

1 **Effects of Built Environment and Weather on Bike Sharing Demand: Station Level**
2 **Analysis of Commercial Bike Sharing in Toronto**

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1 **ABSTRACT**

2 Bike Share Toronto is Canada’s second largest public bike share system. Bike Share Toronto
3 provides a unique case study as it is one of the few bike share programs in a North American city
4 that experiences severe cold climates and operates throughout the entire year. Using year-round
5 real time trip data, this study analyzes the factors affecting Toronto’s bike share ridership. A
6 comprehensive spatial analysis is performed and three regression models are developed at the
7 station level. Results of the trip attraction and generation models provide meaningful insights on
8 the influence of socio-demographic attributes, land use and built environment, as well as different
9 weather measures on bicycle share ridership. The developed models can be used to assist policy
10 makers and city planners to predict the monthly trip activity at potential station locations. A station
11 pair (origin-destination) regression model is developed based on station to station paths’ level of
12 service attributes along with other zonal level factors. Results show that station-to-station distance
13 and the number of intersections with major roads have negative impacts on bike share ridership.
14 In addition, for a given origin-destination pair, the higher the percentage of bicycle infrastructure
15 with respect to the total route length, the higher the corresponding ridership. This model can be
16 used to predict the trip distribution between station pairs based on the total trip activity at each
17 station. The model can also be used to assess potential bike infrastructure development based on
18 expected bicycle routes from/to potential station locations.

1 INTRODUCTION

2 Over 400 cities around the world have implemented or are planning to implement a bicycle
3 share program [1]. This reflects a growing concern for both environmental and personal health.
4 The economic benefits of bicycle use may also be a contributing factor. The City of Toronto
5 introduced its Bike Share as an active and sustainable mobility option for the citizens of Toronto
6 as well as for visitors to Toronto. The program aims to complement the existing transit system. It
7 provides a relatively quick means of travel within the Toronto downtown core area. The bicycles
8 are readily identifiable as belonging to the Bike Share program, thereby eliminating the concern
9 of bike theft or vandalism for the bicycle user. Bicycling, in general, has numerous benefits.
10 Counted among those benefits are: decreasing CO₂ emissions; reducing various diseases such as
11 diabetes and obesity; reducing traffic congestion and noise pollution by providing alternatives to
12 auto-commuting; and increasing public transit use [2].

13 The first public bicycle share system was introduced in Amsterdam, Netherlands, in the
14 1960s. The “White Bikes” were distributed around the city for the public’s use. The program was
15 aborted as the bicycles were repeatedly stolen and vandalized. In 1996, Portsmouth University in
16 England, introduced IT based public bicycle share systems [3]. The program’s users accessed the
17 bicycles using electronic swipe cards. This new generation of bicycle shared systems allowed the
18 operator to identify the customer and provided him or her with the ability to track the use of the
19 bicycle. This addition to the bicycle share concept led to a significant reduction of bicycle thefts
20 as well as vandalism. Today, we witness the evolution of “Multi-modal Systems” that provide:
21 GPS tracking of bicycle use; real time ridership data; moveable bike stations; and system
22 integration with public transit modes [2]. Typically, public bicycle share systems consist of both
23 devoted users who pay annual subscription fees as well as casual users who can pay on a month to
24 month or on a per trip basis. The user can ride the bicycle for a maximum of 30 minutes and then
25 return it to the nearest station [2]. If the user was to exceed his or her allotted 30 minutes, extra
26 charges may be incurred, depending on the company’s rules of use and operation.

27 Bike Share Toronto was established in 2011 as part of the City of Toronto’s Bike Plan [4].
28 Currently, the bicycle mode share for the City of Toronto is estimated to be 1.2% [5]. However,
29 the mode share increases substantially in Toronto’s downtown core area to 17% [6]. It is important
30 to note that the above percentages focus on bicycling for commuter purposes and they do not
31 include utilitarian or recreational bike trips. Thus, it is important to note that the overall actual
32 bicycle mode share may differ from the above mentioned shares.

33 Currently, Bike Share Toronto operates a system composed of 80 stations and 1,000
34 bicycles. The existing stations are distributed in the Toronto downtown core with plans to expand
35 the bicycle’s network and system capacity to a total of 3,000 bicycles [4]. In the first 18 months
36 since its inception, Bike Share Toronto facilitated over 1,000,000 trips and attracted 4,743
37 subscribers [7]. Unlike other North American public bicycle share systems, Bike Share Toronto
38 operates 24 hours per day, and is available 365 days a year.

39 In this paper, we attempt to examine the effect of weather, land use, socio-demographic
40 variables, and built environment attributes on Bike Share Toronto throughout the entire year of
41 2013. Using real time bicycle ridership data provided by Bike Share Toronto, factors affecting trip
42 attraction and trip generation are investigated. Further on, the shortest and most bicycle friendly
43 routes between each station pair in the system are generated and, through utilizing a station-to-

1 station origin destination model, levels of service attributes are then calculated. The objective of
2 the study is to provide a planning tool that can be used by transportation planners and city officials
3 to predict the total monthly trip rates generated at or attracted to potential station locations and/or
4 assess the effect of potential bicycle infrastructure development on bicycle share ridership.

5 **LITERATURE REVIEW**

6 Research on public bicycle share systems is on the rise. Previous research showed that
7 public bike share users tended to be less experienced than regular bike users and therefore had
8 different characteristics than that of bicycle riders for whom bicycle use is part of established
9 behaviour and routines [8]. That is, studying public bicycles share users' behaviour is required to
10 fill this gap in the literature, and is likely to provide pertinent information in regards to policy
11 development for bicycle use in urban settings.

12 Few of the studies used data from customer satisfaction surveys to analyze users' socio-
13 demographic and ridership characteristics. Bachand-Marleau et al. (2012) used data on BIXI users
14 in Montreal, Quebec, (Canada) to conclude that the location of docking stations close to the origin
15 of potential users can increase ridership [8]. Other studies attempted to understand the feasibility
16 and potential of bicycle share systems. North American cities such as Ottawa, Vancouver, Seattle,
17 and New York, through the help of and/or collaboration between consulting firms and government
18 institutions, conducted several feasibility studies on public bicycle share systems. These studies
19 hypothesized several potential station locations and determined, using intuition and previously
20 published studies on cycling behaviour, the various factors that can promote systems' bicycle
21 ridership. Factors such as population and employment density, bicycle infrastructure, socio-
22 demographic characteristics, land use as well as the built environment were investigated [9-12].

23 A third category of studies used ridership data from systems that are currently in operation
24 to predict and hypothesize the number, location and distribution of stations in other cities
25 worldwide. For instance, Krykewycz et al. (2010) used ridership data from peer European cities to
26 estimate demand for a hypothetical bicycle share ridership system in Philadelphia, Pennsylvania
27 (USA) [13]. In addition, Maurer (2011) used a pair-wise suitability analysis to understand the
28 effects of variables such as job density, household income, and alternative commuters on public
29 bicycle share ridership to propose the locations of bicycle stations in Sacramento, California
30 (USA). Ridership data from the Nice Ride in Minneapolis-Saint Paul, Minnesota (USA) was used
31 to perform the analysis. In this research the time period for the study was narrowed down to the
32 month of August. The analysis showed a positive correlation between the number of docks per
33 station and users' ridership. On the other hand, higher proximity to railway stations was negatively
34 correlated with station use [14].

35 Recently, a few studies used real time bicycle ridership data to examine factors that affect
36 public bicycle ridership demand. Gebhart and Noland (2013) used real time ridership data for
37 Capital Bikeshare in Washington D.C. (USA) to investigate the impact of weather variables and
38 proximity of bike share stations to metro stations on ridership levels. Reduced ridership was
39 correlated with cold temperatures, rain, and high humidity levels [15]. Buck and Buehler (2012)
40 investigated the influence of bicycle infrastructure, population density, land use mix around
41 stations, and the number of households without a car using bicycle share systems using ridership
42 data from Capital Bikeshare [16]. The study was conducted using data gathered during the months
43 of September to March. Buck and Buehler concluded that locating stations near bicycle lanes may

1 increase ridership. In addition, Daddio (2012) performed a regression analysis on the usage of
2 Capital Bikeshare stations during the month of October. The study concluded that proximity to
3 retail outlets and the metro rail was positively correlated with trip generation while locating
4 stations away from the centre of the bicycle share system tended to reduce ridership [17]. Socio-
5 demographic factors were also investigated and results showed that a bicycle share system was
6 predominantly used by white, middle-aged riders. Wang et al. (2012) conducted a similar study
7 using data from Nice Ride, Minnesota, which only operated from the months of April to
8 November. The study evaluated the effect of socio-demographic, land use, built environment and
9 transportation infrastructure variables on bicycle share ridership [18]. Station proximity to high
10 job density and food serving enterprises was found to be correlated with higher ridership levels.
11 Rixi (2013) explored the influence of socio-demographic characteristics such as education,
12 income, and employment and population density on monthly ridership data from three United
13 States based operators [19]. Built environment factors such as proximity to colleges and parks
14 were included in the analysis. Nair et al. (2013) studied Paris's public bicycle share system. The
15 study investigated system characteristics, temporal flows and intermodal use [20]. Hampshire
16 (2013) used real time data from the months of May to September for Barcelona's and Seville's
17 bicycle share systems [21]. The ridership data was aggregated on the sub-city district (SCD) level
18 and the analysis of ridership use was conducted on an hourly level. Population and employment
19 density as well as land use attributes were found to be correlated with higher public bicycle use.
20 In addition, higher ridership levels were correlated with the increase morning work-oriented trips.

21 Imani et al. [22] investigated factors affecting bicycle share demand at the station level
22 using real time ridership data from the BIXI bicycle share program in Montreal, Quebec (Canada).
23 A linear mixed modelling was developed and the results showed that stations close to major roads
24 had lower trip activities compared to stations that were situated around minor roads and bicycle
25 lanes. A number of land use and built environment variables, temporal characteristics and weather
26 variables such as temperature were investigated. The study concluded that the installation of a
27 greater number of stations in proximity to existing stations rather than increasing existing stations'
28 capacities would have a greater impact on bicycle share ridership. However, that bicycle share
29 system only operated during summer months and thus, similar to many previously mentioned
30 studies, the study did not provide a full understanding of bicycle share ridership levels in different
31 seasons during the year. In this paper, data from Bike Share in Toronto, Ontario, Canada is used.
32 This system operates year round. It provides, therefore, rich data on seasonal bike demand by
33 investigating the effects of detailed weather variables on bicycle ridership use.

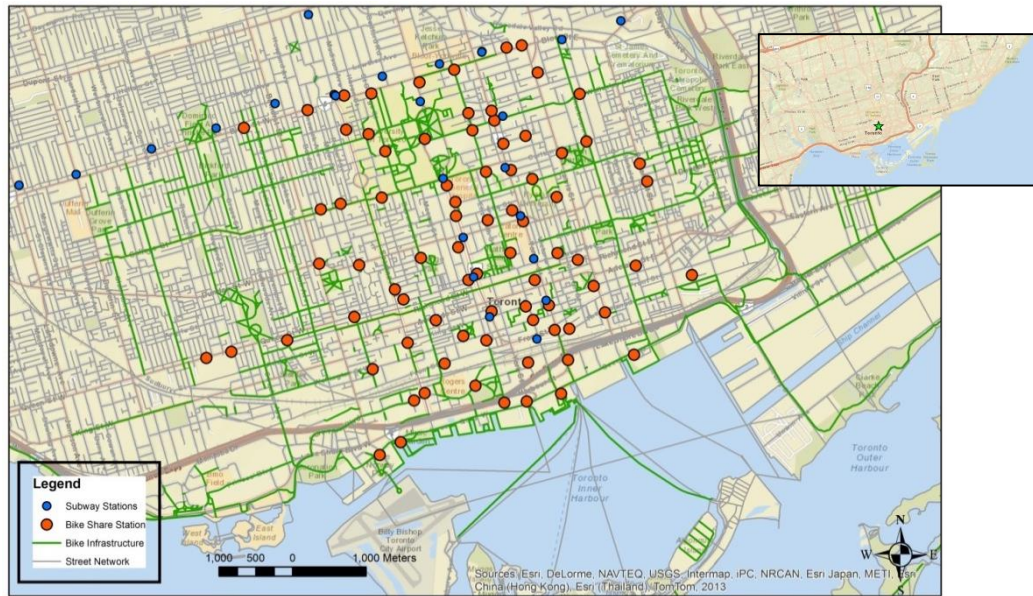
34 **STUDY AREA AND DATA DESCRIPTION**

35 To investigate the factors affecting public bicycle trip generation and attraction, weather
36 information, bicycle ridership data, socio-demographic characteristics, land use and built
37 environment attributes were amalgamated to create a complete and all inclusive dataset.

38 Hourly weather data collected at the Billy Bishop Toronto city airport (also known locally
39 as the 'Toronto Island Airport') weather station was provided by Environment Canada. The
40 database included temperature, wind chill, humidex (humidity index), snow on ground, wind
41 speed, precipitation and relative humidity. Subzero temperature values were adjusted based on
42 wind chill measures that combined the effect of wind speed and measured temperature. Similarly,
43 above zero temperature values were adjusted using humidex levels that combined the effects of
44 humidity and the reported temperature values. Using the formulas for wind chill and humidex [23],

1 the perceived temperature was estimated. The perceived temperature is the amalgamation of
2 humidex and wind chill with the above zero and the below zero recorded temperatures
3 respectively. The perceived temperature is a better indicator of the overall feel of the bike user,
4 and therefore, the perceived temperature is used in this analysis.

5 Real time ridership data for the year of 2013 was made available for this study by Bike
6 Share Toronto. The dataset included trip start time and date, trip end time and date, trip duration,
7 start station, end station, number of docks per station and bicycle number. This allowed for a
8 comprehensive temporal analysis based on the date and time of each trip as well as spatial analysis
9 based on the number of trips generated to and attracted by every station. The availability of data
10 in such a form eliminated possible errors incurred due to rebalancing operations. The bicycle
11 ridership data was analyzed on the station level and trips were aggregated on a monthly basis to
12 account for the variability of weather effects. Figure (1) shows the distribution of the 80 bicycle
13 share station, street network, and bike infrastructure network.



14

15

FIGURE 1 Study Area

16 After “cleaning” the data set to remove invalid trip records, the total number of trips
17 completed using Bike Share Toronto in the year of 2013 was 623,649. The average number of trips
18 generated per station on a monthly basis was 649 ranging from 60 trips to 2,072 trips per station
19 per month. Similarly, the average number of trips attracted per station was 650 with a minimum
20 of 82 trips and a maximum of 2,218 trips. Figure (2) shows the trip attraction as well as trip
21 generation at the station level.

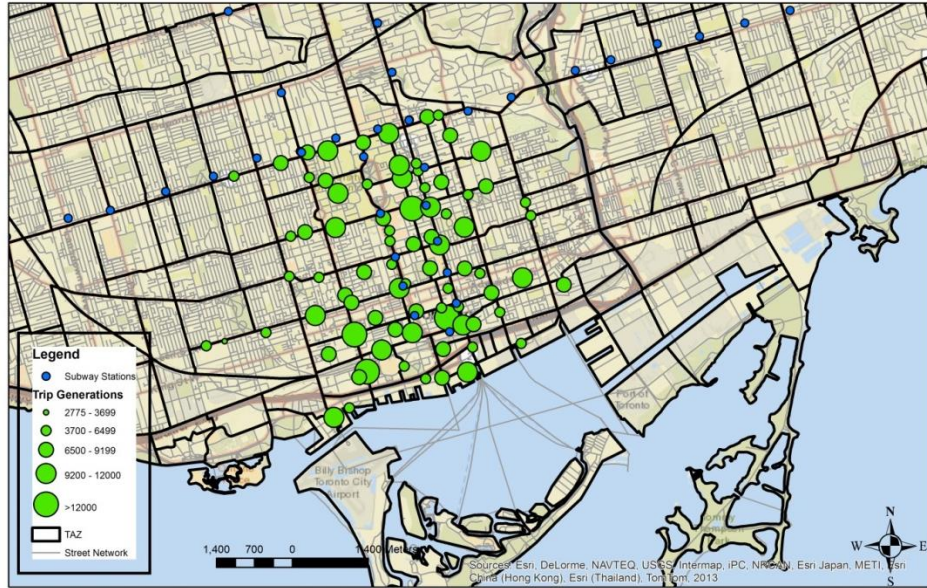


FIGURE 2-a Trip Generations at Bike Share Stations

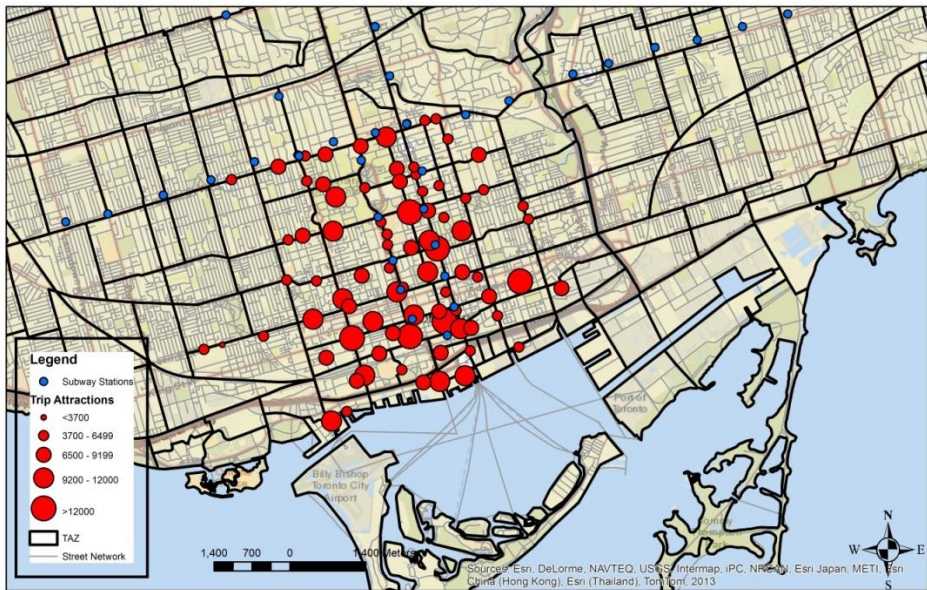


FIGURE 2-b Trip Attractions at Bike Share Stations

FIGURE 2 Trip Activity at Bike Share Stations

1 Using the start and end stations of the trips, hypothetical bicycle paths were generated
 2 using Google Map’s Application Programming Interface (API). Bicycle paths were generated such
 3 that the travelled distance was minimized and percent of bicycle infrastructure along the route was
 4 maximized. Bicycle lanes provide one of the safest means for cyclists to travel in the City of
 5 Toronto. The route selection hypothesis is supported by a study conducted by Winters et al on bike
 6 route safety and bike user preference in Toronto, ON and Vancouver, BC (Canada). The authors

1 concluded that bike friendly routes – routes that exhibit some form of bike infrastructure - are
2 safer, and are generally preferred by bike users [24]. Therefore, they were included in our study’s
3 criteria for path selection. Bicycle users were assumed to be rationale (i.e. pragmatic), in choosing
4 the shortest and safest path to travel on. Travelled distance and trip durations were determined
5 based on the suggested routes. The average actual trip durations between each station pair were
6 compared against the estimated durations. Results showed consistency of station-to-station trip
7 duration. The spatial analysis was done in ArcMap® 10.1, using an updated version of a street
8 network with details on bicycle infrastructure type, if any. The suggested bicycle paths were used
9 along with the street network to generate the percent of bicycle path length compared to the total
10 path length and the total number of intersections with major roads.

11 Socio-demographic characteristics including employment density and percent of male
12 population were also considered. The data was extracted from the Transportation Tomorrow
13 Survey (TTS) to be used in the analysis. The Transportation Tomorrow Survey was chosen as it is
14 one of the largest and most comprehensive household surveys conducted in North America [25].
15 Every five years, approximately 5% of all households of the Greater Toronto and Hamilton areas
16 are randomly selected, and individuals’ trip information and demographics are gathered. Data such
17 as age, gender, home and work locations, and occupation type are aggregated on a zonal level.

18 In addition, the effect of bicycle share stations’ proximities to subway stations and
19 university campuses on bicycle ridership was investigated. Further on, the number of neighbouring
20 stations within the 200 meter buffer zone was also considered as a variable in the study’s analysis.
21 Moreover, we explored the effect of numerous docks per station on trip rates.

22 **METHODS**

23 In order to investigate the effects of weather, socio-economic and demographic factors, as well as
24 land use and the built environment on bicycle share ridership, a regression analysis was performed
25 on three different levels: trip generation, trip attraction, and station-to-station trips. Accordingly,
26 three data sets were created at the station level with zonal variables where applicable. The first and
27 second data sets were developed based on the number of trips originating from or destined to each
28 station on a monthly basis, respectively. The third data set was created using disaggregate trip
29 information as such the number of trips for each origin-destination (OD) station’s pair was
30 determined. Since the number of trips was a non-negative variable (i.e., inherently skewed from
31 the normal distribution), the natural logarithm of the trip counts was used as the dependent
32 variable. Table (1) shows the definitions of variables considered in the analysis. The three multiple
33 log-linear regression models are:

- 34 1. Station-level Generation Model: The natural logarithm of the total number of trips per
35 month originating from each station is the dependent variable.
- 36 2. Station-level Attraction Model: The natural logarithm of the total number of trips per
37 month destined to each station is the dependent variable.
- 38 3. Station-to-Station OD Model: The natural logarithm of the total number of trips between
39 each OD pair is the dependent variable.

40 The three models were estimated using the Ordinary Least Square (OLS) method using the “lm”
41 package in the statistical software “R”.

1 RESULTS

2 Data from 80 stations was used to develop trip generation and attraction models on a monthly basis
3 for a full year. The total number of observations used for the parameter's estimation was 960.
4 Table (2) shows the estimation results of the two models. The reported adjusted R^2 values were
5 0.71 and 0.68 for the trip generation and attraction models respectively. In other words, more than
6 71% and 68% of the variation in trip generation and attraction could be explained by the variables
7 included in the models. This is a relatively high fit considering the small number of trip
8 origins/destinations available for this analysis.

9 Most of the parameters were estimated with the expected signs and were statistically
10 significant at the 95% level of confidence. The results indicated that zones with a higher percentage
11 of males were generating or attracting more trips. This result was consistent with previous research
12 findings that males were more likely to take advantage of the bicycle sharing program than females
13 [8]. Similarly, trip activities were higher in zones that had university campuses as well as transit
14 stations, which indicated that the system users may be using bicycles to both access and egress
15 transit stations [8, 21]. At the station level, stations with a higher number of bicycle docks were
16 more likely to generate or to attract more trips. In general, the values of the parameters' estimates
17 of the two models were close. However, the effect of having more than 30 bike docks at the station
18 on trip generation was about two times its effect on trip attraction. The reason for that is, perhaps,
19 Bike Share Toronto users tended choose stations with a higher number of bicycle docks to increase
20 their chances in finding an available dock to return their bicycles to. Otherwise they would have
21 to travel to a nearby station that had an available dock. The number of stations within a 200 meter
22 buffer area was also significant and was positively correlated with the number of trip attractions.
23 Multiple stations in close proximity provide a Bike Share Toronto user with multiple options to
24 park his or her bicycle while reducing the inconvenience caused by the unavailability of empty
25 docking stations. It is worth mentioning that stations with over 30 bicycle docks were located near
26 high-rise residential towers and in densely populated and high trafficked areas.

27 The models also took weather effects into consideration. Weather data was prepared to
28 enable the average monthly measures to be used for this analysis. The perceived temperature was
29 positively correlated with the number of trip activities. The maximum reported average monthly
30 temperature was 27.5°C during the month of July in Toronto. Such temperature recordings did not
31 pose an eminent risk to outdoor activities such as bicycling. On the other hand, the amounts of
32 snow on the ground, precipitation and humidity levels presented a negative correlation with the
33 total number of bicycle trips taken per month. Users were less likely to bicycle during snowy days
34 or when routes were covered by snow, thus avoiding the risk of accidents and injuries. The amount
35 of precipitation was not significant as it was aggregated on a monthly basis (to be consistent with
36 other analysis measures). This was consistent with the findings of Imani et al. (2014).

37 In order to perform the regression analysis on the number of trips from/to each origin-
38 destination pair, an OD dataset was prepared and data from 6,316 trips were used. Based on the
39 start and end stations, bicycle routes were generated. Bicycle path measures such as distance
40 travelled, number of intersections with major roads, and the percent of bicycle infrastructure of the
41 total bike route were calculated. In addition, zonal attributes of the destination station zone were
42 produced. Table (3) shows the model's results. All the estimated parameters were statistically
43 significant and with the expected correct signs. The reported adjusted R^2 is 0.31.

1 **TABLE 1 Definition of Variables**

Variable		Definition	Unit	Aggregation Level
Socio-demographic	Male	Percent of males	%	Zonal
	Empden	Average employment density	Pers/Km ₂	Zonal
Weather	Temp	Perceived Temperature; adjusted for wind chill and humidex	C°	Monthly
	Snow	Amount of snow on ground	cm	Monthly
	Hum	Relative humidity	%	Monthly
	Precip	Amount of precipitation	mm	Monthly
Built Environment	n_stations	Number of bike share stations in 200m buffer	NA	Station
	University	= 1 if the zone has university campus; = 0 otherwise	Dummy	Zonal
	Transit	Number of subway/commuter rail stations	NA	Zonal
	distance_travelled	Distance travelled between an OD pair	km	Bike Path
	Intersections	Number of intersection with major roads between an OD pair	NA	Bike Path
	bike_infra	Percent of bike infrastructure compared to total bike path; bike infrastructure includes bike lanes, sharrows, park roads, contra-flow bike lanes, trails	%	Bike Path
	Docks	= 1 if the station has more than 30 bike docks; = 0 otherwise	Dummy	Station

2 The results showed a negative correlation between distance travelled and the number of
3 trip activities between each origin-destination pair. Similarly, the increase in the number of
4 intersections between the bike path and major roads had a negative effect on the number of trips.
5 Major intersections inhibit heavy traffic, both automotive and pedestrian, thus bicycle users might
6 attempt to avoid crossing such intersections due to risk of injury or accident, or time delays.

1 Previous research efforts obtained a significant correlation between ridership and bicycle lanes
 2 [16], while other researchers found counterintuitive results with bicycle lanes having a negative
 3 correlation with ridership [19]. However, their analysis focused on quantifying bike lanes in buffer
 4 zones around bicycle share stations. In this paper, we investigated the effect of bicycle
 5 infrastructure found along users' paths from each OD pair. Results showed that the increase of
 6 bicycle infrastructure length compared to the total bicycle path significantly encourages more
 7 bicycle trips. Bicycle infrastructure and the number of intersections can be considered as a safety
 8 proxy for bicycle users.

9 **TABLE 2 Trip Generation and Attraction Models Results**

Variable	Trip Generation Model			Trip Attraction Model		
	Estimate	t-statistics		Estimate	t-statistics	
(Intercept)	6.953336	26.713	*	6.683968	22.96	*
Male	0.009689	5.508	*	0.010661	5.749	*
University	0.195252	5.947	*	0.158966	4.607	*
transit	0.143319	6.329	*	0.126535	5.308	*
Docks (>30)	0.210768	5.077	*	0.120705	2.763	*
temp	0.033687	20.725	*	0.033589	19.648	*
snow	-0.07649	-7.948	*	-0.07913	-7.784	*
hum	-0.02164	-5.762	*	-0.01803	-4.552	*
precip	-0.00867	-0.024		-0.25583	-0.711	
n_stations	0.044623	1.749		0.057974	2.153	*
Adjusted R ²	0.71			0.68		

10 * Significant at the 95% level of confidence.

11

1 **TABLE 3 Station-to-Station Origin-Destination Model Results**

Variable	Estimate	<i>t</i> -statistics	
(Intercept)	1.842000	51.737	*
distance_travelled	-0.000134	-21.372	*
intersections	-0.007579	-11.45	*
bike_infra	0.000652	4.07	*
empden	0.358100	5.531	*
Male	0.007555	11.666	*
university	0.027390	2.284	*
Transit	0.020430	1.963	*
Dock (>30)	0.037500	2.419	*
Adjusted R ²	0.31		

2 * Significant at the 95% level of confidence.

3 At the destination station zonal level, the employment density, male population percentage,
 4 presence of a university campus and transit stations, and the number of available docks had a
 5 positive correlation with the total number of trips, as was expected. A positive correlation with
 6 employment density at the zonal level suggested that users tended to use the system for commuting.
 7 This may be a natural transition in the use of bicycles as bicycle stations are heavily distributed
 8 throughout Toronto’s financial district, which is a heavily populated residential and
 9 commercial/business area. The rationale behind the positive correlation with the number of
 10 docking stations, male population percentage, university campus and transit stations had been
 11 previously indicated in the explanation of the trip attraction and trip generation model results.

12 **CONCLUSIONS AND FUTURE WORK**

13 Previous studies on public bicycle share systems were concerned with identifying the
 14 factors affecting bike share demand at the system terminals. This study builds on the current
 15 understanding of different factors driving bike share ridership. Trip attraction and trip generation
 16 models were developed to study factors affecting public bike share demand at the station level.
 17 The analysis was performed on Toronto’s Bike Share system that operates year round and provided
 18 rich data on seasonal bike demand by investigating detailed weather variables. Nevertheless, this
 19 study goes one step further by analyzing the variables affecting demand along a proxy path of the
 20 bike share user by developing a station pair (origin-destination) regression model. Different factors
 21 were investigated including detailed weather variables, zonal level socio-demographic
 22 characteristics, land use, built environment and levels of service attributes.

1 The trip generation and trip attraction model results revealed that higher temperatures,
2 lower humidity levels, and lower amounts of ground snow were positively correlated with bike
3 ridership. Public bicycle share stations that were located near university campuses and transit
4 stations experienced higher trip activities. In addition, the model's results highlighted the
5 importance of station capacity and station-to-station proximity in providing sufficient bicycles for
6 trip generation and docking spaces for trip attraction.

7 The station pair (OD) regression model was developed based on station to station path level
8 of service attributes along with other zonal level factors. The model's results showed a negative
9 correlation between distance and bicycle ridership. A positive correlation was observed between
10 the increases of bicycle infrastructure along the path and a decrease of number of intersections
11 with major roads. This explained the safety perception of bicycle users. On major intersections
12 and on roads with no marked bicycle paths cyclists would be exposed to higher risks of collisions.
13 Similar to the results obtained from the generation and attraction models, the station pair model
14 showed that public bike users were more attracted to zones of high employment density which
15 potentially indicates that a significant share of users were using the system for commuting.

16 The developed models can be used to predict the total monthly trip rates generated at or attracted
17 to potential station locations. This can help bicycle share systems to examine possible locations of
18 new stations and to choose the one that maximizes the total bicycle ridership. In addition, the
19 station pair model can be used to estimate the distribution of those trips between new and existing
20 stations. The model can also be used to assess potential bicycle infrastructure development based
21 on expected bicycle routes from and to potential station locations.

22 In this study, suggested bike paths based on the hypothesis of utilizing bike infrastructure
23 and following the shortest paths were used to conduct the station pair origin destination analysis.
24 Actual users' paths can be mapped *via* GPS tracking units or through the utilization of mobile
25 applications in order to enhance the developed understanding of public bike share users' preferred
26 routes. In addition, bike share programs are implemented in major cities around the world, thus
27 users interact with heavy traffic and congested roads. Understanding the effect of traffic, both auto
28 and pedestrian, can assist city planners and bike share system operators in making better decisions
29 on station location choices.

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