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Riding through the pandemic: Using Strava data to monitor the impacts of COVID-19 on spatial patterns of bicycling

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\textbf{ABSTRACT}

COVID-19 prompted a bike boom and cities around the world responded to increased demand for space to ride with street reallocations. Evaluating these interventions has been limited by a lack of spatially-temporally continuous ridership data. Our paper aims to address this gap using crowdsourced data on bicycle ridership. We evaluate changes in spatial patterns of bicycling during the first wave of the COVID-19 pandemic (Apr – Oct 2020) in Vancouver, Canada using Strava data and a local indicator of spatial autocorrelation. We map statistically significant change in ridership and reference clusters of change to a high-resolution base map. Amongst streets where bicycling increased, we measured the proportion of increase occurring on pre-existing bicycle facilities or street reallocations compared to streets without. In all our analyses, we evaluate patterns across subsets of Strava data representing recreation, commuting, and ridership generated by women and older adults (55+). We found consistent and unique patterns by trip purpose and demographics: samples generated by women and older adults showed increases near green and blue spaces and on street reallocations that increased access to parks, and these patterns were also mirrored in the recreation sample. Commute ridership highlighted distinct patterns of increase around the hospital district. Across all subsets most increases occurred on bicycle facilities (pre-existing or provisional), with a strong preference for high-comfort facilities. We demonstrate that changes in spatial patterns of bicycle ridership can be monitored using Strava data, and that nuanced patterns can be identified using trip and demographic labels in the data.

1. Introduction

Stay-at-home orders during the first wave of the COVID-19 pandemic induced a sudden and major increase in demand for active transportation in cities around the world (Buehler and Pucher, 2021). Lack of bicycle facilities and network gaps were immediately salient, particularly in large and densely populated cities. Governments responded by making street reallocations, which involved vehicle lanes and parking being transformed into walking or bicycling paths using temporary infrastructure, or entire streets closed to all but bikes and pedestrians (Combs and Pardo, 2021). For example, cities in Europe, South America, and Mexico collectively installed thousands of kilometers of separated bikeways seemingly overnight, and major US and Canadian cities like New York, Oakland, and Seattle (US); and Toronto, Montreal, and Vancouver (Canada) adopted open street policies and implemented provisional bike lanes to create safer and better-connected mobility corridors (NACTO, 2020). Such interventions have potential long-term implications for population health, travel behaviour, and transport equity if cities make these changes permanent.

COVID-19 has provided a unique opportunity to study the impacts of interventions designed to increase access to bicycling. Documenting what programs worked supports evidence-based policy deployed to increase bicycling in cities. Evidence on bicycle ridership through the pandemic documents the sustained resilience of bicycling in cities (Buehler and Pucher, 2021) and implies that street reallocations played a role (Kraus and Koch, 2021). At the same time, active transportation has become a nexus for longer-term policies aimed at improving population health and wellbeing, actioning on climate change, and attending

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to mobility injustices in equity deserving communities (Government of Canada, 2021). Past evaluations of street reallocations are constrained by a lack of data on ridership, and on bicyclist and trip characteristics (Combs and Pardo, 2021; Fischer and Winters, 2021). For example, traditional bicycle count programs often lack details on demographics (age, gender) and trip purpose (recreation, commute). They also have low spatial–temporal resolution (Nelson et al., 2021a), with permanent counters installed at only a handful of locations or temporary counts at more locations but limited in time. Additionally, many jurisdictions have little or no data pre-pandemic to use as baseline data.

Crowdsourced data from GPS-enabled smart phones are a continuous source of data on bicycle volumes (Lee and Sener, 2021; Nelson et al., 2021a). People using smartphone apps to track fitness activities are creating massive volumes of data on where and when they ride bicycles. The leading fitness app used by bicyclists is Strava, which has over 95 million users globally (Strava Metro, 2020b). Strava de-identifies and aggregates tracked activities into the Strava Metro data product, providing Strava bicyclist counts on every street segment with one-hour resolution; hence, the data are highly granular, both spatially and temporally and temporally resolve (Nelson et al., 2021a). While Strava data are generated by a sample of all bicyclists (only those who use the app), moderate to strong correlations to all bicyclists have been demonstrated in several cities (Lee and Sener, 2021), with better correspondence between Strava trips and official counts in city centers (Boss et al., 2018; Conrow et al., 2018). Strava data are freely available to jurisdictions planning policy interventions to increase bicycling, and while caveats about representativeness and sample bias are important, spatial patterns in Strava data are often a reasonable proxy for ridership patterns of all bicyclists, especially when considered alongside official bicycle counts (Nelson et al., 2021b; Boss et al., 2018).

Our goal is to evaluate changes in spatial patterns of bicycling during the first wave of the COVID-19 pandemic in Vancouver, BC, Canada. We leveraged the spatial and temporal coverage and novel attributes in crowdsourced data to look at questions of where bicycling demand was concentrated and why and for whom bicycling changed. Focusing on the period immediately following stay-at-home orders and subsequent public health restrictions, our temporal comparison was for the period of April - October 2019 and 2020. We mapped relative change in Strava ridership and used a local indicator of spatial autocorrelation (Getis Ord Gi*), implemented on a network, to identify streets where ridership was statistically higher or lower than expected if processes of change were random. We relate increases in ridership with the location and quality of existing bicycle facilities and provisional COVID-19 street reallocation interventions to better understand how infrastructure supported an increased demand for active transportation. Our motivation was to tap into the value of novel attributes and highly resolute spatial–temporal data available in Strava to unpack mobility insights beyond what can be done with city bike count programs.

2. Study area and data

2.1. Study area

The study area is the City of Vancouver, British Columbia, Canada. Vancouver is densely populated (population 631,486; 5,492 people/km²) and has a high bike to work mode share (6.1 % of commuters) relative to provincial (2.5 %) and national (1.3 %) rates (Statistics Canada, 2016). The city has an extensive and expanding bike network, with more than 300 km of bicycle facilities in 2020. Facilities include local street bikeways (shared bikeway along local streets, typically traffic-calmed), protected cycle tracks and bike paths, multi-use paths, and on-street painted bike lanes (City of Vancouver, 2021a). Vancouver also boasts the world’s longest uninterrupted waterfront bike path, the Seawall (28 km), which is the most popular site for recreation in the city (City of Vancouver, 2021b). Average daily bike counts on the Seawall are upwards of 6,000 in a normal year (City of Vancouver, 2020a). Peak bicycling season is through spring and summer though winters are amenable to year-round ridership, and winter bicycling is increasing (CAPE, 2021). Temperatures range between a daily average of 4 °C (39 °F) in the winter and 18 °C (64 °F) in summer (Environment Canada, 2021). Total annual precipitation is 1153 mm (45.4 in) with the majority falling between November and March (Environment Canada, 2021).

2.2. City bicycle counter data

We used hourly-level official bicycle counts from 19 permanent automated bicycle counters located throughout the city. Data were provided by staff at the City of Vancouver and cover the period between April 1 - October 31 (2019 and 2020). To evaluate how a crowdsourced sample of bicycle ridership represents all bicycling, we tested correlation between city bike counts and Strava data as described below.

2.3. Strava data

Strava data are counts of Strava bicyclists on all segments of the street network and are packaged at various temporal aggregations (hour, day, week, month). We obtained Strava data through the Strava Metro web platform. Strava Metro is the de-identified and aggregated Strava data product and access to the web platform is freely available (via application) to partner organizations working to improve active transportation (Strava Metro, 2021). These data cover the period of April 1 to October 31 in both years (2019, 2020) and include spatial network and tabular files with aggregate hourly activity counts for each street segment.

Studies show that the pooled sample of Strava ridership can mask patterns driven by subsets of the data (Fischer et al., 2020). For example, in Victoria, BC, Strava recreational ridership was associated with arterial streets and hills while commuting was associated with on-street bicycle facilities, signaling that some subsets of Strava data may be more representative of overall bicycling (Fischer et al., 2020). Subsets of Strava data can be extracted using labels that indicate the number of trips made by gender and age category, and whether trips were for recreation or commuting. We extracted data subsets for recreation and commute trips, and for trips made by women and older adults (55 + ) (Table 1). For privacy, Strava bicyclist counts are rounded to increments of five (i.e., if counts are less than three the segment is rounded down)

Table 1 Strava data descriptions and rationale for use in spatial analysis.

| Strava data subsets | Description | Rationale |
|---------------------|-------------|-----------|
| Overall bicycling (pooled sample) | Aggregate counts of all Strava bicycling activities combined | Used to measure overall city correlation. Not used in spatial statistical analysis as it may mask spatial patterns driven by subsets of the data. |
| Recreation | Counts for trips labeled recreation | Studies suggest increase in pandemic bicycling driven by trips for recreation (Buehler and Pucher, 2021). |
| Commute | Counts for trips labeled commute | Bicycling is a health and equity promoting alternative transportation option, especially for essential workers and transit riders (Cusack, 2021). |
| Women | Counts for trips with gender labeled woman | Women tend to be underrepresented in bicycling in low bicycling countries like Canada (Aldred et al., 2016; Firth et al., 2021a). |
| Older adults (55 + ) | Counts for trips with aged labeled 55 and over | Older people tend to be underrepresented in bicycling in low bicycling countries like Canada (Aldred et al., 2016; Firth et al., 2021a). |
For commuting trips, Strava has a feature allowing users to tag their activities by type (e.g., commute, e-bike ride, virtual ride), and commute trips in Strava data are labeled by a model which uses information on the spatial and temporal characteristics of the ride and the commute tag on Strava activities as a ground truth (Strava Metro, 2020b). Age and gender labels are derived from Strava app user input. Gender and age are represented as the count of people rather than trips. The number of trips to people could be disproportionate, however, on streets with any trips, trips per person ranged between 1 and 48 (mean = 1.64, median = 1.33), and more than 75% of all segments had a ratio of 1.8 or less. Visualized on a map, the spatial patterning of trips per person shows that higher ratios occur on short, disconnected segments, implying that very active Strava users were not driving larger spatial patterns in the study area, but instead might have been using certain short segments to access the bicycle network (Hochmair et al., 2019).

We created a geospatial count database for the period April 1 - October 31, comparing 2019 and 2020. This temporal window represents peak bicycling season in Vancouver when bicycling levels tend to be less impacted by inclement weather. As a sensitivity analysis we investigated temporal variability in ridership within the study period by weekly, monthly, and aggregate monthly (April - October) time bins, and while there was some variability in temporal patterns (e.g., higher ridership immediately following the first set of stay-at-home orders in 2020), the spatial patterning of change in ridership was consistent regardless of time bin. Thus, we used the longer time period (April - October) as it was most appropriate for our purpose. We removed observations with invalid data, which included days with missing values or zero counts, or days with unusually high or low counts. Then we matched Strava counts to official counts by location, date, and hour of the day.

We calculated total Strava counts for each street segment for each period and aggregated totals to segments using the “EDGE_ID” attribute provided by Strava. The aggregate data represented the sum of daily Strava counts on each street from April - October 31. Aggregate data were then joined to the spatial network files for mapping. All data cleaning was completed in R Statistics software 4.0.5 (R Core Team, 2021) and ArcGIS Pro (2.8.3) (ESRI Inc, 2021a).

2.4. Bicycle facilities and street reallocation programs

Spatial files for bicycle facilities were downloaded from the City of Vancouver’s Open Data Portal (City of Vancouver, 2021a). We classified facilities using the Can-BICS classification system (Fig. 1). Can-BICS has three classes of bicycle facilities (high, medium, and low comfort) based on separation from motor vehicles, safety, and user comfort (Winters et al., 2020). High comfort facilities prioritize separation from motor vehicles and/or lower traffic volumes, and include local street bikeways, separated bicycle paths, and cycle tracks (344.5 km); multi-use paths (75.2 km) are medium comfort routes; and painted bike lanes (128.7 km) are low comfort (Winters et al., 2020).

In April 2020 the City of Vancouver launched their Making Streets for People Program (City of Vancouver, 2021c), with several measures to reallocate street space in response to COVID-19 demand for active transportation. Traffic lanes were removed to install 11 km of provisional bike lanes on Beach Ave and Stanley Park Dr, which were intended to expand space on the English Bay and Stanley Park sections of the Seawall and increase access to Stanley Park (Fig. 1). Concurrently, the Seawall through English Bay and Stanley Park was closed to bicyclists from April - September (2020) to make more space for people walking (City of Vancouver, 2021d). Slow Streets were implemented on 39 km of residential streets, including streets designated as local street

![Fig. 1. Map of study area, pre-existing bicycle facilities, and provisional street reallocations. Pre-existing facilities are mapped in black and white. High comfort facilities (344.5 km), shown in black, prioritize separation from motor vehicles and/or lower traffic volumes, and include local street bikeways, separated bicycle paths, and cycle tracks; multi-use paths (75.2 km), shown in solid white, are medium comfort facilities; and painted bike lanes (128.7 km), shown as a dashed white line, are low comfort. The Seawall, Vancouver’s most popular site for recreation, is highlighted in blue, and street reallocations are mapped in green (provisional bike lanes) and yellow (Slow Streets).](image-url)
bikeways. The intention was to create more room for people to exercise and use active transportation by calming vehicle traffic and restricting access to local residents and emergency and service vehicles (City of Vancouver, 2021b, 2020b). Slow Streets were selected based on several factors including traffic volumes, access to green space and neighbourhood amenities, and social equity (City of Vancouver, 2021b, 2020b). Both provisional bike lanes and Slow Streets were implemented using lightweight and temporary infrastructure including traffic cones, barriers, and signs. Spatial data for street reallocations were digitized in ArcGIS by referencing data from the City of Vancouver (City of Vancouver, 2021c).

3. Methods

3.1. Comparing Strava and bicycle counter data

Qualifying correlation is a first step in assessing whether Strava ridership is a reasonable proxy for spatial analysis of bicycling patterns in cities (Conrow et al., 2018; Hochmair et al., 2019; Hong et al., 2019; Lee and Sener, 2021; McArthur and Hong, 2019). We conducted bivariate correlation analysis on the overall (poled) sample and for data subsets representing trip purpose (recreation and commute), women, and older age (55 +).

3.2. Spatial patterns of change in ridership

To evaluate change in ridership while accounting for the year over year increase in Strava app users we first calculated a normalized measure of ridership (Boss et al., 2018). We summed the total of all Strava bicycle counts across the study area for each period and divided activity counts on each segment by the summed total. Thus, our outcome for mapping and analysis is a relative measure and represents the segment-level proportion of all Strava counts. We refer to this outcome as ‘relative ridership’ for the remainder of this paper. To visualize spatial change in ridership we then created maps of difference in relative ridership. For each data subset we subtracted relative ridership during the period of April - October 2019 from April - October 2020, producing segment level change in relative Strava ridership (Boss et al., 2018). We classified maps using manual class breaks to create three classes of change in ridership. Classes illustrate streets where ridership declined (change was negative), had little to no change, or increased (change was positive).

Visual pattern analysis is useful for understanding the general distribution of spatial patterns but identifying whether patterns were statistically significant or due to random processes is not possible (Anselin, 1995). Spatial statistics differentiate random and minor patterns from significant ones, allowing important spatial patterns to be detected (Boss et al., 2018; Nelson and Boots, 2008). The null hypothesis is complete spatial randomness (O’Sullivan and Unwin, 2010)—that events occur with equal probability anywhere and are independent of each other. Spatial patterns can emerge from complex spatial randomness, and spatial statistics provide information on how likely it is that patterns are non-random—in other words, how likely they are to be linked to an underlying spatial process (O’Sullivan and Unwin, 2010). Following methods developed by Boss et al. (2018), we used the Getis Ord G_i^* statistic, a local indicator of spatial autocorrelation (LISA), to identify statistically significant clusters of increase and decrease in relative Strava ridership (Getis and Ord, 1992; O’Sullivan and Unwin, 2010). The Getis Ord G_i^* spatial statistics tool is available in ArcGIS Pro (ESRI Inc., 2021b), and works by evaluating the proportional sum of an attribute value and its neighbours against the global value of the same attribute. A significant cluster is detected when the local sum for a feature and its neighbors is very different from the expected local sum and when the difference is too great to result from random chance (Getis and Ord, 1992; ESRI Inc., 2021b). The tool returns a new spatial data file with z-scores, p-values, and confidence bins (p < 0.10, < 0.05, or < 0.01). In our case, the outcome we measured was change in relative ridership between the two study periods. Statistically significant positive clusters are hot spots where ridership increased more than expected and significant negative clusters are cold spots where ridership decline was statistically greater than expected. For context we referenced clusters of change to a high-resolution world imagery base map to describe and contextualize where change occurred.

3.3. Linking increase in ridership with bicycle facilities and street reallocations

To better understand how infrastructure supported bicycling, we overlaid the statistically significant increase in ridership detected in our Getis Ord G_i^* analysis with bicycle facilities and street reallocations. For each data subset we then measured the total distance (km) of increase within hot spots and calculated the distance and proportion of increase that occurred on each type of bicycle facility (high, medium, low comfort) or street reallocation (provisional bike lanes, Slow Streets). We used these lengths to contextualize how much significant increase occurred on each type of bicycling facility (pre-existing or provisional) relative to increases on streets without.

4. Results

4.1. Comparing Strava and bicycle counter data

Correlation between Strava ridership and counts collected at bicycle counters was reasonably strong at the city level (0.73). Across the data subsets, correlation was moderate at 0.58 for both the commute and older adult sample, and higher for the recreation sample (0.70). The sample of Strava data generated by women was the most representative of all bicycling, with a correlation with city bike counts of 0.79.

4.2. Spatial patterns of change in ridership

We present the map of difference in relative ridership for the sample of women bicyclists in Fig. 2, which was the sample that best represented overall bicycling based on our correlation analysis. The map provides a cartographic representation of where Strava ridership increased, decreased, or stayed the same. In general, Fig. 2 shows that ridership declined in the downtown core and along major commuting routes and increased on recreational routes and in residential neighbourhoods adjacent to the downtown core. There was little change in the south and east of the city compared to the north and west. While maps of change are useful as a preliminary visualization tool, they do not indicate if changes were statistically significant, nor do they clearly identify spatial clustering of change.

In Fig. 3 we show the results for Getis Ord G_i^* on the difference in relative ridership for the subsample of women bicyclists, which had the highest correlation with city bike counts. The map identifies where change in ridership is statistically higher or lower than expected based on a random process. By referencing where these clusters were located on the base map, we observed that statistically significant increases were around green and blue spaces (e.g., parks, greenways, coastal areas). For example, there were increases on most of the Seawall bike route, the Beach Ave and Stanley Park provisional bike lanes, and the Arbutus and Ridgeway greenways, which are all connected routes popular for recreation. Statistically significant declines occurred on commuting routes to and through downtown and the University of British Columbia, which was expected given mass business and school closures during the study period. We also detected diversions in bicycle ridership where ridership declined on closed sections of the Seawall and increased on adjacent provisional bike lanes on Beach Ave (3b) and Stanley Park (3c), indicating that street reallocations in this area worked as intended to reroute bicyclists.

Spatial patterning in the subsets of Strava data representing
recreation and the sample of older adult Strava bicyclists were consistent with the map of ridership generated by women but highlight additional hot spots with statistically significant increases in ridership. From the recreational ridership sample additional hot spots were on the Central Valley Greenway and W 10th Ave local street bikeway, which span the city and link neighbourhoods outside the core area to the popular recreational routes featured above (Seawall, Beach Ave and Stanley Park provisional bike lanes). Increases on Slow Streets connecting to John Hendry (Trout Lake) Park, a premier community park in East Vancouver, were also statistically significant, suggesting Slow Streets in this area were well-used. Spatial patterns of change in the Strava sample generated by older adults were like the recreation sample, but with more increases concentrated on low comfort bicycle facilities. This sample also showed concentrated increases on short segments with access to the Seawall. Spatial patterning in the commute sample showed distinctions compared with the other subsets. Notably, significant increases were in the hospital district on high comfort local street bikeways and nearby Slow Streets. Commuting also increased on streets where there was no or low comfort bicycle facilities. (Fig. 4).

4.3. Linking increased ridership with bicycle facilities and street reallocations

For each data subset we measured the total distance of streets with statistically significant increases in ridership as detected in our Getis Ord Gi* analysis and calculated the proportion that occurred on each type of bicycle facility (high, medium, low comfort) or street reallocation (provisional bike lanes, Slow Streets). Across data subsets from 52.7 to 100.0 km of streets segments had statistically significant increases in ridership volumes. Proportionally, between 59.2 and 80.4% of the total length of segments with statistically significant increases occurred on pre-existing bicycle facilities, rising to a high of 99.4% (recreation subset) with provisional street reallocation interventions. All data subsets demonstrated a strong preference for high comfort facilities (local street bikeways, separated bicycle paths, and cycle tracks). By trip purpose, a larger proportion of increase was concentrated on bicycle facilities (pre-existing and provisional) for the recreational sample of ridership compared to commuting. Of the demographic subsets, the sample of Strava data generated by women had a greater proportion of increase on bicycle facilities and showed the strongest preference for high comfort facilities; this subset also demonstrated the most increase on provisional bike lanes. The older adults’ sample had the highest proportion of increase on streets with low comfort or no bicycle facilities. Results are further detailed in Table 2 and illustrated in Fig. 5.

5. Discussion

A lack of spatially continuous ridership data has hampered a thorough spatial evaluation of the impacts of COVID-19 on where and when people were bicycling. Building on a methodology established by Boss et al. (2018), we used crowdsourced data from the Strava fitness app and applied spatial statistics on a network (Getis Gi*) as a spatially explicit approach to monitor change in ridership during the early months of the COVID-19 pandemic. We identified hot spots of increased ridership on high comfort bicycle facilities and provisional street reallocations. We also detected diversions in bicycle ridership around bike path closures on the Seawall, demonstrating how Strava data can help identify the broader network impacts of infrastructure interventions on bicycle flows. Using Strava data to study bicycling is increasingly common, however most studies use the pooled sample of ridership which could mask important and nuanced patterns. In this paper we found both consistent and unique spatial patterns by trip purpose and demographics, and to our knowledge this is the first study to evaluate differences across these novel Strava data subsets in relation to COVID-19 bicycling.

Our results indicate a strong preference for high comfort bicycling facilities. Though not significant in our LISA analysis, maps of difference in relative Strava ridership demonstrate little change or even declines in
bicycling in the areas south and east of the city core, possibly due to a lower density of bicycle facilities and/or poorer connectivity to desirable bicycling routes (see Figs. 2 and 3). Indeed, inequities in access to low stress, high comfort bicycle facilities have persisted for more than a decade in south Vancouver (Firth et al., 2021b). Bicycling patterns in these areas may be poorly understood as the city bicycle counters are concentrated downtown. Equity promoting policy should focus on understanding spatial patterns of bicycling in underserved areas, which could be supported using Strava data. Heatmaps of Strava activities can be used to identify ‘Strava deserts’, which are areas with no or very low Strava bicycling, rendering potential spatial inequities in bicycling more visible (Reddinger, 2019). Such information can aid city planners in targeting community engagement and interventions around active transportation.

Increases on street reallocations were concentrated on the provisional bike lanes on Beach Ave and Stanley Park Dr. These interventions acted as a pressure valve to ease crowding on the Seawall by creating more room for people walking, rolling, and bicycling. City estimates show average daily ridership on Beach Ave was 10,000 bicyclists per day (City of Vancouver, 2020c)—1.6 times the average at the busiest Seawall location pre-pandemic; and that 720,000+ people rolled through Stanley Park during summer 2020. We also detected significant increases around green and blue spaces, and on high comfort facilities connecting these areas. Bicycling and access to green and blue spaces in cities offer co-benefits for population health and the environment (de Hartog et al., 2010; James et al., 2015), especially in populations who experience health inequities (McCullough et al., 2019; Mitchell and Popham, 2008). Hence, increasing access and connectivity to green and

Fig. 3. Getis Ord Gi* results showing where change in ridership was significantly higher or lower than expected. The lines in red indicate statistically significant increase in ridership, blue lines indicate declines, and street segments with insignificant change are shown in grey.
blue spaces by bicycle is a key policy recommendation for building healthier, more pandemic resilient cities. Transportation planning should include green and blue spaces as important destinations when planning bicycle facilities. Our findings support that Strava data can be used to monitor variation in activities in green and blue spaces (Venter et al., 2020). In practice, then, cities might use Strava data to help identify green and blue spaces where infrastructure investment would have the greatest impact.

There were consistent spatial patterns of decline along major commuting routes in the downtown core across all Strava data subsets, likely due to business and school closures and the shift to teleworking. But patterns of increase in the Strava commuting data uncover distinct spatial patterns that were masked in the other data subsets. Importantly, we detected statistically significant increases in ridership on Slow Streets.

### Table 2

Total distance of streets with statistically significant increases in ridership as detected in our Getis Ord G* analysis and the distance and proportion of increase that occurred on each type of bicycle facility (high, medium, low comfort) or street reallocation (provisional bike lanes, Slow Streets).

| Strava data subset | Measure of increase in ridership | Total increase | Increase on bicycle facilities by comfort level | Increase on pre-existing bicycle facilities | Increase on street reallocations | Increase on any bicycle facilities | Increase on streets with no bicycle facilities |
|--------------------|----------------------------------|----------------|-----------------------------------------------|------------------------------------------|----------------------------------|-----------------------------------|------------------------------------------|
|                     |                                  |                | High  | Med  | Low  | High  | Med  | Low  | Prov. bike lanes | Slow Streets | Any street reallocation | |

#### Note

- Increase in ridership denotes the total distance of streets with statistically significant increases in ridership as detected by our Getis Ord G* analysis on change in ridership between April - October 2019 and April - October 2020.
- Maximum distance possible on high comfort facilities: 329.9 km.
- Maximum distance possible on medium comfort facilities: 69.3 km.
- Maximum distance possible on low comfort facilities: 96.4 km.
- Maximum distance possible on provisional bike lanes: 11.1 km.
- Maximum distance possible on Slow Streets: 38.9 km.

![Fig. 4](image-url) This map highlights unique spatial patterns of statistically significant changes in ridership uncovered in the commute sample of Strava data. Notably, significant increases were in the hospital district on high comfort local street bikeways and nearby Slow Streets.
Streets and local street bikeways connecting to the hospital district, thus it is plausible that front line workers were using them for bicycling to work. Commuting also increased on several streets around neighbourhood commercial nodes where there was low comfort or no facilities, signalling potential latent demand for utilitarian bicycling in those areas. Telework is likely to remain higher than pre-pandemic (Statistics Canada, 2021), which means that cities may need to adjust their planning for active transportation to support new patterns of bicycling (e.g., getting groceries, going to school, socializing, recreation). However, those most likely to telework in Canada are higher income population groups (Statistics Canada, 2021) who may already benefit from greater access to bicycle facilities (Fuller and Winters, 2017). Sociospatial equity approaches could be used to guide bicycle network investment and expansion. For example, if the goal is to enhance access to bicycling opportunities for equity deserving populations, Strava ridership could be overlaid with census data on social equity to locate candidate corridors for investment.

Few empirical studies have measured the impacts of COVID-19 on bicycling by demographics such as age, ethnicity, or gender, presumably because disaggregated data on the demographics of who is bicycling are rare. In our analysis the sample of Strava ridership generated by women and older adults indicate that the proportional share of all Strava bicycling activities represented by these populations increased during the study period, implying that gender and age disparities in who is represented in Strava data may have narrowed over the period. More research and disaggregated bicycling data are needed to understand the equity impacts of COVID-19 on different populations, but proprietary data from Strava in 2020 suggest that women were driving some of the observed increase in all bicycling during COVID-19 (Goldbaum, 2020; Strava Metro, 2020b). National survey data from Australia reveal that women were more likely to take up or return to bicycling during the first wave and that improved competence gained during this period was important to maintaining post-COVID bicycling habits (Fuller et al., 2021). Quieter streets through pandemic lockdowns may have created a unique window for women and other interested but concerned bicyclists to ride. “Time in the saddle” (i.e., gained experience operating a bicycle, becoming acclimatized to bicycling on city streets) has been linked to bicycling uptake for women in Vancouver (Sersli et al., 2021), thus it is possible that improved competence gained during the first lockdown period could have long lasting impacts if new bicycling habits are maintained. Disparities in women’s bicycling persist in many North American cities, thus from an equity perspective, a key policy imperative for cities to increase the share of people from underrepresented groups (i.e., low income, gender diverse, racialized, older people, people with disabilities) in bicycling is to plan and invest in low stress bicycling facilities that serve destinations these populations regularly go (Sersli et al., 2020). More parity in representation of women and older adults in Strava data can bolster such efforts as it becomes possible to map where these populations ride (Nelson et al., 2022).

Pandemic lockdowns forced individuals to change their travel patterns (including modes and destinations), which could impact the stability of the changes in ridership observed in this study. Future studies on the long-term impacts of COVID-19 on bicycling will illustrate if these shifts persist. Our methodology could be deployed in other settings, including studies on the longer-term impacts of COVID-19 on bicycling. While we recognize that Strava data are a sample of bicyclists (typically 1–5% in North American cities) biased toward app users (Lee and Sener, 2021), numerous studies have found Strava data to be a reasonable proxy for evaluating spatial patterns, rather than total counts, of all ridership (Nelson et al., 2020; Nelson, Roy, et al., 2021). However, there are equity considerations in using big data to understand the patterns of all people bicycling as representation in crowdsourced data is gendered and associated with access and privilege (Perster et al., 2017; Garber et al., 2019; Gardner et al., 2020). While moderate to strong correlations between Strava and all ridership in our study area give confidence that the patterns represented in the data are meaningful at the population level, when working with crowdsourced big data it is always important to consider who data are sampled from.

6. Conclusions

As Canadian national, provincial, and municipal governments amp
up investment in active transportation to support healthy, resilient city building and intersecting climate and social equity goals, the need to monitor and evaluate interventions is critical. We have demonstrated a spatial methodology that can be applied to Strava bicycling data to meet this need and highlight the value of evaluating spatial patterns across subsets of these data. Our results demonstrate that in Vancouver, a well-connected network of pre-existing and high comfort bicycle facilities alongside provisional street reallocations that supported active transportation and increased connectivity to green and blue spaces were key in absorbing a rapid increase in demand for bicycling during first wave lockdowns. Street reallocations inspired by the COVID-19 pandemic rapid response can be part of wider strategies to co-create healthy streets for all (Atherton, 2020). Importantly, a large and retrospective Strava Metro database is now freely available to cities and community advocates for planning and monitoring infrastructure investments and other changes to the bicycling network.

CRediT authorship contribution statement

Jaimey Fischer: Conceptualization, Data curation, Formal analysis, Visualization, Software, Writing – original draft, Writing – review & editing.
Trisalyn Nelson: Supervision, Conceptualization, Methodology, Writing – review & editing.
Meghan Winters: Supervision, Conceptualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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