawkins et al., 2020; Strully et al., 2021). ON-Marg is a validated census-based composite index that includes several measures of marginalization based on demographic indicators (Matheson & van Ingen, 2016) and has been used to investigate the effects of marginalization on health outcomes in the past (Moin et al., 2018; Zygmunt et al., 2020). The study used the four dimensions from the ON-Marg index: *residential instability*, which measures community-level concentrations of people experiencing high rates of housing or family instability; *material deprivation*, linked to poverty and attributed to a community's or individual's inability to access essential material needs; *dependency*, a measure of residents lacking income from employment; and *ethnic concentration*, a measure of recent immigrants and/or members of a "visible minority" (Matheson & van Ingen, 2016). When used nationally, ON-Marg factor scores have a mean of 0 and standard deviation of 1, with higher values demonstrating increased marginalization.

Other census variables included average household size, population density, income, and proportion of the workforce considered essential workers. They were selected from Toronto's 2016 Neighbourhood Profiles, derived from the 2016 Canadian census, the most recent census available to the study (City of Toronto, 2021a). The essential workers variable was calculated as the percentage of the workforce over 15 in "essential" employment sectors as defined by National Occupation Classification categories following the same grouping as Rao et al. (2021): health, sales, service, trades, transportation, natural resources, agriculture, manufacturing, and utilities. Each census variable has an established relationship with COVID-19 incidence and is individually important enough to include in the study regardless of confounding in ON-Marg (Jing et al., 2020; Kavanagh et al., 2020; Lou et al., 2020; Maroko et al., 2020; Strully et al., 2021).

Analysis methods

First, Pearson correlation analyses were conducted to identify the direction and strength of the relationship among the select socioeconomic variables, COVID-19 rates, and the mobility indicator that is represented by time away. Next, the spatial patterns of neighbourhood-level mobility and incidence were analyzed via hot spot analysis using the Python Spatial Analysis Library (PySAL) (Rey & Anselin, 2007). Hot spots and cold spots were determined independently for the two cluster variables (COVID-19 incidence and time away) using the Getis Ord Gi* statistic using contiguity to define neighbours (i.e. where any two neighbourhoods shared a boundary) (Maroko et al., 2020). The Getis Ord Gi* statistic analyzes each feature in the context of itself and its neighbours to identify regions that have statistically significant spatial groupings of the input variable (Getis & Ord, 1992). It is a useful tool for analyzing the spatial patterns of COVID-19 in urban areas (Maroko et al., 2020). The resulting hot and cold spots were deemed significant only if they exceeded a 95% confidence level. These clusters demonstrated areas of Toronto where rates of COVID-19, and, independently, time away from home, were disproportionately concentrated.

Finally, Wilcoxon two-sample tests were conducted in R to determine whether the distribution of demographic characteristics between the two neighbourhood groups (i.e. the neighbourhoods in hot spots and the neighbourhoods in cold spots) were different, for each time period for mobility and COVID-19 clusters. Due to a small sample size and non-normally distributed cluster variables (Chen-Shapiro, $p < 0.01$), a Wilcoxon two-sample test was deemed most appropriate for testing whether socioeconomic composition between groups was different (Brzezinski, 2012; Maroko et al., 2020). For summary purposes, group medians for ON-Marg and other census variables were calculated to present a single representative value for each hot and cold spot per variable and time period for comparative analysis between the two cluster groups of disproportionately affected neighbourhoods. Statistical results for the analysis variables were then summarized and compared across variables and time periods and mapped using PySAL and QGIS.

Table 3 Pearson correlation results on analysis variables with means and standard deviations (SD) ($n = 140$)

	Mean	SD	1	2	3	4	5	6	7	8	9	10
1. Case rate (per 1000)	47.8	25.4	1.00									
2. Time away	17.2%	1.9%	.35*	1.00								
3. Household size	2.5	0.4	.56*	.09	1.00							
4. Population density	6374	4840	−.15	−.26*	−.53*	1.00						
5. Residential instability	0.76	0.78	−.23*	−.07	−.84*	.66*	1.00					
6. Material deprivation	0.26	0.89	.77*	.07	.50*	−.05	−.19*	1.00				
7. Dependency	−0.23	0.39	.09	.03	.41*	−.41*	−.46*	.10	1.00			
8. Ethnic concentration	1.04	0.84	.62*	−.02	.51*	.02	−.04	.65*	.17*	1.00		
9. Income	51,882	38,738	−.50*	.08	−.24*	−.08	−.02	−.61*	.00	−.50*	1.00	
10. Essential workers	43%	12%	.87*	.27*	.67*	−.20*	−.34*	.89*	.23*	.64*	−.63*	1.00

*$p < 0.05$

Results

Correlation analysis

The Pearson correlation analysis results on socioeconomic variables, COVID-19, and time away are found in Table 3. COVID-19 rates were most positively correlated with essential workers, material deprivation, and ethnic concentration. Time away had a moderate positive correlation with incidence and essential workers, but low correlation with other variables. Two of the ON-Marg factors had strong individual relationships with non-ON-Marg variables—material deprivation with income, and residential instability with household size, suggesting the two non-composite variables have high collinearity with their respective ON-Marg factor. However, their strong correlation with cases and relative importance in explaining COVID-19 cases in other studies suggest they are important to include for further analysis.

Spatial clusters of COVID-19 and mobility

Over the entire study period, neighbourhoods in COVID-19 hot spots ($n = 23$) were in the city's northwest, whereas cold spot neighbourhoods ($n = 27$) aligned closely with the city's downtown core and extended north towards the city's geographic centre (Fig. 2). Neighbourhoods in hot spots of mobility ($n = 25$) were also in the city's northwest, although they included five additional neighbourhoods to the south and east that were not identified as COVID-19 hot spots and excluded three neighbourhoods to the west. Mobility cold spots neighbourhoods ($n = 14$) were primarily located in

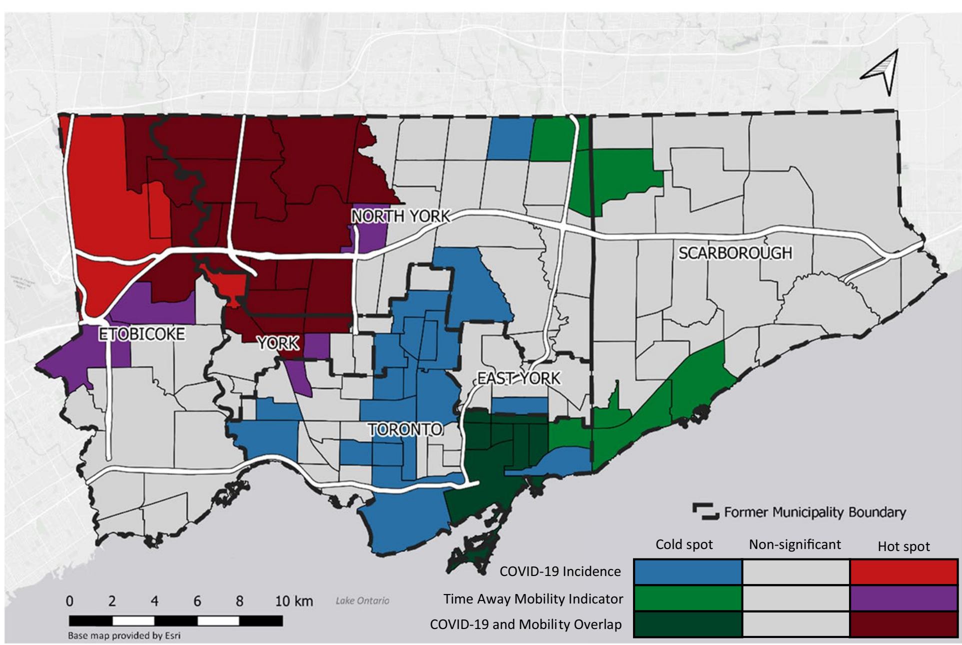

Fig. 2 Cluster analysis overlay of COVID-19 case rate and time away mobility indicator in Toronto during the full study period

Toronto's downtown and extended east along the lakeshore, with one pocket of three neighbourhoods on the northern border between North York and Scarborough. Clusters of mobility and COVID-19 incidence aligned closely in hot spots (91% of COVID-19 hot spot neighbourhoods were also mobility hot spots) but had considerably different spatial distribution in cold spots (25% of COVID-19 cold spot neighbourhoods coincided with mobility cold spots). Importantly, a neighbourhood's lack of designation as a hot spot does not imply that a neighbourhood fared well, but rather that it and its neighbours were not significantly above the citywide average since many neighbourhoods that were not in hot spots experienced considerable caseloads.

The dynamic spatiotemporal distribution of COVID-19 and mobility are demonstrated in Fig. 3. In the earliest phase of the pandemic, hot spots for each cluster variable were primarily in the centre of Toronto on a north–south axis. Later, hot spots consistently aligned in Toronto's northwest for both mobility and COVID-19. Relative to hot spots, there was greater spatial variance in cold spot distribution in both cluster variables over time. COVID-19 cold spots were frequently in the city's centre after the first time period, but mobility cold spots stretched along the lakeshore eastward from downtown and included sections of Scarborough in the first three time periods prior to aligning downtown in the latter two time periods. Interpretation of the temporal hot spot analysis results must be conducted carefully, as earlier phases of the pandemic had considerably fewer cases than later phases and increased chance of underdetection due to limited testing capacity. Figure 3 is best interpreted as showing spatial patterning rather than COVID-19 severity across phases.

Demographic characteristics of COVID-19 and mobility clusters

Over the full study period, Toronto's COVID-19 hot spot neighbourhoods had statistically significant higher material deprivation, ethnic concentration, spent more time away from home, had a greater proportion of essential workers, and had larger household sizes than their counterparts in cold spots

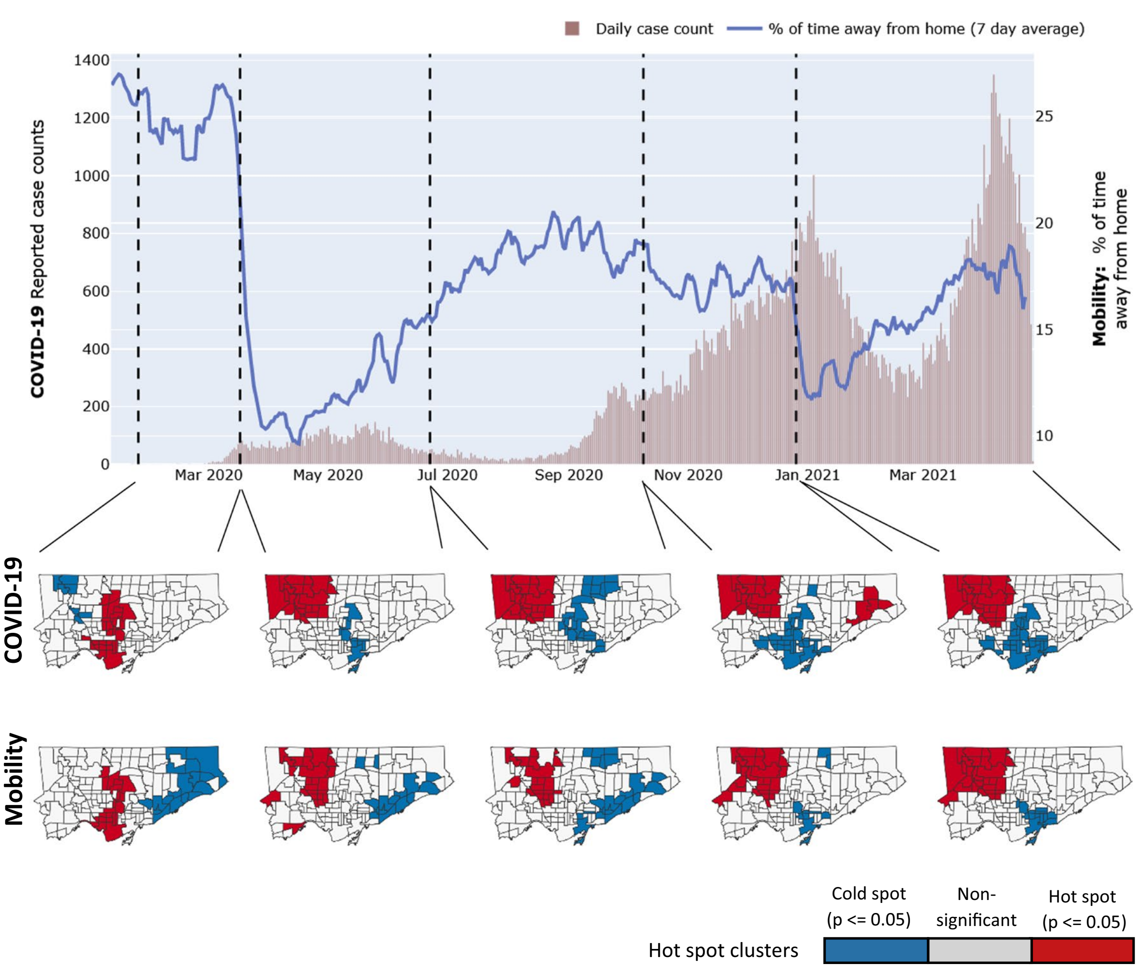

Fig. 3 Epidemic curve of COVID-19 cases in Toronto with Toronto-wide time away mobility indicator and corresponding clusters of COVID-19 case rates and mobility

(Table 4). Complete time period-specific results are available in the Appendix Table 5. Hot spots also had lower residential instability and population density than cold spots. Notably, two of the four ON-Marg dimensions, residential instability and dependency, were not significantly different between the two groups. Hot spots were also found to have much lower population density and lower income than cold spots. The non-clustered "other" neighbourhoods' group average for every variable except dependency and time away was consistently between that of the hot and cold spots, demonstrating the relatively consistent demographic traits not only between clusters, but also with neighbourhoods that did not fall into either category.

Geographic concentrations of high and low levels of mobility had fewer defining demographic characteristics than the COVID-19 cluster analysis (Table 4). Neighbourhoods in mobility hot spots had significantly higher rates of COVID-19, material deprivation, and household sizes than mobility cold spots, as well as lower income and a greater share of essential workers. As a group, mobility hot spots had lower residential instability, lower population density, and higher ethnic concentration than cold spots. The "other" neighbourhoods were occasionally higher or lower than both hot and cold spots for some variables, suggesting nuanced relationships between the time away mobility indicator and the demographic characteristics selected for this analysis. These relationships can be seen in comparing the COVID-19 neighbourhood map in Figs. 1 and 4 that highlights the spatial patterns of select variables from Table 4.

While the spatial pattern of clusters of COVID-19 cases and mobility shifted slightly over time, the group socioeconomic characteristics that clusters shared remained similar in all but the first time period. In this initial phase, COVID-19 clusters occurred in neighbourhoods that were well below the citywide averages for material deprivation and essential workers, the variables that were most consistently a significant measure of between-group differences, and cold spots were in areas that were above the city average. Time away from home was not significantly different between COVID-19 clusters in the first time period, although this period took place before Toronto's earliest mobility restrictions.

Neighbourhoods in COVID-19 hot spots in time periods 2 through 5 consistently had significantly more material deprivation and essential workers, higher ethnic concentration, larger household sizes, lower income, and spent more time away from home. In mobility hot spots, material deprivation and percentage of essential workers were again consistently significant between groups, except for over the summertime period, with greater deprivation associated with an increase in time spent away from home. In periods 4 and 5, which accounted for the bulk of the cases in the study period, lower income and higher ethnic concentration were strongly associated with clusters of increased mobility.

Table 4 Wilcoxon two-sample significance test results between hot and cold spots of COVID-19 incidence and time away from full study period with median group values

Cluster variable	Variable	Hot spots	Cold spots	Other	Hot vs. cold *p* value
COVID-19		*n* = 23	*n* = 27	*n* = 90	
	COVID-19: Case rate (per 1000)	84.7	21.4	37.6	**< 0.001**
	Mobility: Time away (%)	18.9	16.6	16.5	**0.010**
	ON-Marg: Material deprivation	1.28	-0.68	0.15	**< 0.001**
	ON-Marg: Ethnic concentration	1.45	0.05	0.81	**< 0.001**
	ON-Marg: Residential instability	0.39	0.97	0.61	0.103
	ON-Marg: Dependency	−0.26	−0.48	−0.22	0.415
	Census: Average income ($)	32,815	70,600	44,139	**< 0.001**
	Census: Household size (individuals)	2.7	2.2	2.6	**< 0.001**
	Census: Population density (per km^2)	4012	7838	4931	**0.019**
	Census: Essential workers (%)	60.1	28.7	43.5	**< 0.001**
Time away		*n* = 25	*n* = 14	*n* = 101	
	COVID-19: Case rate (per 1000)	78.1	26.8	34.5	**0.008**
	Mobility: Time away (%)	18.4	15.6	16.7	**0.009**
	ON-Marg: Material deprivation	1.25	0.08	−0.05	**0.022**
	ON-Marg: Ethnic concentration	1.28	0.37	0.59	0.131
	ON-Marg: Residential instability	0.34	0.54	0.73	0.955
	ON-Marg: Dependency	−0.27	−0.37	−0.27	0.955
	Census: Average income ($)	33,528	51,157	47,384	**0.022**
	Census: Household size (individuals)	2.7	2.4	2.4	0.198
	Census: Population density (per km^2)	4007	7107	5395	0.065
	Census: Essential workers (%)	60.0	34.5	39.3	**< 0.001**

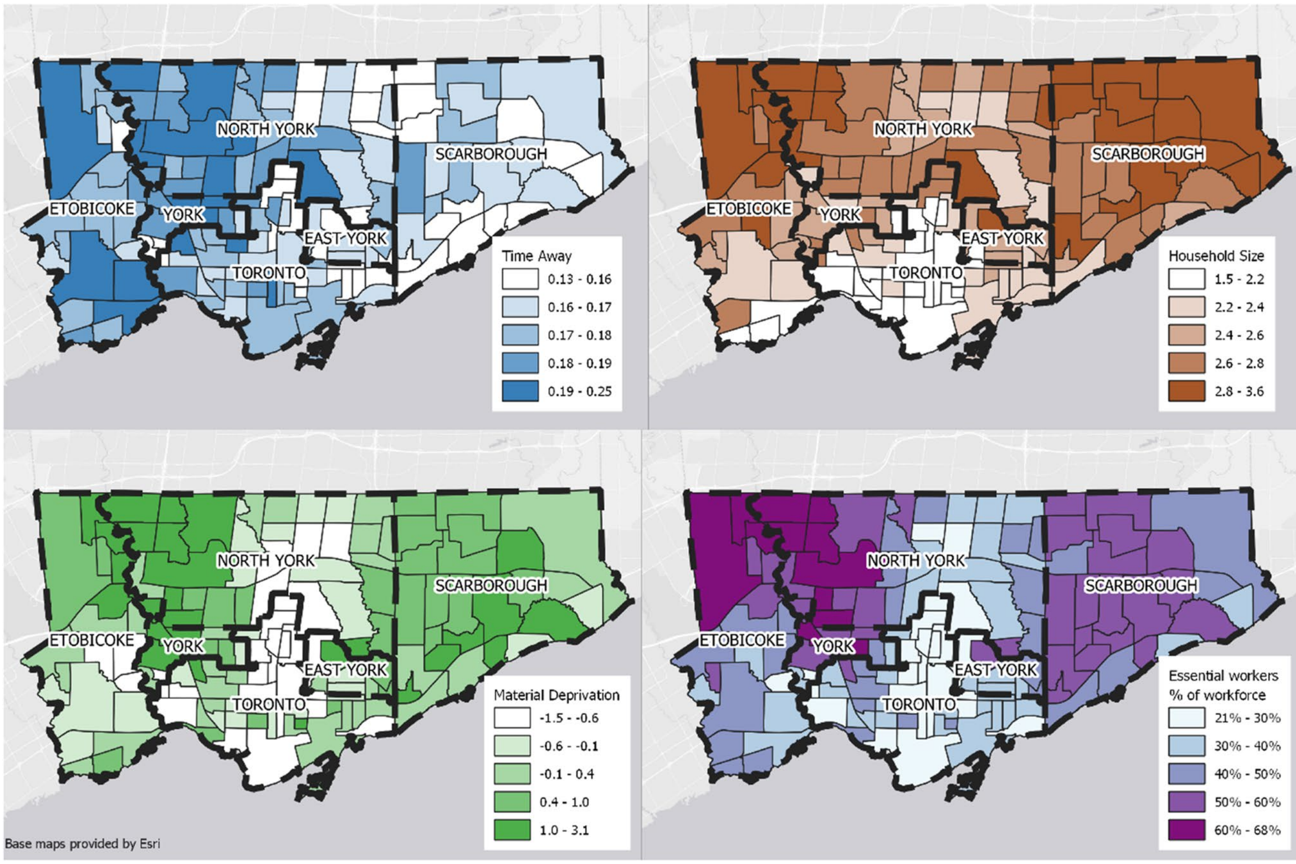

Fig. 4 Spatial distribution of time away (mobility indicator), household size, material deprivation, and percentage of essential workers in Toronto neighbourhoods

Discussion

The findings in this study demonstrate Toronto's neighbourhoods have experienced the COVID-19 pandemic in significantly different ways, with hot spots of COVID-19 cases occurring in more materially and racially marginalized communities that disproportionately experienced the impacts of the virus. Furthermore, these same marginalized neighbourhoods tended to be less likely to reduce their mobility relative to more advantaged communities within the city and had a greater proportion of essential workers.

The strong correlation between material deprivation and essential workers with hot spots in all but the earliest phase of the pandemic aligns with other research findings that COVID-19 has frequently affected more marginalized communities (Chang et al., 2021; Choi et al., 2021; Dasgupta et al., 2020). Furthermore, the spatial overlap between COVID-19 and time away hot spots, with 95% of COVID-19 hot spot neighbourhoods coinciding with mobility hot spots over the full study period, suggests that neighbourhoods with higher levels of poverty had increased exposure to the virus, likely due to more frontline workers in jobs that cannot be done remotely (Huang et al., 2022).

Spatial distribution of clusters

The spatial patterning of COVID-19 hot and cold spots was generally consistent over the study period, with one important exception. In the first time period, 47% of cases had travel-related sources of infection, resulting in a spatial pattern where hot spot neighbourhoods were more strongly associated with higher income neighbourhoods, indicating that individuals with the means for international travel were more affected in the earliest days of the pandemic when COVID-19 was primarily imported from other countries. The spatial concentration of cases when travel-related sources of infection were most common suggests disease surveillance measures early in the pandemic would be most prudent in neighbourhoods with the propensity for travel and at border crossings. However, unseen nuances in the distribution of cases likely exist due to the greater surveillance efforts applied towards testing international travelers at a time when testing capacity was limited.

The lack of alignment between cold spots (25% of COVID-19 cold spot neighbourhoods were also mobility cold spots in the full study period) shows that the spatial correlations between low mobility as indicated by the time away indicator and infection are complex. The correlation analysis (Table 3) revealed a moderate positive relationship between time away and COVID-19, but the Wilcoxon results comparing hot and cold spots of COVID-19 show that neighbourhoods that were not part of a cluster had the lowest average mobility. This relationship is explored further in the section "Socioeconomic characteristics of mobility clusters".

Socioeconomic characteristics of COVID-19 clusters

The link between poverty, crowded housing, and social vulnerability during public health events is well documented (Dasgupta et al., 2020; Huang et al., 2022). Higher population density can act as a catalyst for the spread of COVID-19 because it makes it difficult to reduce contact rates (Tammes, 2020). At an intracity level, this study found the most densely populated neighbourhoods were not those that experienced the most severe COVID-19 case burden in Toronto, aligning with findings in Chicago and New York (Maroko et al., 2020). In fact, over the full study period, some of the most densely populated neighbourhoods in Toronto were in COVID-19 cold spots (7838 people per km^2), and outlying, lower density neighbourhoods were in hot spots (4012 people per km^2). However, neighbourhoods in hot spots had an average 0.5 more individuals per household (2.7 people), indicating that within-household contact rates were a stronger indicator of COVID-19 than neighbourhood-wide population density. The risk of COVID-19 infection has been found to increase tenfold for those living in a household with a diagnosed case (Jing et al., 2020), demonstrating the variable's utility for understanding the spatial distribution of COVID-19 incidence.

Higher material deprivation and ethnic concentration had strong relationships with hot spots. Ethnic concentration was positively correlated with both COVID-19 hot spots and increased mobility, although only statistically significant between groups in the COVID-19 analysis. Recent immigrants and materially deprived individuals are often at a higher risk of exposure due to crowded housing, lower-wage employment, and residency in low-income neighbourhoods (Strully et al., 2021). Race-based social determinants of health like structural racism and xenophobia can act as a barrier to healthcare and negatively affect communities. Racially marginalized communities in Toronto also face increased exposure to negative environmental determinants of health such as air pollution (Awuor & Melles, 2019), which has been correlated with cases of severe COVID-19 and other respiratory diseases (Sundaram et al., 2020). The connection between ethnic concentration and COVID-19 hot spots in Toronto suggests efforts towards community outreach for new immigrants and continued robust offerings in as many languages as possible to share information accessibly could support some of the city's most affected neighbourhoods.

Socioeconomic characteristics of mobility clusters

The socioeconomic characteristics of mobility clusters shared similar traits with those of COVID-19, although there are important distinctions between the two cluster analyses. Unlike COVID-19, mobility cold spots in Toronto were often not in the city's most affluent neighbourhoods but rather in Scarborough and along the city's eastern lakeshore. Although reductions in mobility have been found to be closely associated with a reduction in COVID-19 caseloads (Huang et al., 2021; Leung et al., 2021), the spatial mismatch and corresponding neighbourhood characteristics between mobility and COVID-19 cold spots show higher income and lower economic and racial marginalization were stronger spatial indicators of reduced COVID-19 rates than reductions in time away from home.

Compared to COVID-19 clusters, fewer variables in the mobility cluster analysis had statistically significant differences between hot and cold spots of mobility, demonstrating there were complex relationships in the demographics of mobility. Many studies that investigated the relationship between mobility, marginalization, and COVID-19 have been conducted at larger spatial scales (such as US counties) and have highlighted the disproportionate impact between marginalized communities relative to those that are less marginalized, but less research has been conducted on the differences between middling and well-off areas in terms of mobility at finer spatial resolutions. Further research may be warranted to clarify the relationship between economically advantaged communities and their relative movement in contrast with average neighbourhoods to improve how we understand mitigation strategies outside of the economic extremes.

Policy implications

The way individuals interact with the physical and social constructs of neighbourhoods can cause profound impacts on human health (Awuor & Melles, 2019). Inequitable access to social programs, services, and facilities often negatively affects neighbourhood health and can lead to neighbourhood segregation by various sociodemographic strata, such as income or race. Place plays a central role in understanding social determinants of health due to the wide-ranging spatial nature of accessibility to services, local environmental factors, and the socioeconomic composition of residents. The findings support an increasingly growing body of literature that shows that marginalized communities have disproportionately suffered the effects of COVID-19 (Dasgupta et al., 2020; Hawkins et al., 2020; Strully et al., 2021; Sundaram et al., 2020).

The association between larger household sizes and COVID-19 hot spots has relevant implications for policymakers during future infectious disease-related events. The distribution of services, density of services, and walkability to services vary greatly within the City of Toronto, with the city core having the highest concentration of services in close proximity to residents. Providing increased access to voluntary isolation (Sundaram et al., 2020) and wraparound services, like grocery and prescription drug delivery (Madad et al., 2020), may reduce chains of transmission that disproportionately affect more vulnerable households. For frontline workers with increased occupational risk of COVID-19 exposure, paid sick leave and workplace testing could reduce their personal and, by extension, household exposure (Sundaram et al., 2020). Increased economic support for individuals and businesses deemed essential through greater focus on workplace safety and increased public transportation frequency would allow safer practices to be followed by those who do not have the financial means to strictly adhere to stay-at-home orders and could limit chains of household transmission.

Policy makers can use findings to manage spatially targeted public awareness and testing campaigns, coordinate healthcare resources, and boost communities' ability to observe government recommendations in future outbreaks, especially in lower income neighbourhoods in Toronto's northwest. Increased focus on the neighbourhoods identified in hot spot analyses is particularly important because they not only experienced disproportionate case rates, but by extension also have the highest risk of exposure. The spatial alignment in mobility and COVID-19 hot spots and the relationship between COVID-19 hot spots and essential worker populations suggest that short-term policies to reduce contact rates are not necessarily fraught with engrained determinants of health. These findings can be used for more equitable response in future public health crises, and support decision making and prioritization of resources to the disadvantaged populations that are most likely to be worst affected by COVID-19.

Limitations and future research

There are several limitations to this study. First, using neighbourhoods as the unit of analysis poses challenges due to the modifiable areal unit problem (MAUP) and the ecological fallacy. These issues arise from applying arbitrary spatial bounds on a dataset that can result in different findings if the data were delineated into different spatial units (Hennerdal & Nielsen, 2017). Neighbourhood-level metrics can also mischaracterize the individuals who live there, as applying a single value to a group of people can lead to false conclusions (Dalton & Thatcher, 2015). Furthermore, the spatial analysis results were limited by the neighbourhood effect averaging problem that can fail to fully capture health impacts from residence-based exposures as individuals' exposure to environmental exposures regresses towards the local mean (Kim & Kwan, 2021b), and by the uncertain geographic context problem that arises due to uncertainty around the geographic areas that influence individuals (Kwan, 2012). In examining geographic variations in health, past studies revealed the importance of contextual effects reflecting different physical and social attributes of a neighbourhood (or another spatial unit, or group) and compositional effects resulting from differences in individuals (Diez Roux & Mair, 2010; Wang and Hu, 2013; Awuor & Melles, 2019). Due to data availability, the study primarily used a contextual approach to analyze neighbourhood-level data in exploring the association between the collective socioeconomic condition of neighbourhoods and the COVID-19 rates of neighbourhoods. Based on the study, composition of persons in neighbourhoods such as share of essential workers and level of material deprivation are found to be positively associated with COVID-19 rates, highlighting the important role neighbourhood-level population composition plays in COVID-19 risks regardless of individual-level attributes. Similarly, those living in COVID-19 cold spots enjoy the protective effect of the neighbourhood, regardless of their individual risk factors. These findings indicate the ambiguity of compositional versus contextual effects in exploring the neighbourhood variations of COVID-19 risks. Future study can analyze the individual characteristics of COVID-19 patients such as age, gender, and ethnicity, depending on data availability, to further investigate the complex relations between contextual and compositional effects on COVID-19 and its variations at different spatial scales.

Additionally, identification of COVID-19 case data is strongly tied to testing, which is voluntary and not universally accessible to all groups. While an Ontario-wide study found that likelihood of testing is largely consistent across socioeconomic groups (Sundaram et al., 2020), targeted testing of individuals who travelled internationally may have led to a detection bias earlier in the pandemic. This analysis could be extended by investigating case outcomes (hospitalizations and deaths) rather than just cases to provide an even deeper understanding of the health inequities experienced during the pandemic.

Mobility data do not capture the type of activity undertaken out of home and may underestimate out of home movement in the downtown core, and the daily sample of the population may not be consistent. Time spent away from home, which has frequently been used as a proxy for measuring lockdowns, may not sufficiently measure the range of activities taken during lockdowns. This finding aligns with other research that found mobile device–derived indicators after the first few months of the pandemic had less predictive power in estimating COVID-19 case rates (Gatalo et al., 2021). Mobility data are drawn from an unknown population sample and may be skewed by demographic characteristics such as income, age, or race, although they have been demonstrated to be reasonably consistent across various socioeconomic groups (Squire, 2019). One comparative analysis between other mobility providers found general agreement, but notable differences between four open-source datasets (Huang et al., 2021). Evidently, no single dataset is a perfect proxy for human mobility regardless of data provider, but this should not invalidate a novel form of data that has provided valuable insights into the complicated dynamics of COVID-19. This research does not imply causation between mobility and COVID-19 incidence, as there are many factors that contribute to disease incidence.

Future research directions that incorporate alternative quantitative and qualitative data would help to create an improved understanding of local contexts and support policy-making decisions. Additional forms of quantitative data that could be incorporated into a similar, neighbourhood-level study could include industry of employment, transit usage during the pandemic, proportion of residential area in neighbourhoods as an alternative measure of population density, and a risk perception index derived from qualitative surveys. This index could be derived from surveys with questions pertaining to risk perception and individuals' interest in adopting various policy options, such as voluntary self-isolation or wraparound services broken down by various demographic and geographic strata. Separately, surveys could also be designed to include questions around motivating factors behind following or disregarding government policy to refine future messaging. Additionally, industry-specific data points could provide researchers with additional information on how to reduce workplace exposure risk by pinpointing where best practices were not followed to provide clear recommendations to workplaces for improved safety.

Conclusion

This research investigated spatiotemporal trends in COVID-19, mobility, and social determinants of health at a neighbourhood level in Toronto. Neighbourhoods in the city's northwest suffered disproportionate impacts of COVID-19 and tended to have more essential workers, increased material deprivation, ethnic concentration, and lower reductions in mobility. In contrast, the clusters of neighbourhoods with the lowest rates of COVID-19 were in the city's more advantaged neighbourhoods, which had higher incomes and smaller household sizes. The strong spatial alignment between hot spots of mobility and COVID-19 cases aligns with other findings around the efficacy of reducing overall mobility and time spent away from home, or lack of, while the misalignment between cold spots suggests there may be deeper interactions at play in communities that had not only low COVID-19 incidence but also less reduction in mobility. The temporal trends explained in this paper also highlight the changing demographic dynamics of the pandemic, as wealthier neighbourhoods were most affected at the outset of the pandemic and neighbourhoods with higher levels of material deprivation and essential workers quickly became hot spot locations for COVID-19 once the disease became widespread in Toronto.

The strong spatial and socioeconomic relationships between COVID-19 and mobility have important policy implications for the current COVID-19 and future pandemics. Short-term policies to enable marginalized communities and essential workers to effectively follow government guidelines through paid sick leave, wraparound services, voluntary self-isolation, and improved access to testing could mitigate the disproportionate impacts experienced in these neighbourhoods. Providing the necessary short- and long-term supports to encourage healthier communities and limit healthcare inequities will reduce the economic and social impact of future pandemics. The location of the neighbourhood in which individuals live does not necessarily need to define their risk of contracting COVID-19 or a future disease if proactive measures are taken to support marginalized residents before and during the next pandemic.

Contributions to knowledge

What does this study add to existing knowledge?

- This study provides solid evidence on the spatial and social patterning of COVID-19 cases and mobility in urban neighbourhoods in a Canadian context. It provides an in-depth understanding of the social determinants of health in Toronto during the COVID-19 pandemic.
- By analyzing a wide range of datasets including Canadian Census, On-Marg, and device-level mobility data, the study adds to the existing literature on neighbourhood and health in a COVID-19 context and contributes to the growing work on the relation between population movement and infectious disease from a spatiotemporal perspective.

What are the key implications for public health interventions, practice, or policy?

- The study provides implications for developing equitable response in future public health crises and supports decision making and prioritization of resources to the disadvantaged populations that are most likely to be worst affected by COVID-19 such as population of a lower socioeconomic status, households of larger sizes, and essential employees.
- Policy makers can use findings to manage spatially targeted public awareness and testing campaigns, coordinate healthcare resources, and boost communities' ability to observe government recommendations in future outbreaks, especially in lower income neighbourhoods in Toronto's northwest.

Appendix

Table 5 Complete Wilcoxon two-sample significant test results by time period and cluster variable

Variable	Time period	Incidence: hot spots	Incidence: cold spots	Incidence: other	Incidence: hot vs. cold p value	Incidence: significance
ON-Marg: Material deprivation	1	−0.69	1.678	0.442	0.024	*
ON-Marg: Material deprivation	2	1.374	−0.489	0.115	0.009	**
ON-Marg: Material deprivation	3	1.387	−0.258	0.146	0.000	***
ON-Marg: Material deprivation	4	1.334	−0.617	0.236	0.000	***
ON-Marg: Material deprivation	5	1.362	−0.608	0.277	0.000	***
ON-Marg: Ethnic concentration	1	0.445	1.531	1.162	0.031	*
ON-Marg: Ethnic concentration	2	1.603	0.096	1.002	0.007	**
ON-Marg: Ethnic concentration	3	1.572	0.869	0.969	0.003	**
ON-Marg: Ethnic concentration	4	1.73	0.313	1.078	0.000	***
ON-Marg: Ethnic concentration	5	1.568	0.282	1.156	0.000	***
ON-Marg: Residential instability	1	−0.572	−0.505	−0.152	1.000	
ON-Marg: Residential instability	2	−0.19	−0.325	−0.235	0.097	
ON-Marg: Residential instability	3	−0.163	−0.025	−0.296	0.944	
ON-Marg: Residential instability	4	−0.187	−0.505	−0.158	0.096	
ON-Marg: Residential instability	5	−0.213	−0.503	−0.153	0.041	*
ON-Marg: Dependency	1	1.558	0.86	0.576	0.582	
ON-Marg: Dependency	2	0.385	0.773	0.821	0.295	
ON-Marg: Dependency	3	0.376	0.55	0.885	0.645	
ON-Marg: Dependency	4	0.27	1.551	0.639	0.000	***
ON-Marg: Dependency	5	0.39	1.613	0.573	0.002	**
Mobility: Time away (%)	1	27.7	24.3	24.5	0.098	
Mobility: Time away (%)	2	15.3	13.2	13	0.029	*
Mobility: Time away (%)	3	20.2	17.1	18	0.001	***
Mobility: Time away (%)	4	18.9	17	17.1	0.011	*
Mobility: Time away (%)	5	18.5	14.4	15.4	0.000	***
Census: Average income ($)	1	85,863	32,214	44,710	0.024	*
Census: Average income ($)	2	32,689	104,870	51,880	0.007	**
Census: Average income ($)	3	32,820	79,173	49,584	0.000	***
Census: Average income ($)	4	31,626	81,617	48,028	0.000	***
Census: Average income ($)	5	32,512	82,275	46,809	0.000	***
Census: Household size (individuals)	1	2.1	2.5	2.6	0.176	
Census: Household size (individuals)	2	2.9	2.3	2.5	0.009	**
Census: Household size (individuals)	3	2.8	2.5	2.4	0.001	**
Census: Household size (individuals)	4	2.9	2.0	2.5	0.000	***
Census: Household size (individuals)	5	2.8	2.0	2.6	0.000	***
Population density (per km^2)	1	8996	6215	5791	0.726	
Population density (per km^2)	2	4088	6002	6795	0.023	*
Population density (per km^2)	3	4104	5400	7072	0.257	
Population density (per km^2)	4	4209	8919	6171	0.002	**
Population density (per km^2)	5	4331	9592	5836	0.004	**
Census: Essential workers (%)	1	30.0	62.7	46.1	0.044	*
Census: Essential workers (%)	2	60.1	27.8	40.9	0.007	***
Census: Essential workers (%)	3	60.1	32.8	41.8	0.000	***
Census: Essential workers (%)	4	59.0	28.9	43.2	0.000	***
Census: Essential workers (%)	5	60.4	28.9	43.5	0.000	***

Table 5 (continued)

Variable	Time period	Mobility: hot spots	Mobility: cold spots	Mobility: other	Mobility: hot vs. cold *p* value	Mobility: significance
ON-Marg: Material deprivation	1	−0.692	0.838	0.368	0.001	***
ON-Marg: Material deprivation	2	1.14	0.777	−0.009	0.565	
ON-Marg: Material deprivation	3	1.334	0.647	−0.033	0.006	**
ON-Marg: Material deprivation	4	1.224	−0.283	0.105	0.000	***
ON-Marg: Material deprivation	5	1.228	−0.334	0.1	0.000	***
ON-Marg: Ethnic concentration	1	0.467	1.521	1.074	0.008	**
ON-Marg: Ethnic concentration	2	1.248	1.423	0.934	0.832	
ON-Marg: Ethnic concentration	3	1.402	1.382	0.888	0.768	
ON-Marg: Ethnic concentration	4	1.385	0.407	1.013	0.024	*
ON-Marg: Ethnic concentration	5	1.434	0.039	1.047	0.000	***
ON-Marg: Residential instability	1	−0.569	−0.12	−0.176	0.002	**
ON-Marg: Residential instability	2	−0.211	−0.202	−0.243	0.832	
ON-Marg: Residential instability	3	−0.216	−0.064	−0.279	0.431	
ON-Marg: Residential instability	4	−0.171	−0.145	−0.252	0.589	
ON-Marg: Residential instability	5	−0.154	−0.408	−0.235	0.001	**
ON-Marg: Dependency	1	1.797	0.101	0.647	0.021	*
ON-Marg: Dependency	2	0.392	0.495	0.878	0.414	
ON-Marg: Dependency	3	0.443	0.418	0.9	0.731	
ON-Marg: Dependency	4	0.377	0.763	0.833	0.464	
ON-Marg: Dependency	5	0.368	0.837	0.838	0.022	*
Mobility: Time away (%)	1	27.9	23	24.8	0.000	***
Mobility: Time away (%)	2	15	11.6	13.3	0.000	***
Mobility: Time away (%)	3	19.8	16.4	18.3	0.000	***
Mobility: Time away (%)	4	19.4	16.1	17.1	0.001	***
Mobility: Time away (%)	5	18.2	13.3	15.3	0.000	***
Census: Average income ($)	1	83,538	35,269	47,775	0.001	***
Census: Average income ($)	2	36,001	38,077	57,497	0.694	
Census: Average income ($)	3	35,339	38,995	58,154	0.085	
Census: Average income ($)	4	34,513	76,158	53,734	0.001	***
Census: Average income ($)	5	33,953	79,906	53,248	0.000	***
Census: Household size (individuals)	1	2.0	2.9	2.5	0.001	***
Census: Household size (individuals)	2	2.7	2.7	2.4	0.694	
Census: Household size (individuals)	3	2.8	2.7	2.4	0.313	
Census: Household size (individuals)	4	2.8	2.3	2.5	0.013	*
Census: Household size (individuals)	5	2.8	2.2	2.5	0.000	***
Population density (per km^2)	1	10,303	3770	5987	0.004	**
Population density (per km^2)	2	4979	5135	6872	0.650	
Population density (per km^2)	3	5526	5231	6817	0.806	
Population density (per km^2)	4	4421	5684	6811	0.215	
Population density (per km^2)	5	4221	6931	6806	0.002	**
ON-Marg: Material deprivation	1	−0.692	0.838	0.368	0.001	***
ON-Marg: Material deprivation	2	1.14	0.777	−0.009	0.565	
ON-Marg: Material deprivation	3	1.334	0.647	−0.033	0.006	**
ON-Marg: Material deprivation	4	1.224	−0.283	0.105	0.000	***
ON-Marg: Material deprivation	5	1.228	−0.334	0.1	0.000	***
Census: Essential workers (%)	1	28.1	52.8	43.5	0.001	***
Census: Essential workers (%)	2	59.8	49.4	37.0	0.03	*
Census: Essential workers (%)	3	60.1	45.2	37.4	0.000	***
Census: Essential workers (%)	4	59.8	32.5	39.4	0.000	***
Census: Essential workers (%)	5	60.0	32.0	40.3	0.000	***

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