Are Dominant Routes the Least Stressful Routes in a Bike Share System? An Investigation of Hamilton Bike Share using Weighted Level of Traffic Stress

Are Dominant Routes the Least Stressful Routes in a Bike Share System? An Investigation of Hamilton Bike Share using Weighted Level of Traffic Stress

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Abstract

Level of Traffic Stress (LTS) is a four-level system that classifies the stress experienced by cyclists on road segments and at intersections. While LTS has been used in past studies to assess cycling connectivity, accessibility, and safety, very little is known concerning its influence on cycling preferences. This study investigates this topic using a dataset containing 323,163 unique GPS trajectories of Hamilton Bike Share (HBS) users collected over a 12-month period (January 1st to December 31st, 2019). A GIS-based map-matching algorithm is used to generate users' routes from these trajectories along with attributes such as route length, number of intersections, and number of turns. Unique routes and their use frequencies are then extracted from all routes. The most popular routes between bike share hub (station) pairs are then identified as dominant routes while shortest distance routes are derived by minimizing distance traveled. Weighted level of traffic stress (WLTS), a novel measure of impedance (travel cost) developed for this study, is used to derive the least stressful routes between hub pairs. The three types of routes are compared statistically. The comparison finds that HBS users tend to choose longer routes with bicycle infrastructure in an effort to reduce their traffic stress. However, they do not choose to minimize traffic stress in its entirety by choosing the lowest WLTS routes. In other words, dominant routes are not the least stressful routes in a bike share system. Likewise, minimizing distance is not the sole consideration of HBS users. The findings suggest that other factors also influence route choice. This study not only enhances our understanding of cyclist route preferences with respect to LTS, it also presents a novel measure of impedance – WLTS – that could be used when planning new cycling infrastructure or as an alternative means to route cyclists between origins and destinations.

Keywords: Active travel; Bike Share; Cycling; Dominant Route; Level of Traffic Stress; Route Choice

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1. Introduction

Studies have shown that regular physical activity has significant health benefits and can help prevent various chronic diseases (Burtin and Hebestreit, 2015; Colberg et al., 2016; Rhodes et al., 2017), some mental illnesses (Vancampfort et al., 2015), and improve an individual's well-being and quality of life (Spinney et al., 2009). Cycling, a form of physical activity, has grown in popularity in recent years in part due to investments in cycling infrastructure (bike lanes) and bike share programs (Fishman, 2016; Shaheen et al., 2010; Shaheen et al., 2013). In Canada, for example, bike share programs have emerged and grown in popularity in several cities including Hamilton, Montréal, Ottawa-Gatineau, Toronto, and Vancouver (Hosford and Winters, 2018).

While cycling has well-recognized benefits, injuries and deaths, do occur. Between 2006 and 2017, 890 cyclists died in Canada, averaging 74 deaths per year. Collisions with motor vehicles made up 73% of these fatal cycling events. In addition to deaths, about 7,500 cyclists were seriously injured every year during the same period (Statistics Canada, 2019). Given grim statistics such as these, transportation agencies have sought to improve cyclist safety by focusing on traffic stress (Chen et al., 2017; Ferenchak and Marshall, 2020;), which is a combination of perceived dangers and stressors to cyclist safety associated with cycling close to vehicular traffic. The first scheme developed for classifying road segments based on the traffic stress tolerance of cyclists is Level of Traffic Stress (LTS) developed by Mekuria et al. (2012). This scheme is an ordinal system with four levels. These levels depend on cycling infrastructure, road attributes (e.g., road width, traffic speed, presence of a parking lane), and intersection characteristics (Harvey et al., 2019; Mekuria et al., 2012). The four levels of traffic stress are: LTS 1 – safe for children, LTS 2 – tolerable by the mainstream adult population, LTS 3 – tolerable by cyclists who are 'enthused and confident' but still prefer having their own dedicated space for riding, and LTS 4 – tolerable only by those characterized as 'strong and fearless' riders (Mekuria et al., 2012). Adaptations of this original LTS method have been developed to overcome data deficiencies and to account for differences in roadway infrastructure between cities. While researchers have used LTS to assess cycling connectivity, accessibility, and safety, little research has been done to ascertain whether LTS influences the route choice behavior of cyclists. One study compared the distance traveled between low stress (exclusively LTS 1 or 2 road segments), shortest, and observed cycling routes (Crist et al., 2019). The authors concluded that while cyclists choose slightly longer routes to travel on lower stress roads, they are unwilling to travel an excessive distance to remain on low stress roads. Their analysis was based on a small sample of individual cycling trips, taken primarily by experienced, male cyclists. The study did not assess other predictors of route choice including cycling infrastructure, number of turns, and topography, to name a few. Additionally, a low stress route did not exist for over half of all trips analyzed. Building on earlier work by Crist et al. (2019) and Lu et al. (2018), this study generates routes for all trips taken in 2019 between bike share hubs using the GPS data of Hamilton Bike Share users.

In this study, a route is a particular path between an OD hub pair. A trip is the physical movement between an OD hub pair along a route. Multiple trips can take the same route. Lima et al. (2016) introduced the idea of dominant routes to describe frequent trips along the same route. They found that car drivers prefer one route over another between an OD pair. Lu et al. (2018) extended the use of dominant routes to cycling by demonstrating that unique routes are often chosen by multiple cyclists in a bike share system between OD hub pairs. In this case, a dominant route could be considered the route that captures the preferred path of travel for cyclists since the usage frequency of a dominant route is greater than that of all other routes. Alternatively, the least stressful route could be considered to capture the safest path of travel between each OD hub pair since the combination of perceived dangers and stressors to cyclist safety is minimized. This poses the question: are dominant routes the least stressful routes? In other words, are the preferred routes of bike share users the safest routes in a bike share system according to their perceptions?

This study evaluates whether dominant routes are equivalent to the lowest traffic stress routes between OD hub pairs in Hamilton, Ontario's bike share system. This is achieved by comparing the Weighted Level of Traffic Stress (WLTS) of each type of route. WLTS is a novel distanced-weighted value of LTS developed in this study to capture the traffic stress of a route. Routes are equivalent if the WLTS of a dominant route is the same as the WLTS of a lowest traffic stress route (lowest WLTS route) between an OD hub pair – that is, the routes follow the same path of travel. If the WLTS of dominant routes differs from the WLTS of their lowest WLTS counterparts, comparing other attributes that have been found to influence route choice decisions in past studies (e.g., Khatri et al., 2016; Scott et al, 2021; Ton et al., 2017; Ton et al., 2018) can be used to understand factors that influence route choice behavior other than LTS. Additionally, dominant routes are also compared to their shortest distance alternatives to reveal additional factors that may affect bike share users' route choices.

The remainder of this paper is organized as follows. Section 2 reviews briefly the literature on LTS. It summarizes various LTS methods and the use of LTS to analyze network connectivity, accessibility, safety, and route choice. Section 3 describes the study area, the cycling network, and the GPS dataset. Section 4 describes how routes are derived using a GIS-based map-matching algorithm, and the workflow developed for identifying dominant, lowest WLTS, and shortest distance routes between OD hub pairs. Results from the analysis are found in Section 5 compares the attributes relating to cycling infrastructure, road attributes, route characteristics, and network topography between routes using paired *t*-tests. Section 6 summarizes the major findings of this study, as well as limitations, and recommendations for future areas of research. Section 7 outlines the digital deliverable that accompanies this study.

2. Background

2.1 Cycling Traffic Stress Methods

Multiple scoring methods exist for classifying road segments and intersections according to the traffic stress they impose on cyclists. The score is based on attributes related to cycling infrastructure, road attributes, and intersection characteristics either as input to a mathematical model or as criteria in a decision table. Davis (1987) pioneered the Bicycle Safety Index Rating (BSIR), a mathematical model that requires attributes to be combined and factored based on two indices, the Roadway Segment Index (RSI) used for roadways and the Intersection Evaluation Index (IEI) used for intersections. Each index is used in combination to classify road segments and intersections as either excellent, good, fair, or poor for cycling (Callister and Lowry, 2013). Both indices require a substantial amount of manually collected data including pavement condition, width of the outside traffic lane, and driveway frequency, making it a tedious and expensive model. Also, BSIR has never been validated against observed cycling behaviour, leading to questions regarding its accuracy in practical use (Turner et al., 1997).

Over time, simpler and more intuitive methods have been developed requiring less data to better support the development of traffic stress networks for cycling. Sorton and Walsh (1994) developed the Bicycle Stress Level (BSL) method to determine the bicycle compatibility between roadways and cyclists. Using traffic volume, speed limit, and curb lane width, bicycle stress levels ranging from 1 (no problem for cyclists) to 5 (a major problem for cyclists) were established. Similarly, Turner et al. (1997) created a Bicycle Suitability Score (BSS) for all state-maintained roadways in Texas using shoulder width, average daily traffic volume, speed limit, and shoulder pavement conditions. Harkey et al. (1998) published the Bicycle Compatibility Index (BCI), a linear equation comprised of 9 attributes including curb lane width, traffic volume, and vehicle speed, to assess the 'bicycle friendliness' of roadways excluding major intersections. Other traffic stress classification methods include the Bicycle Environmental Quality Index (BEQI), the Bicycle Interaction Hazard Score (BIHS), the Bicycle Suitability Assessment (BSA), and the Rural Bicycle Compatibility Index (RBCI) (Callister and Lowry, 2013; Pritchard et al., 2019). Though each method uses similar attributes, many do not experience mainstream application due to their niche uses, which include classification specific to rural areas or intersections, and intensive attribute requirements. For example, BSA requires 27 attributes while BEQI requires 22 attributes (Ferenchak and Marshall, 2020).

The best-known method for classifying road segments according to the stress they impose on cyclists is the Bicycle Level of Service (BLOS) method (Mekuria et al., 2012). BLOS is a non-linear, discontinuous equation used to evaluate cycling conditions of shared roadway environments using an alphabetic score between A to F (Callister and Lowry, 2013; Pritchard et al., 2019). Though BLOS does experience mainstream application, the immense data requirements are a critical barrier against its practical use in most jurisdictions (Callister and Lowry, 2013). Alternatively, Level of Traffic Stress (LTS) has become a widely used method for analyzing traffic stress on road segments and at intersections. By adopting Geller's 'Four Types of Cyclists' methodology, cyclists are divided based on their level of traffic tolerance, with group 1 being the least tolerant and group 4 being the most tolerant (Geller, 2006; Mekuria et al., 2012). A corresponding classification for road segments, intersection approaches, and intersections reflects traffic tolerance by categorizing the stress imposed on cyclists into scores of LTS ranging from 1 to 4. Criteria for calculating the level of traffic stress depends on road attributes (e.g., road width, speed limit, number of lanes, on-street parking availability) and whether cyclists ride in mixed traffic, on cycling infrastructure (e.g., bike lane), or on segregated paths (e.g., paved multi-use paths) (Mekuria et al., 2012) (see Table 1).

Researchers and municipalities have adopted LTS over other classification methods as it is a simple, data-driven approach requiring little input, and it is relatively easy to implement compared to mathematical methods like BCI and BLOS (Griswold et al., 2018; Harvey et al., 2019; Ralph & Von Hagen, 2019). LTS has become popular amongst jurisdictions like Maryland, Washington, and Delaware (Furth et al., 2018; Kittelson & Associates, 2019; Prabhakar & Rixey, 2017) to assess and propose improvements to cycling infrastructure.

Table 1. Description of LTS classifications and their corresponding Geller classifications

LTS Classification	Geller Classification	Description
LTS 1	Interested but concerned	Novice cyclists, including children, physically separated from traffic, or next to slow traffic where intersections are easy to approach and cross
LTS 2	Interested but concerned	Adult cyclists, excluding children, either physically separated from traffic, or in an exclusive cycling zone (e.g., bike lane), next to slow traffic where crossings are not difficult
LTS 3	Enthused and confident	Experienced adult cyclists, comfortable with varying levels of traffic stress in an exclusive cycling zone (e.g., bike lane), next to moderate traffic
LTS 4	Strong and fearless	Most experienced cyclists, capable of cycling on high speed and mixed traffic roadways

Note: No way no how (Geller Classification) is not classified into any LTS level.

2.2 Adaptations of LTS for Connectivity, Accessibility, and Safety Analysis

Variations of the original LTS method have been developed to overcome data deficiencies for small- and medium-sized jurisdictions and to account for differences in roadway infrastructure between cities. Additionally, cycling connectivity, accessibility, and safety have been assessed using adaptations of the original LTS classification scheme. The Conveyal LTS method extracts 4 widely available attributes from OpenStreetMap (OSM). The difference between each LTS level is reduced because of fewer data requirements. However, the simplified approach can be implemented in almost all cycling networks across the world (Harvey et al., 2019). Similarly, People for Bikes (PFB) developed a two-level (low and high stress) method, calculating LTS using 6 attributes extracted from OSM. The simple output dilutes differences in LTS levels that are present in more data-intensive methods (Harvey et al., 2019).

Furth et al. (2018) developed LTS 2.0 using 9 attributes, drawing on average daily traffic, number of lanes, and speed limit as key inputs to respond to traffic situations common in Delaware. This includes reclassifying high traffic 2-lane roads with 25 miles per hour (mph) speed limits as LTS 3 instead of 2. Similarly, Bearn et al. (2018) introduced the adapted LTS quality of service measure. This metric incorporates readily available data in the City of Atlanta to assess cycling connectivity. The adapted LTS method re-classifies protected cycle paths and side paths as LTS 2 instead of 1 due to the presence of conflict zones such as driveways (Bearn et al., 2018). Imani et al. (2019) did not include attributes like the width of cycling lanes or the presence of medians when calculating LTS because it was not available in the City of Toronto’s Open Data Portal. Instead, an alternative LTS classification method was developed based on speed limits in kilometers per hour (kph) to examine job accessibility. They created 30-minute isochrones of LTS 1 to 4 for each dissemination area (DA) using a consistent travel speed of 15 kph. The cumulative counts of jobs were then calculated for each DA at each LTS level. Their results showed that road segments with low levels of traffic stress (LTS $\leq$ 2) access less than 5000 jobs across the city. Only at an LTS of 3, does cycling accessibility rise above 15,000 jobs (Imani et al., 2019).

Prior research has explored the correlation between LTS and cyclist safety. Ferenchak and Marshall (2020) developed LTS scores and collected cycling rates for 612 roadway scenarios to determine the suitability of LTS to the cycling behaviour of children. They validated that road segments of LTS 1 are safe for children of all ages. Using ten years of adult vehicle-cyclist collision data for four New Hampshire cities, Chen et al. (2017) showed some geospatial correlation between higher LTS road segments and injuries. Results from a mixed logit model using independent variables including road attributes, vehicle volumes, and collision history, show that LTS can effectively predict crash severity (Chen et al., 2017). Though LTS has been used to assess cycling connectivity, accessibility, and safety, there is little research that uses LTS to understand the route choice behaviour of cyclists.

2.3 Route Choice Analysis using LTS

Both stated preference (SP) and revealed preference (RP) surveys have been used to collect route choice data (Broach et al., 2012; Yang & Mesbah, 2013). SP surveys ask participants to rank their preference of different route options, meaning large datasets can quickly be collected (Scott et al., 2021). Though easy and inexpensive to collect, SP data depends on the quality of the survey questions. A mistake by the respondent when ranking preferred routes or matching their usual routes to a generated choice set in the survey may lead to a loss of information (Abraham et al., 2002; Lu et al., 2018; Stinson & Bhat, 2003). Meanwhile, RP surveys gather information based on observed (actual) routes chosen by participants. The collection of RP data has benefitted greatly from the ubiquity of GPS technology. In many RP cycling studies, GPS is the most common means by which observed routes have been captured (Scott et al., 2021). Though complete routes are accurately collected using GPS technology, it can be costly to acquire GPS devices, and can present challenges with respect to converting GPS point data to observed linear routes within a cycling network (Scott et al., 2021).

Harvey et al. (2019) collected crowd-sourced GPS data using a mobile application called Ride Report to compare LTS scores of each road segment in Portland and Austin to the cyclist satisfaction scores of each trip. Satisfaction scores were recorded using a thumbs up or thumbs down in the Ride Report app. Using a grouped regression model, routes with bike lanes, paved multi-use paths, separated bike lanes, and low-traffic streets, increased cyclist satisfaction. However, Ride Report misidentified transportation modes in some cases. For example, it would estimate that a user was riding a bicycle when riding a bus. Ride Report relies on aggregations of binary ratings across partially overlapping trips, making it an imprecise metric with response bias (Harvey et al., 2019). While crowd-sourced mobile applications have seen a dramatic increase in popularity, samples of contributors tend to be a small subset of tech savvy, younger participants compared to actual cycling populations. This also makes crowd-sourcing prone to user-selection bias and geographic bias (Romanillos et al., 2016).

Despite GPS crowd-sourced data being prone to potential biases, Crist et al. (2019) compared the distances of lowest stress, shortest, and observed routes using GPS trip data from 104 cyclists making 1038 unique cycling trips in San Diego. Though a low stress route (composed of LTS 1 or 2 road segments) did not exist for more than half of all trips, they were 56% longer than observed routes and 74% longer than shortest routes. Cyclists chose longer routes to travel on lower traffic stress roads but were unwilling to travel an excessive detour distance to remain on a low traffic stress route (Crist et al., 2019). Aside from distance, other predictors of route choice, including cycling infrastructure, road attributes, route characteristics, and network topography were not assessed.

3. Data

3.1 Study Area

Hamilton is a major city in the province of Ontario, Canada, with a population of 536,917 in 2016 (Statistics Canada, 2016). Hamilton is located at the westernmost end of Lake Ontario. Residents of the city rely on personal motor vehicles (e.g., cars), public transit, and active transportation modes to travel. In March 2015, the Hamilton Bike Share (HBS) program was launched. HBS provides bikes and software that allow riders to use 825 smart bikes across over 20 square kilometers of Hamilton. With 132 hubs across the city, bikes can be reserved and released using an active membership and returned to any hub. The HBS service area has two parts. The core (shown in Figure 1) extends across downtown Hamilton, below the Niagara Escarpment. A secondary, smaller service area extends along Van Wagner's Beach. It stretches along the Queen Elizabeth Way (QEW) between Hamilton Harbour and Lake Ontario.

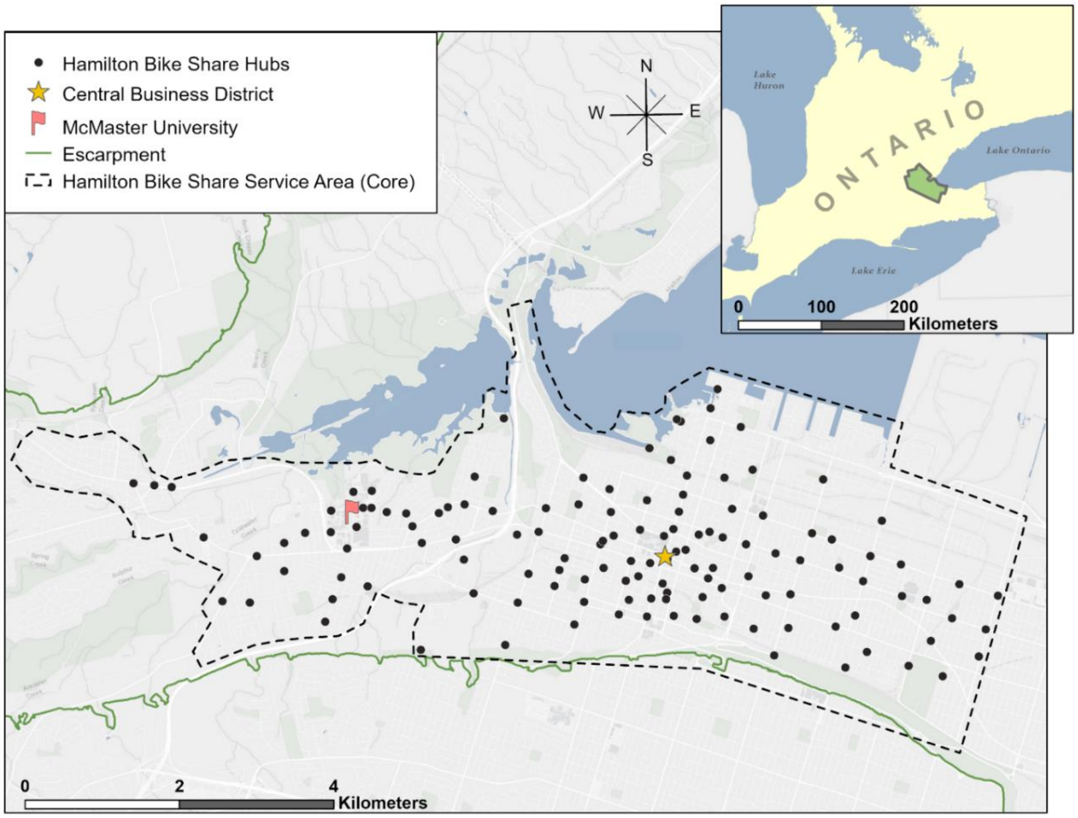

Figure 1. Hamilton Bike Share's core service area

3.2 Building the Cycling Network

A cycling network was created for this study using road and trail data to capture accurate cycling routes using the GIS-based Episode Reconstruction Toolkit (GERT) (Dalumpines & Scott, 2018) and a GIS-based map matching algorithm (Dalumpines & Scott, 2011). Open data from Hamilton's Open Data Portal was used for the cycling network, which was subsequently enriched with another open dataset containing information (i.e., bikeway classification) (see Figure 2) (Open Hamilton, 2018). Data sets provided by the City of Hamilton and McMaster Library's Maps, Data & GIS Centre were added to further enrich the network with accurate trail features. Road segments from the 2018 Ontario Road Network (ORN) (Ontario GeoHub, 2018) and DMTI Spatial (2019) were used to enrich the network with the number of lanes and speed limits in kph, respectively. Further, manual digitization of the network using satellite imagery as reference was done in high traffic areas (e.g., McMaster University) to create trail features that were commonly used by HBS users, but not captured in any previous dataset. Finally, slope and elevation for each road segment were calculated in ArcGIS Pro using a 30m digital elevation model.

Designated bike lane 	Cautionary un-signed bike route 
Signed on-street bike route 	Paved multi-use trail (shared with pedestrians) 

Figure 2. Examples of cycling infrastructure in Hamilton, Ontario

Before calculating WLTS for each route, LTS was calculated for each road segment comprising the cycling network based on LTS criteria. LTS criteria are defined separately for different street types – roads with mixed traffic, roads with cycling infrastructure along parking lanes, and roads with cycling infrastructure not along parking lanes (Furth et al., 2018; Imani et al., 2019). Paved multi-use recreational trails and park trails were assigned the lowest level of traffic stress, LTS 1. Highways and expressways were assigned LTS 0 and removed from the cycling network because cyclists are prohibited from using high-speed, high-volume roads. For the remaining road segments, the LTS criteria applied was an adaptation of LTS 2.0, published by Furth et al. (2018). An adapted LTS classification scheme was developed to accommodate the Canadian metric system and to supplement missing network data. Changes included the following: speed limits in mph were converted to kph; it was assumed that all bike lanes were not adjacent to parking lanes; bike lane widths were converted from feet to meters; it was assumed that bike lanes were not frequently blocked; the bike lane width of all bicycle infrastructure, regardless of infrastructure type, was set to 1.5 meters according to Hamilton's Cycling Master Plan (City of Hamilton, 2009; 2013); and one-way roads were used to represent streets without a centerline while all two-way roads were used to represent streets with a centerline.

LTS for road segments with bicycle infrastructure was determined using the number of lanes, bike lane width, and speed limit. For example, a 2-lane street per direction with a bike lane and a speed limit between 41 to 50 kph was assigned LTS 2 (see Table 2). LTS for road segments in mixed traffic was determined using the number of lanes, travel direction, annual average daily traffic (AADT), and speed limit. For example, a 2-lane major road with a centerline, AADT between 751 and 1500 vehicles per day, and a speed limit between 51 to 60 kph was assigned LTS 3 (see Table 3). LTS 2 makes up 67% of all network links, followed by LTS 3 (13%), LTS 1 (10%), and LTS 4 (5%). LTS at intersections was not derived. WLTS was calculated by multiplying the LTS of each network segment by its length in meters. WLTS and length were then used as impedance attributes to develop lowest WLTS routes and shortest distance routes between OD hub pairs. Upon completion, the network was converted into a network dataset to be used with the map-matching algorithm. The final network dataset had 22,484 links and 18,367 junctions (nodes). The cycling network is shown in Figure 3.

Table 2. Level of Traffic Stress for network segments with bicycle infrastructure

Number of Lanes (per direction)	Bike Lane Width (m)	Speed Limit (kph)					
		≤40	41-50	51-60	61-70	71-80	81-90
1	1.5	1	2	2	3	3	4
2	1.5	2	2	2	3	3	4
3+	1.5	3	3	3	4	4	4

Table 3. Level of Traffic Stress for network segments in mixed traffic

Number of Lanes (per direction)	Travel Direction	AADT	Speed Limit (kph)						
			≤30	31-40	41-50	51-60	61-70	71-80	80+
1*	One-way	0-1125	1	1	2	2	3	3	3
		1126-2250	1	1	2	3	3	3	4
		2251-4500	2	2	2	3	4	4	4
		4501+	2	3	3	3	4	4	4
1	Two-way	0-750	1	1	2	2	3	3	3
		751-1500	2	2	2	3	3	3	4
		1501-3000	2	3	3	3	4	4	4
		3001+	3	3	3	3	4	4	4
2	Two-way	0-8000	3	3	3	3	4	4	4
		8001+	3	3	4	4	4	4	4
3	Two-way	Any ADT	3	3	4	4	4	4	4

Note: * Without centerline.

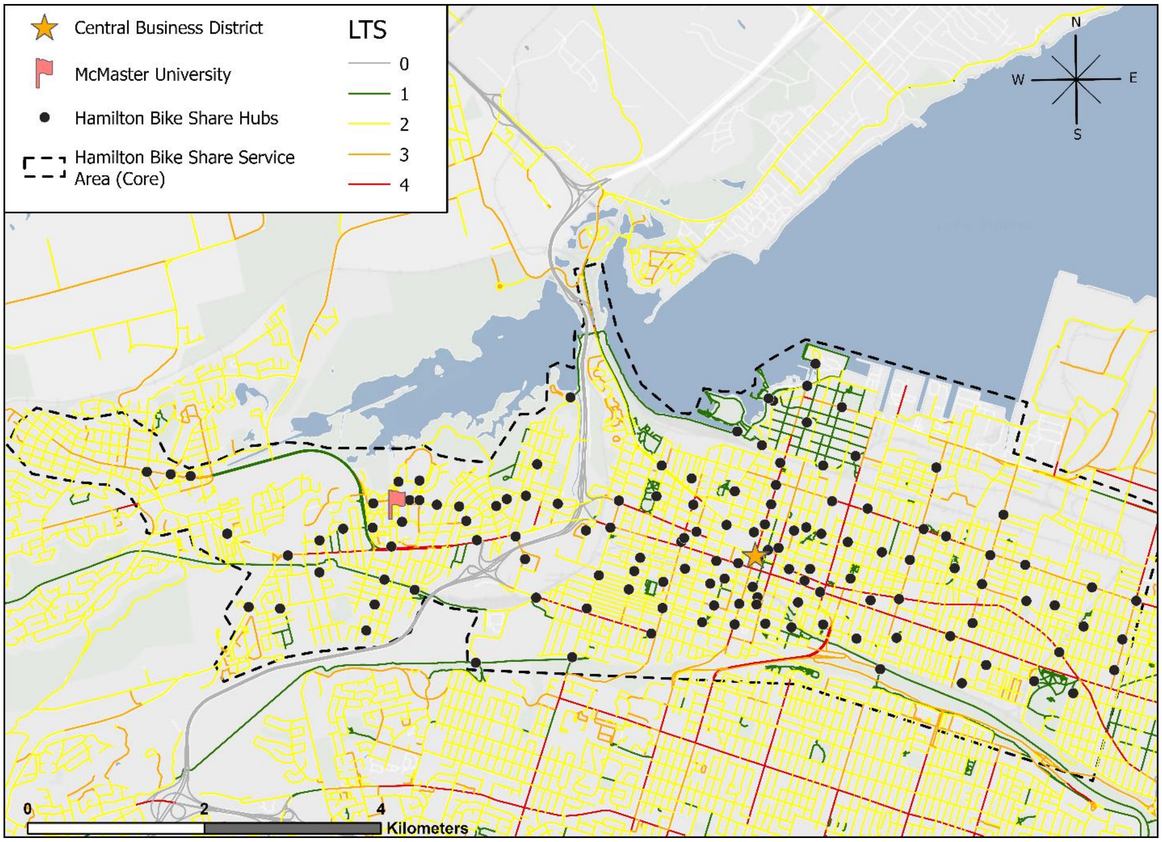

Figure 3. Cycling network showing LTS for each link

3.3 GPS Dataset

HBS bicycles are GPS-equipped meaning each bicycle's XY coordinates are recorded in real-time. GPS data of all trips in the year 2019 (from January 1st to December 31st) were obtained from HBS. The original 2019 dataset contained 323,163 unique GPS trajectories. Upon processing using the GIS-based Episode Reconstruction Toolkit (GERT) (Dalumpines and Scott, 2018) and the map-matching algorithm (Dalumpines and Scott, 2011), a total of 252,310 trips remained. 70,853 GPS trajectories (~22%) were removed during processing. Although most trajectories (~16%) were eliminated due to GPS errors, approximately 6% were lost because trips could not be map-matched (e.g., GPS trajectories did not follow the defined cycling network).

4. Methodology

4.1 Deriving Routes

The GIS-based Episode Reconstruction Toolkit (GERT) (Dalumpines and Scott, 2018) and the map-matching algorithm developed by Dalumpines and Scott (2011) were used to convert cycling GPS trajectories into polyline routes on the cycling network. The map-matching algorithm uses the shortest path to generate routes using GPS trajectories between an origin and a destination. The map-matching process is illustrated in Figure 3. First, the origin and destination points of each trip are identified as stops – for example, HBS start and end hubs. A polyline is generated between the stops and all intermediate GPS points comprising the trip (Figure 4a). Next, a buffer is created around the polyline based on a distance specified by the user. The buffer acts as a barrier, used to constrain a route's generation (Figure 4b). The observed route, which follows the stream of GPS trajectories, is then created within the buffer area along the cycling network (Figure 4c). Dalumpines and Scott (2011) found that a 50m buffer maximizes the accuracy of the map-matching algorithm for GPS data. As a result, a 50m buffer was chosen as the default buffer distance for this study.

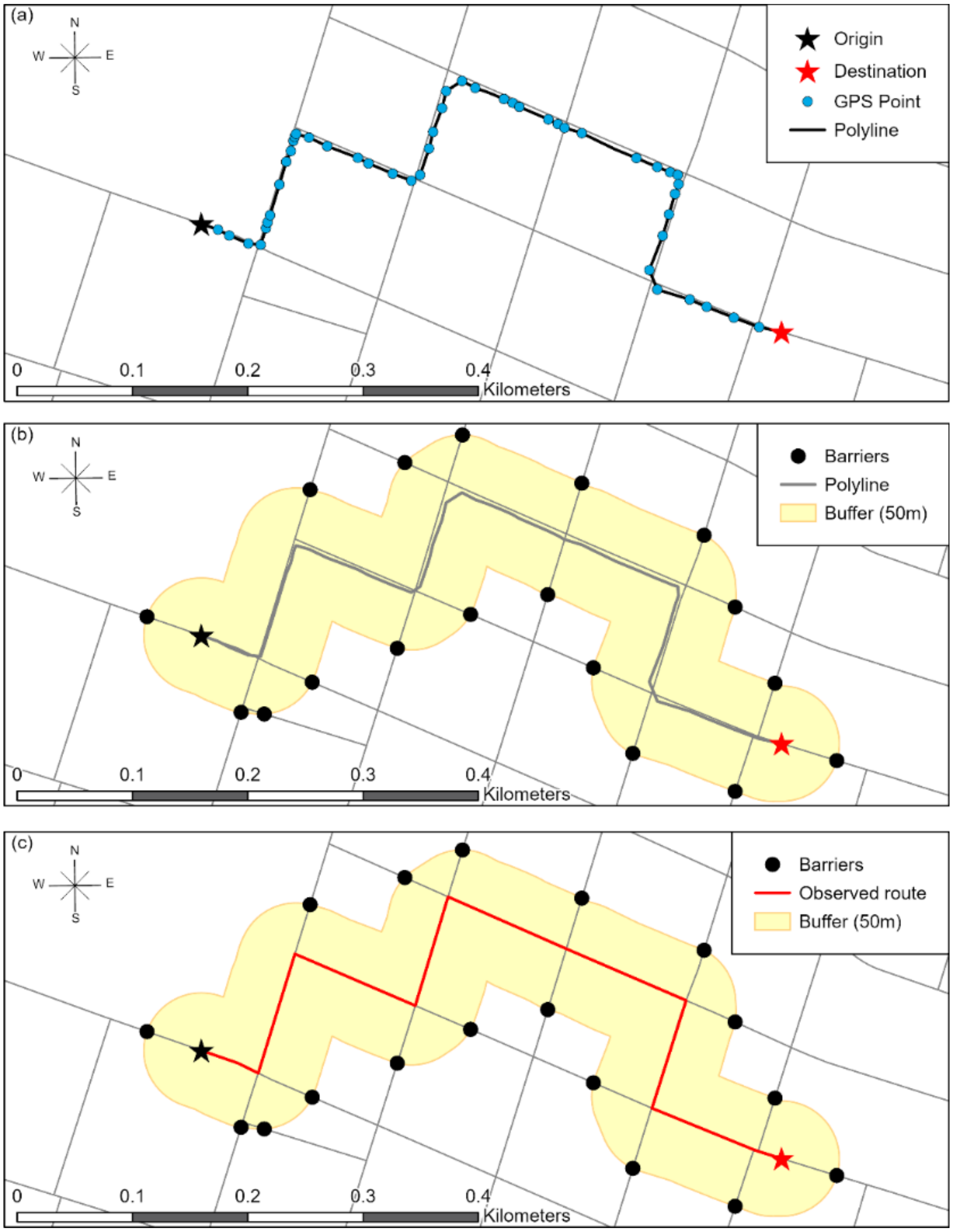

Figure 4. The conversion process from GPS trajectories to an observed route using the map-matching algorithm

4.2 Identifying Dominant Routes

Dominant routes capture the preferred travel behavior of cyclists between OD hub pairs given that the usage frequency of dominant routes is greater than that of all other routes. In this case, dominant routes have the highest number of overlapping trips between OD hub pairs. Overlapping trips may be slightly different at their origins and destinations due to, for example, a delay in GPS activation time. However, the routes of such trips should still be considered the same. Lu et al. (2018) developed a link signature extraction tool to remove the links at the start and end of each route based on their link IDs. As a result, all unique routes from hub-to-hub were extracted from all map-matched trips according to their core link signatures. Following this, the use frequency of each unique route was calculated according to the number of trips traversing it (Lu et al., 2018). This study developed an alternative method to extract the core route of each trip and determine dominant routes using python and ArcGIS Pro. The polyline features generated by the map-matching process were first intersected with the cycling network. This process 'broke' each route into its constituent links using the network junctions of the underlying cycling network as breakpoints. Using a 25m buffer around each hub, the links at the start and end points were removed. The remaining links were then merged to generate the core portion of each trip. Following this, the unique routes from hub-to-hub were extracted from the set of actual map-matched routes according to their core route geometry. To determine the dominant route, the use frequency of each unique route was calculated using the number of trips traversing it. The route with the highest trip count was extracted as the dominant route for each OD hub pair. To compare dominant routes with their lowest WLTS and shortest distance counterparts, the first and last links of each alternative were also removed using a 25m buffer from each hub. By retaining the core route geometry of dominant routes, lowest WLTS routes, and shortest distance routes between each OD hub pair, the comparison of attributes remains consistent throughout the study.

4.3 Paired t-tests

Paired *t*-tests were used to compare the mean differences between three sets of observations. In this study, paired *t*-tests were used to compare the differences among dominant routes, lowest WLTS routes, and corresponding shortest distance routes. The attributes investigated are listed, along with their definitions in Table 4. The paired *t*-test has been used in past studies to compare attributes of observed routes to shortest distance routes (e.g., Lu et al., 2018; Papinski and Scott, 2013; Winters et al., 2010).

Table 4. Attributes and their definitions

Attribute	Definition
Sum WLTS	Weighted level of traffic stress of route
Mean LTS	Weighted mean level of traffic stress of route
Mean speed (kph)	Weighted mean posted speed limit in kilometers per hour of route
Mean number of lanes	Weighted mean number of lanes along route
Mean AADT	Weighted mean annual average daily traffic of route (vehicles per 24 hours)
Distance (m)	Length of route in meters
Mean elevation (m)	Mean elevation of route
Mean slope (%)	Weighted mean slope of route
Trail (%)	Percentage of route on trails
Major (%)	Percentage of route on roads designated as “major” or “collectors”
Minor (%)	Percentage of route on roads designated as “minor” or “local”
MCOS (%)	Percentage of route on cautionary un-signed bike routes on streets with moderate traffic volumes
LCOS (%)	Percentage of route on cautionary un-signed bike routes on streets with low traffic volumes
HCOS (%)	Percentage of route on cautionary un-signed bike routes on streets with high traffic volumes
SBR (%)	Percentage of route on signed on-street bike routes
PMURT (%)	Percentage of route on paved multi-use recreational trails
BL (%)	Percentage of route on designated bike lanes
Number of segments	Number of unique road segments that a route travels along
Left turns	Number of left turns
Right turns	Number of right turns
Sharp left turns	Number of turns between 180° and 270°

Sharp right turns	Number of turns between 90° and 180°
Total turns	Total number of turns
RDI	Route directness index (compared to straight line distance)
Intersections	Number of intersections along a route

5. Results

5.1 Data Processing

Table 5 summarizes information concerning the processing of the map-matched dataset to arrive at the dataset used in this study. Of the total number of map-matched trips, only 77% (i.e., 195,467 trips) were between hubs. The trips occurred between 11,869 hub pairs. However, 5834 of them were removed for this study. Excluded were hub pairs with round trips only (i.e., same origin and destination) and pairs with one trip. The number of unique trips for all hub pairs was 79,736. Of these, only 49,784 were between the 6034 hub pairs used in this study. With respect to these hub pairs, the average number of unique routes is 7, while the maximum is 152 and the minimum is 1. Crist et al. (2019) found only half of all observed routes in their study had an alternative route where it was possible to travel exclusively on low stress (LTS 1 or 2) road segments. In this study, WLTS was used to find 6,034 low stress routes. Using WLTS to identify low stress routes increases the number of routes analyzed compared to the method used by Crist et al. (2019). Of all dominant routes, only 544 were identical to lowest WLTS routes (~9%) and 803 were identical to shortest distance routes (~13%). These findings suggest that bike share users consider additional attributes when choosing their routes between OD hub pairs. Between lowest WLTS routes and shortest distance routes, only 153 (~2%) were identical meaning that given the current configuration of the cycling network, bike share users are unable to minimize both their level of traffic stress and distance at the same time.

Table 5. GPS data processing summary

Description	Number	Notes
Map-matched trips	252,310	
Trips between hubs	195,467	
Hub pairs	11,869	
Hub pairs for study	6,034	Excludes 1) Pairs with round trips only, 2) Pairs with 1 trip
Unique hub-to-hub routes	79,736	
Unique hub-to-hub routes for study	49,784	
Average # routes between hub pairs	7	
Maximum # routes between hub pairs	152	
Minimum # routes between hub pairs	1	
Dominant route = lowest WLTS route	544	
Dominant route = shortest route	803	
Lowest WLTS route = shortest route	153	

5.2 Paired t-tests Results

Results for the paired -*t*-tests are found in Tables 6, 7, and 8. If HBS users were to choose shortest distance routes over lowest WLTS routes to travel between OD hub pairs, travel distance would decrease by 9%, while traffic stress (Sum WLTS) would increase by 24% (Table 8). Instead, by choosing dominant routes over shortest distance routes, HBS users increase their travel distance by 7%, but reduce their traffic stress by 11% (Table 7). Interestingly, choosing dominant routes over lowest WLTS routes, HBS users decrease their travel distance by only 1%; however, their traffic stress is increased by 15% (Table 6). This finding begs the question: Why are HBS users choosing dominant routes over lowest WLTS routes when the distances, although statistically different, are practically the same?

Of the 25 attributes compared between dominant routes and lowest WLTS routes, all but one was statistically significant at the 0.05 significance level – the exception being trails (Table 6). Since only 9% of dominant routes are equivalent to lowest WLTS routes, it is clear that HBS users do not choose their routes in terms of minimizing WLTS. Instead, based on the findings in Table 6, it appears that other factors may play a role in their route choice decisions. The mean speed (45.79 kph), mean number of lanes (2.70), and mean AADT (8358.12 vehicles/24 hours) of dominant routes are statistically higher than those of lowest WLTS routes. Significant differences are also found for turn frequency. The mean number of turns is 5.68 for dominant routes with 2.71 left turns and 2.69 right turns, compared to 7.01 for lowest WLTS routes divided between 3.55 left turns and 3.36 right turns. While sharp turns are uncommon for both dominant and lowest WLTS routes, the number of sharp left and right turns is statistically greater for dominant routes. On average, dominant routes have fewer unique road segments (8.86) and cross fewer intersections (37.76) compared to lowest WTS routes. With respect to slope, cyclists do not like climbing a slope over 4% (Transport Canada, 2010). In this study, the average slope of dominant routes is 3.85% while the average slope of lowest WLTS routes is 4.01%. Similar to findings by Lu et al. (2018), HBS users may seek to avoid slopes as a possible trade-off for other route attributes. Likewise, the mean elevation of dominant routes (94.34m) is statistically lower than lowest WLTS routes (94.62m).

Dominant routes tend to follow minor roads, which cover ~58% of a route compared to major roads, which comprise ~35% of a route. As expected, lowest WLTS routes are primarily composed of minor roads (~78% of a route) instead of major roads (~16% of a route). Figure 5 and Table 9 show and describe a sample dominant route, lowest WLTS route, and shortest distance route for the same OD hub pair, extracted from this study's dataset. 61% of the dominant route consists of major roads while 38% of the route is made up of minor roads. On the other hand, 6% of the lowest WLTS route consists of major roads. Instead, it is mostly made up of minor roads - 93%. This example illustrates that while the distance of such routes can be similar, the proportions of major and minor roads can vary significantly. It also suggests that HBS users may choose to travel longer distances on major roads. Preference to travel on major roads may be influenced by the increased availability of bike lanes. In the cycling network, about 75% of designated bike lanes are along major roads and 25% are along minor roads. Additionally, 100% of signed on-street bike routes in medium to high traffic are on major roads. Results from the paired *t*-tests suggest that it is more likely for HBS users to choose higher traffic stress routes with bike lanes or signed on-street bike routes instead of lowest WLTS routes. Though paved multi-use recreation trails (segregated paths) significantly decrease traffic stress, dominant routes have a lower proportion of such paths because these types of facilities are farther away from most OD pairs.

Table 6. Attributes of dominant routes compared to those of their corresponding lowest WLTS alternatives (*n* = 6034)

Attribute	Dominant Route	Lowest WLTS Route	Difference	*t*-stat
Sum WLTS	6325.94	5351.06	974.87	*42.58
Mean LTS	2.24	1.95	0.29	*51.29
Mean speed (kph)	45.79	44.78	1.01	*28.89
Mean number of lanes	2.70	2.53	0.17	*23.74
Mean AADT	8358.12	7525.34	832.78	*20.78
Distance (m)	2832.21	2859.43	-29.44	*-3.67
Mean elevation (m)	94.39	94.62	-0.22	*-6.44
Mean slope (%)	3.85	4.01	-0.16	*-13.96
Trail (%)	6.18	6.34	-0.15	-1.12
Major (%)	35.48	15.59	19.89	*63.95
Minor (%)	57.78	77.94	-20.16	*-67.26
MCOS (%)	1.14	1.01	0.12	*2.42
LCOS (%)	1.14	1.58	-0.44	*-7.11
HCOS (%)	1.65	2.25	-0.60	*-7.34
SBR (%)	10.16	9.40	0.75	*5.38
PMURT (%)	7.29	11.57	-4.26	*-22.97
BL (%)	39.37	36.43	2.94	*10.12
Number of segments	8.86	11.09	-2.21	*-23.42
Left turns	2.71	3.55	-0.84	*-28.22
Right turns	2.69	3.36	-0.67	*-21.57
Sharp left turns	0.13	0.05	0.08	*14.39
Sharp right turns	0.14	0.02	0.11	*19.25
Total turns	5.68	7.01	-1.31	*-23.95
RDI	1.83	1.33	0.50	*7.02
Intersections	37.77	38.42	-0.65	*3.60

Note. Differences are calculated as attributes of dominant routes minus those of lowest WLTS routes. Thus, positive *t*-statistics correspond to higher values for dominant route attributes, while negative *t*-statistics correspond to higher values for lowest WLTS route attributes. * = statistically significant at the 5% significance level.

Table 7. Attributes of dominant routes compared to those of their corresponding shortest distance alternatives (n = 6034)

Attribute	Dominant Route	Shortest Distance Route	Difference	*t*-stat
Sum WLTS	6327.13	7015.55	-688.41	*-28.06
Mean LTS	2.24	2.53	-0.29	*51.29
Mean speed (kph)	45.79	46.34	-0.55	*-14.02
Mean number of lanes	2.70	2.99	-0.29	*-37.69
Mean AADT	8358.12	9543.73	-1185.61	*-28.65
Distance (m)	2832.74	2635.80	194.48	*24.83
Mean elevation (m)	94.39	94.44	-0.04	-1.23
Mean slope (%)	3.85	4.04	-0.19	*-15.32
Trail (%)	6.18	2.32	3.86	*30.64
Major (%)	35.50	49.91	-14.40	*-41.39
Minor (%)	57.76	47.94	9.81	*30.24
MCOS (%)	1.14	1.23	-0.08	-1.70
LCOS (%)	1.14	1.25	-0.11	*-2.52
HCOS (%)	1.65	4.27	-2.61	*-28.15
SBR (%)	10.16	8.82	1.33	*9.33
PMURT (%)	7.29	4.41	2.87	*19.73
BL (%)	39.38	27.16	12.22	*40.94
Number of segments	8.96	7.07	1.88	*21.94
Left turns	2.72	2.69	0.03	1.19
Right turns	2.71	2.22	0.48	*15.87
Sharp left turns	0.13	0.04	0.08	*14.72
Sharp right turns	0.15	0.03	0.11	*20.20
Total turns	5.73	5.00	0.72	*12.79

RDI	1.36	1.25	0.11	*11.04
Intersections	38.77	37.03	1.73	*10.34

Note: Differences are calculated as attributes of dominant routes minus those of shortest distance routes. Thus, positive *t*-statistics correspond to higher values for dominant route attributes, while negative *t*-statistics suggest higher values for shortest distance route attributes. * = statistically significant at the 5% significance level.

Table 8. Attributes of lowest WLTS routes compared to those of their corresponding shortest distance alternatives (n = 6034)

Attributes	Shortest Distance Route	Lowest WLTS Route	Difference	*t*-stat
Sum WLTS	7015.55	5351.06	1663.22	*81.02
Mean LTS	2.53	1.95	0.58	*108.32
Mean speed (kph)	46.34	44.78	1.56	*50.23
Mean number of lanes	2.99	2.53	0.58	*74.34
Mean AADT	9543.73	7525.34	2018.39	*39.67
Distance (m)	2635.80	2859.43	-224.18	*-70.04
Mean elevation (m)	94.44	94.62	-0.18	*-8.54
Mean slope (%)	4.04	4.01	0.03	*3.23
Trail (%)	2.32	6.34	-4.01	*-39.24
Major (%)	49.91	15.59	34.33	*110.41
Minor (%)	47.94	77.94	-30.00	*-100.30
MCOS (%)	1.23	1.01	0.21	*5.12
LCOS (%)	1.25	1.58	-0.33	*-6.03
HCOS (%)	4.27	2.25	2.03	*24.19
SBR (%)	8.82	9.40	-0.58	*-4.68
PMURT (%)	4.41	11.57	-7.16	*-51.73
BL (%)	27.16	36.43	-9.27	*-39.70
Number of segments	7.07	11.09	-4.02	*-32.66
Left turns	2.69	3.55	-0.86	*-31.67
Right turns	2.22	3.36	-1.14	*-34.29
Sharp left turns	0.04	0.05	-0.01	-0.65
Sharp right turns	0.03	0.02	0.01	1.11
Total turns	5.00	7.00	2.00	*-35.54
RDI	1.25	1.33	-0.08	*-13.79
Intersections	37.03	38.76	-0.73	*-10.94

Note: Differences are calculated as attributes of shortest distance routes minus those of the lowest WLTS routes. Thus, positive *t*-statistics correspond to higher values for the shortest distance route attributes, while negative *t*-statistics suggest higher values for lowest WLTS route attributes. * = statistically significant at the 5% significance level.

Figure 5. Example of a dominant route, lowest WLTS route, and shortest distance route between a hub pair.

Table 9. Descriptive statistics for Figure 5

Type of Route	Distance (m)	Major (%)	Minor (%)	Mean LTS	WLTS
Shortest Distance Route	1534	59	41	2.5	3835
Lowest WLTS Route	1580	6	93	2.1	3318
Dominant Route	1588	61	38	2.3	3652

Of the 25 attributes compared between dominant routes and shortest distance routes, all but 3 were statistically significant at the 0.05 significance level – the exceptions being MCOS, mean elevation and left turns (Table 7). Dominant routes are 7% longer than shortest distance routes. The mean route directness index (RDI) of dominant routes is larger than that of shortest distance routes. RDI measures the efficiency and circuity of a route by calculating the ratio of a route's distance to the straight-line distance between its origin and destination (Lu et al., 2018). The mean RDI values of dominant routes and shortest distance routes are 1.36 and 1.25, respectively indicating that routes are 36% and 25% longer than the straight-line distances between hubs. Similar to findings from Lu et al. (2018), this means that dominant routes are, on average, 11% less efficient than corresponding shortest distance routes. Additionally, shortest distance routes have statistically fewer unique road segments (7.07) and cross fewer intersections (37.03). Likewise, the number of right turns (2.22) and total turns (5) of shortest distance routes are statistically lower than dominant routes.

Dominant routes are characterized by significantly lower WLTS (6327.13) compared to their shortest distance (7015.55) counterparts. As expected, the mean speed (46.34 kph), mean number of lanes (2.99), and AADT (9543.73 vehicles/24 hours) of shortest distance routes are significantly higher than those for dominant routes. The average slope of shortest distance routes is 4.04%, suggesting shorter routes are achieved through somewhat steeper slopes. The proportion of major roads (49.91%) along shortest distance routes is statistically greater than dominant routes while the proportions of minor roads (47.94%) and trails (2.32%) are statistically lower. Concerning the use of bicycle infrastructure between dominant routes and shortest distance routes, it is more likely for HBS users to choose routes with longer paved multi-use recreational trails, signed on-street bike routes, and bike lanes instead of the shortest distance alternative between an OD hub pair.

Of the 25 attributes compared between shortest distance routes and lowest WLTS routes, all but 2 were statistically significant at the 0.05 significance level – the exceptions being sharp left turns and sharp right turns. Though WLTS routes are, on average, over 200 meters longer than their shortest distance counterparts, their AADT is significantly lower at 7525 vehicles/24 hours compared to 9544 vehicles/24 hours. This is to be expected as the proportion of major roads, which experience higher levels of daily traffic, along shortest distance routes is significantly higher than the proportion of minor roads. In terms of perceived cyclist safety, all other road attributes and route characteristics compared significantly favor lowest WLTS routes, suggesting that shortest distance routes are not the safest routes. In other words, the shortest distance between an OD hub pair could be the most stressful. The large differences in attributes are further emphasized as only 2% of shortest distance routes are equivalent to lowest WLTS routes, suggesting that the two types of routes are the least equivalent among the three types of routes compared.

To summarize, the findings suggest that while HBS users favor bicycle infrastructure, they do not choose to minimize their overall level of traffic stress by choosing the lowest WLTS routes between OD hub pairs. Likewise, minimizing distance is not their sole consideration as only 13% of dominant routes are also shortest distance routes. When comparing attributes between dominant, lowest WLTS, and shortest distance routes, HBS users prefer traveling longer distances on major roads, which have higher speeds, more bike lanes, and higher AADT, cycling across fewer intersections, using bike lanes or signed on-street bike routes along higher traffic stress roads, taking fewer turns, and cycling below slopes of 4%. Cycling in Hamilton, especially for utilitarian trips, requires the use of major roads, accessways, and large connector streets that provide critical links between origins and destinations. Preferred bicycle infrastructure such as bike lanes and signed on-street bike routes are found predominately along major roads in Hamilton. Additionally, located along such roads are popular cyclist destinations. In this case, the built environment may influence cyclist route choice, as preferred bicycle infrastructure and the destination of most trips are located on high traffic stress roads, explaining why dominant routes are characterized by higher traffic stress than their lowest WLTS counterparts.

6. Conclusion

Level of Traffic Stress (LTS) is a four-level classification system that classifies the stress experienced by a cyclist on road segments and at intersections. Based on road attributes and whether cyclists ride in mixed traffic, on cycling infrastructure, or on segregated paths, each road segment is categorized into LTS scores ranging from 1 to 4. Researchers and municipalities have adopted LTS over other classification methods as it is a simple, data-driven approach requiring little input, and is relatively easy to implement (Griswold et al., 2018; Harvey et al., 2019; Ralph & Von Hagen, 2019). Though most studies have used LTS to assess cycling connectivity, accessibility, and safety, very little research has been undertaken that uses LTS to understand the travel behavior of cyclists. Past research by Crist et al. (2019) compared the distance between low stress, shortest, and observed cycling routes, but user bias, a small sampling size, and a lack of analyzing other route predictors of traffic stress limited their findings. To address this research gap, this study used an entire year's worth of GPS trajectories from users of a bike share system to analyze cyclists' route choices. A GIS-based map-matching algorithm was used to produce routes between OD hub pairs, and a new method for identifying dominant routes between OD hub pairs was introduced, building on past research from Lu et al. (2018). Additionally, a novel impedance attribute based on LTS and segment length called Weighted Level of Traffic Stress (WLTS) was developed to measure the overall traffic stress of a route between cycling origins and destinations, which, in this study, corresponded to bike share hub pairs. By comparing dominant routes to lowest WLTS and shortest distance alternatives, this study identified route attributes that could contribute to cyclists' route choices.

Only 9% of dominant routes chosen by HBS users are lowest WLTS routes. Additionally, only 13% of dominant routes are shortest distance routes. This suggests that HBS users do not choose routes to minimize only traffic stress or distance traveled. In other words, dominant routes are not the least stressful routes in a network. Instead, users likely choose dominant routes taking into consideration a combination of several attributes. While the findings of this study show that dominant routes and lowest WLTS routes have similar distances, the former have higher posted speed limits, more lanes, and AADT. Dominant routes are characterized by major roads followed by minor roads. The fact that HBS users prefer traveling longer distances on major roads is likely influenced by the greater availability of preferred cycling infrastructure such as bike lanes and signed on-street bike routes on such roads compared to minor roads. Moreover, although paved multi-use recreational trails reduce traffic stress, on average a very small percentage of a route takes place on such infrastructure because, in the study area, it is quite peripheral to the locations of bike share hubs. The number of unique road segments, intersection crossings, and total turns on dominant routes are less than those pertaining to lowest WLTS routes. Hub-to-hub dominant routes are 11% less efficient than their corresponding shortest distance routes, suggesting that shortest distance routes are not the optimal choice for HBS users. Additionally, since only 2% of shortest distance routes are equivalent to lowest WLTS routes, the two types of routes are the least equivalent between all routes compared. This suggests shortest distance routes are not the safest routes, as the shortest distance between an OD hub pair may be the most stressful. By choosing dominant routes over shortest distance routes, HBS users increase their travel distance by 7% and decrease traffic stress by 11%. When compared to lowest WLTS routes, HBS users choose to increase traffic stress by 15% while decreasing travel distance by only 1%. A possible explanation for such behavior is that popular cyclist destinations including schools, recreational facilities, businesses, and stores, are located along major roads characterized by higher traffic stress.

The validity of the LTS attribute developed for each road segment of the cycling network depends on the accuracy of the data available and the assumptions made for missing data. As mentioned in section 3.2, it was assumed that all bicycle infrastructure is not adjacent to parking lanes, bike lanes are not frequently blocked, and that the width of infrastructure, regardless of type, is 1.5-meters wide in accordance with Hamilton's Master Cycling Plan (City of Hamilton, 2009). The implication of these assumptions is that WLTS could be over or underestimated compared to the true traffic stress of each route. This can be overcome by incorporating missing data into the cycling network. GPS devices inherently contain a margin of error when reporting locations. Though routes with unrealistic distances (300m) from either hub pair were removed, the HBS GPS tracking units are accurate to within a 10m horizontal diameter. Though over and undershooting the origin or destination hubs by 10m for any particular trip could affect the WLTS of that route, it was assumed that by removing all start and end links of a route within a 25m buffer of all OD hub pairs, GPS inaccuracies would be overcome. While efforts were made to incorporate unofficial links into the cycling network according to GPS data and manual editing, it is possible that some links were missed. The assumption to assign multi-directional travel on the cycling network was made because cyclists are not constrained by the same level of regulation as automobile travel. One issue that affects further interpretation of the results is the absence of demographic data. It has been shown in other studies that route choice decisions are influenced by the characteristics of cyclists (e.g., age, gender, income, cycling experience) (Winters et al., 2010; Dey et al., 2018; Vidana-Bencomo et al., 2018)

While this study provides an alternative method to identify and extract dominant routes from a large dataset of trips between origins and destinations, its primary contribution to the cycling literature is the introduction of a new impedance attribute, Weighted Level of Traffic Stress (WLTS), to measure the overall traffic stress of routes. While dominant routes and WLTS are used to explore the route choices of HBS users in an effort to better understand their behavior, the concepts can be used to further understand the route choices of cyclists in general. By identifying the spatial distribution of dominant routes, city planners could make changes to specific network segments that are part of existing popular cycling routes. In other words, the goal would be to make existing routes safer by adding new or improved cycling infrastructure to them. In fact, network segments could be prioritized for improvement by aggregating the usage frequencies of all dominant routes. In this case, multiple routes would be improved at once. However, this may result in a limited improvement to the overall level of traffic stress along a route if the posted speed limit is more than 40 kph. As shown in this study, dominant routes in Hamilton tend to follow major roads that have speed limits much greater than 40 kph. WLTS routes, on the other hand, offer another alternative for adding or improving cycling infrastructure as they tend to follow minor roads at a cost of an increase of 1% travel distance, on average. It could be that reducing traffic stress on the parts of such routes with higher levels of traffic stress, at least in the case of Hamilton, is a more effective solution than focusing on dominant routes if the goal is to minimize traffic stress in a cycling network. Further improving an already safer route may induce traffic along that route by diverting traffic from other routes, including dominant routes, and generating new traffic. It is also important to note that the results of this study are for one bike share program – Hamilton Bike Share. Future work should focus on comparing dominant routes to WLTS routes in different cities and exploring the underlying attributes that influence cyclists' route choices. In this way, it can be determined the extent to which the findings in this study are generalizable.

7. Dissemination

Copenhagen has increasingly embraced the benefits of cycling as 36% of all commuter destinations can be reached by bicycle. Over 80% of the Danish population uses a bicycle for utility cycling (Neilsen et al., 2013). Since 1996, cycling in the city has gradually increased as data on cycling trends is collected using surveys and publicly shared through bi-annual cycling indicators. Cyclist user groups and stakeholders are frequently consulted by the municipality on cycling conditions. The municipality also leverages digital technologies by inviting cyclists to submit electronic suggestions for improving urban design to reduce cycling inconveniences (Neilsen et al., 2013). As a result, Copenhagen is one of the leaders in cycling across the world (Neilsen et al., 2013). A similar approach to cycling can be adopted by the City of Hamilton to increase public engagement and help steer decision-making for bicycle infrastructure projects (Desjardins et al., 2021). Additionally, publicizing local research made available to decision-makers may promote stronger advocacy campaigns for better planning and cycling infrastructure.

To the knowledge of the author, this study is the first to develop a digital deliverable using ArcGIS to summarize and publicly share key findings, visualize level of traffic stress for the City of Hamilton, and develop an online survey to promote engagement between the cycling community and municipality.

ArcGIS StoryMaps is a web-based application that can be used to share maps, images, applications, and surveys. The digital architecture makes it easy to share and host content publicly (Esri, 2021). For this study, an ArcGIS StoryMap titled *Level of Traffic Stress and Dominant Routes* was created. It is separated into the following sections: Background, Methods, Results, Infrastructure, Policy, Collaboration, Conclusion, References. The first three sections summarize the objective of this study, LTS network development for the City of Hamilton, route analysis using WLTS, and key findings. Also embedded in the story map is a web application developed using ArcGIS Web AppBuilder called *LTS Hamilton*. ArcGIS Web AppBuilder includes widgets and pop-ups to display, analyze, and edit data on any web browser (Esri, 2021). LTS Hamilton is an interactive web application developed to visualize LTS along major and minor roads. Road and bicycle infrastructure data for this application were downloaded from the City of Hamilton's Open Data Portal in June 2021. Widgets on the top ribbon and left corner can be used to: change the basemap, turn the LTS network on or off, view the legend, and share the application. The pop-up functionality allows users to view additional road characteristics of each road segment by clicking on it (e.g., speed limit (kph), bicycle infrastructure, number of lanes) (Figure 6). The City of Hamilton can use the web-based LTS network to plan new bicycle infrastructure projects along road corridors categorized with high traffic stress. The LTS network in the web application can also be regularly updated with new road and bicycle infrastructure data to best reflect the most up to date datasets available from the city. Additionally, LTS Hamilton can be used to visualize individual routes between hub pairs and compare route characteristics between dominant, lowest WLTS, and shortest distance routes. Using the Filter widget, a start and end hub can be selected from a drop-down list. This filters through over 40,000 routes from this study and displays the relevant routes on the map (Figure 7). The Chart widget can then be used to compare route characteristics on a bar graph (e.g., weighted level of traffic stress, percent minor roads, weighted average speed) (Figure 8). Route visualization and comparison using LTS Hamilton is a novel approach to accessing data used in a study, allowing users to further analyze cycling patterns and cyclist route preferences for individual hub pairs. Access to cycling routes through LTS Hamilton may influence additional research across the city. Also integrated into the web application and accessible through the story map under the Collaboration section is an online survey. The survey was built using ArcGIS Survey 123, a form-centric add-on for collecting data through a web or mobile device (Esri, 2021). The survey is developed to capture cyclist demographics, experiences, and opinions using multiple choice questions, short answers, images, and maps. Cyclists can plot points on a map to specify areas that they perceive have the most traffic stress across the city. Points can also be captured and geolocated using a smartphone or tablet with GPS services enabled. Short descriptions and images can be attached to each point to further explain how the current or lack of cycling infrastructure and policy causes traffic stress. Optionally, cyclists can suggest ways to improve cycling safety and reduce traffic stress at the identified points. Survey results are automatically transferred to LTS Hamilton and can be toggled on or off from the map view. The pop-up for each point includes responses to the survey questions and any images taken by the respondent (Figure 9). By integrating a cycling survey into LTS Hamilton, the web application promotes engagement between cyclists and the municipality. It functions as a platform for sharing cycling experiences and opinions while also collecting geolocated data that the municipality can use to plan new cycling infrastructure projects based on public suggestions.

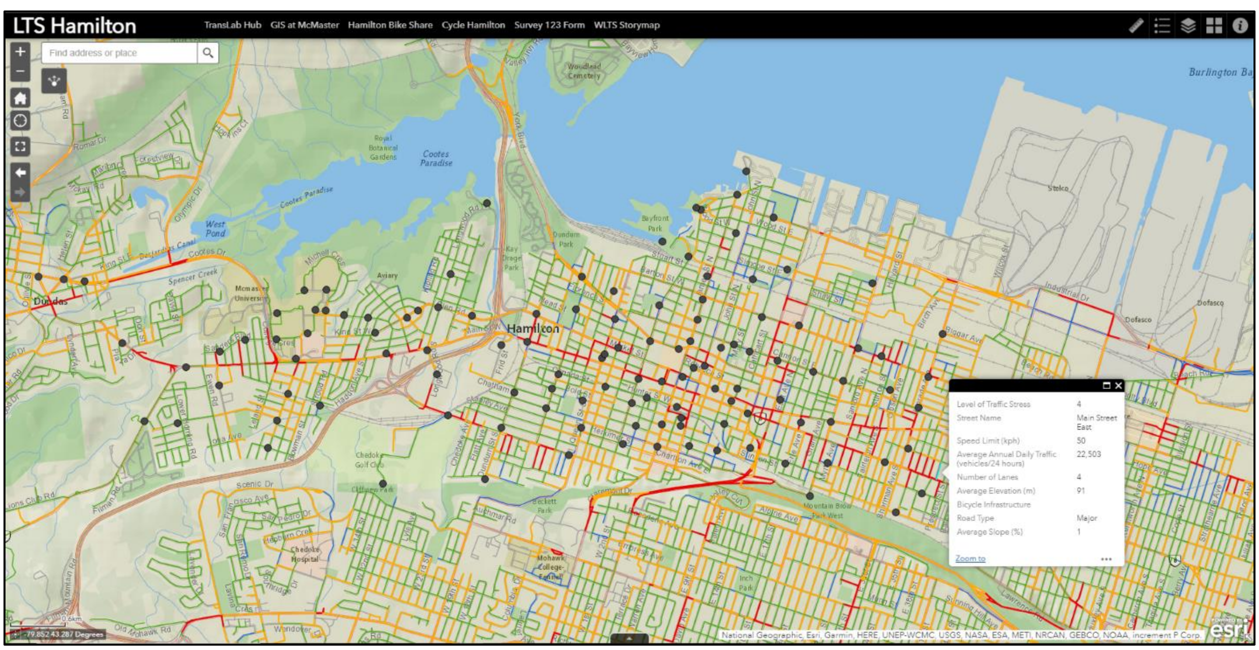

Figure 6. Pop-up functionality using LTS Hamilton

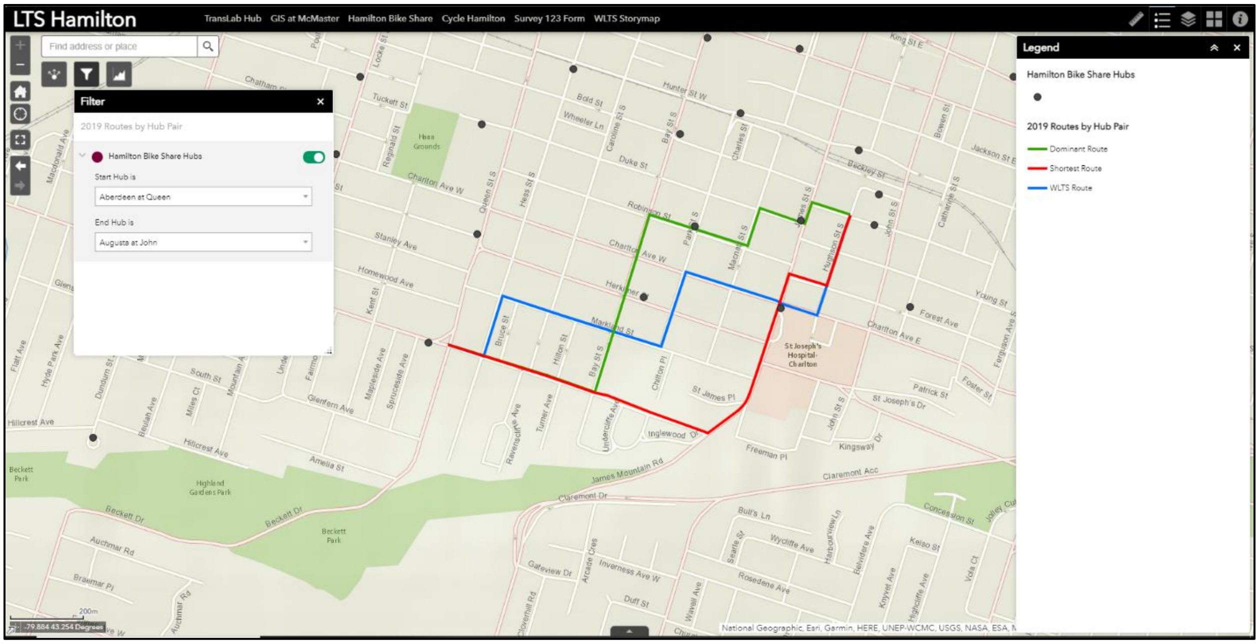

Figure 7. Route visualization using LTS Hamilton

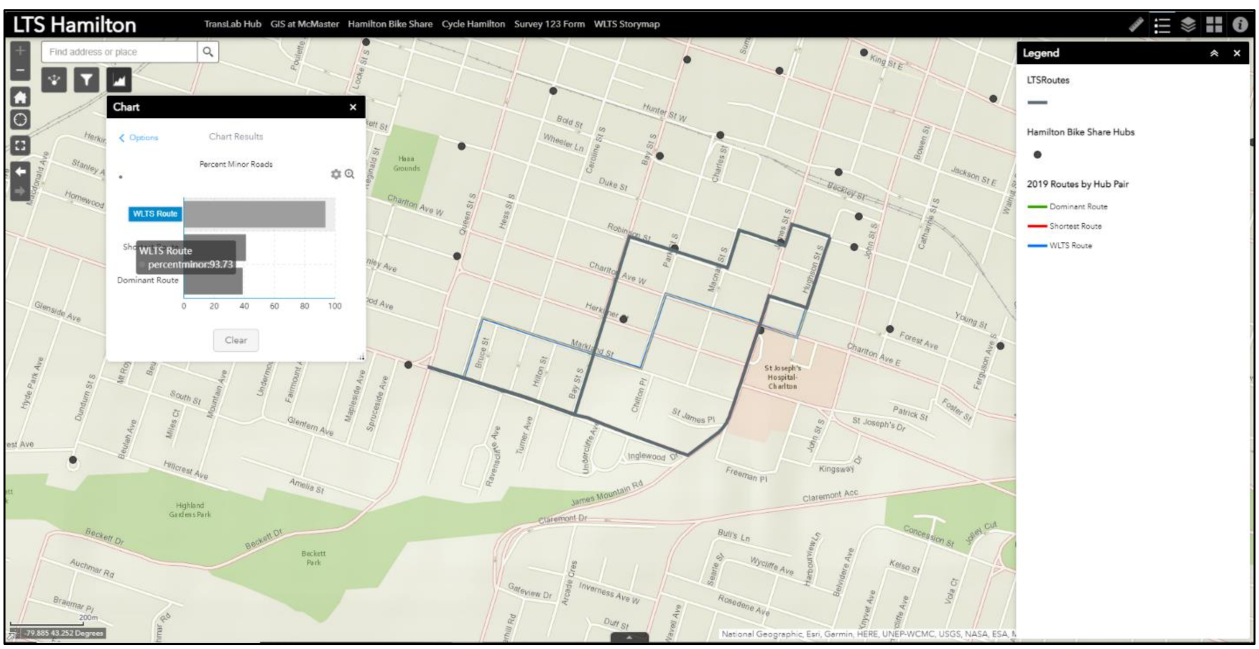

Figure 8. Route comparison using LTS Hamilton

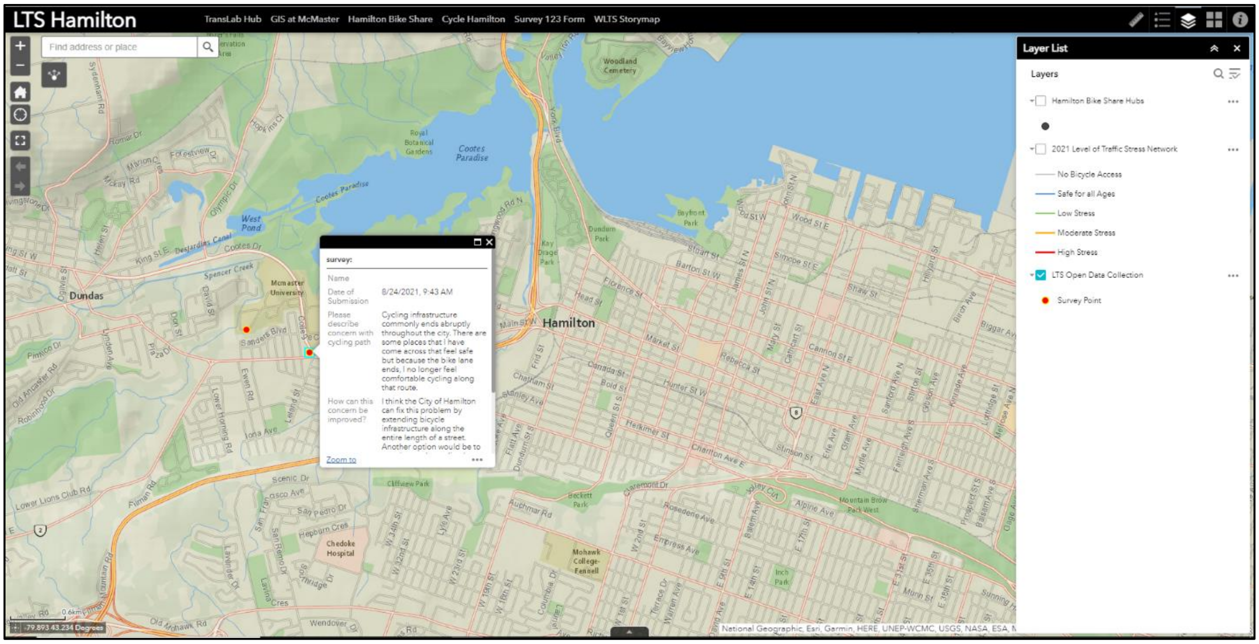

Figure 9. Visualizing survey results using LTS Hamilton

LTS Hamilton was developed to publicly share key findings from this study. It includes an interactive web based LTS network and dominant, lowest WLTS, and shortest distance routes. The integrated survey invites cyclists to submit electronic suggestions for improving cycling safety and reducing traffic stress. Similar to Copenhagen, the City of Hamilton can leverage the experiences and opinions of cyclists, collected using LTS Hamilton, to gradually improve cycling and to develop new cycling infrastructure that can impact more of the cycling community. An alternative to developing new cycling infrastructure projects may be to better rank proposed cycling infrastructure projects. The Transportation Planning Section within the City of Hamilton is responsible for managing the implementation of new cycling projects. Scheduling of these projects depends on project rankings and opportunities for coordination with other projects. As of 2018, there are 202 ranked cycling infrastructure projects that the city intends to implement (City of Hamilton, 2018). The Infrastructure section of the story map uses multiple web maps to detail how dominant routes developed in this study can be used as an alternative ranking system to rank proposed cycling infrastructure projects listed in the City of Hamilton's Master Cycling Plan. This approach prioritizes bicycle infrastructure on road segments most used by cyclists. As a result, proposed cycling infrastructure projects can have a faster impact on more of the cycling community.

Findings from studies can be publicly shared as community deliverables through simple and interactive applications like ArcGIS StoryMaps and Web AppBuilder. The dynamic text, media and embedded content used within these applications may be the preferred platform to share research with the public. Engagement and communication between cyclists, city planners, and researchers through digital deliverables can become a routine practice that may help improve cycling planning and infrastructure.

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