# Exploring Commute and Non-work Cycling Behavior in the Greater Toronto and Hamilton Area, Canada

By

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## ABSTRACT

Increasingly, urban planners and policy makers in North America are considering active transportation, and cycling in particular, as a solution to congestion and as a healthier alternative to traditional sedentary forms of transportation such as driving. Yet, cycling remains understudied and perhaps the least understood mode of travel. An emerging research has explored the potential influences on cycling uptake. This research contributes to this literature by conducting a regional analysis of cycling behaviour, relating to both commute and non-work trips, in the Greater Toronto and Hamilton Area (GTHA), Canada. A set of negative binomial regressions were estimated using travel data from the 2011 Transportation Tomorrow Survey, which identified several socio-demographic, built environment and trip characteristics correlated with cycling incidence rates. In general, the results indicated that the neighbourhood environment and travel distance had more important influences on commute trips in comparison to non-work trips. Furthermore, the presence of other cyclists had an important influence on the expected incidences of cycling, the causal implications of which, however, could not be confirmed in this study. The model outcomes were mapped next, a process that helped identify local differences in the propensity of cycling across the GTHA region. This study proposes an easy-to-implement analytical framework to enable examination of cycling behaviour and identification of cycle-friendly communities, at a regional scale, and perhaps systematically direct limited resources available to improve cycling rates in targeted localities across a metropolitan region.

## INTRODUCTION

The evidence and support from urban planners, policy makers, and activists in favor of active transportation (e.g., walking and cycling) has been mounting in recent years. The potential benefits range from reducing motorized traffic and congestion and improving air quality to personal health benefits from the accumulated physical activity (*1*, *2*). Yet active transportation and in particular cycling is understudied and perhaps is the least understood mode of travel (3). While cycling has become a major mode of transportation in some western countries like Germany, Denmark, and the Netherlands, the rates remain very low in cities and regions across North America, including major urban areas like the Greater Toronto and Hamilton Area (GTHA) (*4*). In this context, a recent policy emphasis on improving modal share of cycling, and more broadly active transportation, can be seen across North America (*5*).

Given that cycling is of great interest to urban planners, engineers, policy makers and community-based advocacy groups, many researchers have explored the potential influences on the choice of cycling as a means of transportation. Recent studies have indicated the importance of the built environment (6, *7*, *8*, *9*), the socio-demographic characteristics of cyclists (*1*, *10*, *11*), and the trip characteristics (*12*, *13*). However, the direction and significance of these relationships are not fully understood.

In addition, the majority of research into cycling focuses on disaggregated individual-level studies (*12*, *14*) or aggregate studies at the city wide scale (*1*, *9*, *10*, *13*). Very little credence has been given to regionally examining cycling, particularly modelling cycling at a regional scale. Very low rates of cycling in suburban and rural communities, which sometimes constitute the majority of the geographical extent of a large North American metropolitan area, could be partially to blame for limited research on this topic. We know that transportation policies are often developed and implemented by regional authorities, and findings from research that largely focuses on urban, and arguably more cycle-friendly, areas may not be fully representative of cycling behaviour at a regional scale, which include urban, suburban and rural communities. In this context, research analyzing cycling at a regional scale is important, and can be very useful for transportation planners interested in cycling. More specifically, despite being one of the largest urban regions in North America, cycling behaviour in the GTHA remains surprisingly understudied.

In this paper, a regional analysis was conducted to explore cycling behaviour for both commute trips and non-work trips in the GTHA, Canada. In particular, this research identifies the socio-demographic conditions, built environment features, and trip characteristics that are correlated with cycling uptake within a census tract (CT), using data from the 2011 Transportation Tomorrow Survey (TTS). The study highlights the relative impacts of the correlates, to identify the differences between commute trips and non-work trips. The study also utilizes a propensity-analysis approach to map and examine the geographical distribution of the areas that may be more or less amenable to cycling (*15*, *16*). The results from this study offers a comparison between cycling behaviour in the Toronto region and what has been reported in international literature. Furthermore, this study proposes an easy-to-implement analytical framework to enable examination of cycling behaviour at a regional scale and perhaps systematically direct limited resources available to improve cycling rates in targeted localities across a metropolitan region.

## A BRIEF REVIEW OF CURRENT RESEARCH ON CYCLING BEHAVIOUR

While the existing literature on cycling behaviour is relative new and smaller when compared to other alternative transportation options such as driving, transit or walking, an emerging body of research has provided empirical evidence on the correlation between various neighbourhood, socio-demographic, trip characteristics, and the cycling rate and/or the likelihood of cycling. This section provides a very brief summary of this research; more extensive summaries of current research in cycling behaviour can be found elsewhere.

In terms of the built environment, research has identified the significance of cycling facilities such as cycle tracks and bicycle lanes, stating that improving the quality and amount of cycling facilities can be an effective strategy for increasing cycling rates at a population level (*2, 18, 19, 21*). Other researchers have addressed the significance of various neighbourhood environmental characteristics, correlating cycling rates with measures of density and land use. Saelens, Sallis & Frank (*22*), in their review of literature on cycling behaviour, presented evidence suggesting that residents from communities with higher density report higher rates of walking/cycling than low-density neighborhoods. However, other researchers have emphasized that population density does not automatically result in higher cycling rates (*13*), and emphasized the role of land use mix and street design characteristics.

Previous studies have also emphasized the importance of travel distance on the likelihood of cycling. For example, Dill & Carr (*12*) reported that trip distance was the most frequently cited reason for avoiding cycling as a means to commute to work. In a recent study conducted in the GTHA, Mitra and Smith Lea (*4*) identified that 74% of all cycling trips in the region are less than 5 kilometers in length.

Socio-demographic factors such as gender, income, age, home and automobile ownership are of importance as well. Research related to household income has found that higher income individuals are more likely to cycle than lower income individuals (*23, 25*). Car ownership has been reported to negatively correlate with cycling. For example, access to one car per household was reported to have a positive correlation with higher cycling rates (*9, 22, 25*). In contrast, owning more than one car per household may negatively influence cycling rates (*22, 25*). Research has identified family sizes having a potentially negative influence on cycling (*10*).

## STUDY DESIGN

### Study Area

The study area for this research is limited to the City of Toronto, which is the largest municipality in Canada by population, as well as five other upper and lower-tier municipalities surrounding the City, namely: Durham, York, Peel, Halton, and Hamilton. Together, the region is known as the Greater Toronto and Hamilton Area (GTHA). With a population of 6,574,140 (*26*), this is the largest urban region in Canada, and is the subject of a Regional Transportation Plan called The Big Move (*27*). The built environment within the GTHA is diverse. While Toronto and Hamilton have grown over the last two centuries, the urban development in other municipalities have largely taken place during the post World War II period, and is dominated by automobile-oriented land use and street network (*28*). The population living in this region also represents a great diversity with regard to socio-demographic and ethno-cultural characteristics; the GTHA has one of the most multi-cultural population composition in the world.

## Travel Data

Travel data for analysis came from the 2011 version of the Transportation Tomorrow Survey (TTS). The TTS is a repeated cross-sectional household travel survey focusing on urban areas that potentially constitute the commuter-shade for Toronto, an area that is much bigger than the GTHA. The survey is conducted once every five-years; 2011 is the latest version of the survey (*29*). For the 2011 TTS, data was collected from a 5% random sample of all households within the study area, using a computer-aided telephone interview (CATI) method. An adult household member proxy-reported all household trips for the day prior to the survey date (Fall of 2011 or 2011). The survey included a total of 160,000 completed interviews. The available data is aggregated at the level of 1,328 CTs within the region, and was expanded to be representative of GTHA's population.

Cycling counts per CT, more specifically, the number of trips within a CT where the primary mode of transportation was cycling, was explored as the travel outcome for this research. Both commute and non-work trips were analyzed in order to examine the difference in the correlates of cycling uptake between these two trip types within the GTHA. A commute trip was defined as a trip where the destination of the trip was work, subsequent-work, school, or subsequent school. Likewise, a non-work trip was defined as a trip where the destination of the trip as market/shop or "other" (i.e., does not include work or school trips). Additionally, the analysis was restricted only to people aged between 15 and 64 years. Conceivably, travel needs, preferences and choice processes relating to a cycling trip by a child or an older adult might be different from that of a working-age adult (*2*, *30*). While an examination of travel behaviour among those, often more vulnerable, population group is critically important for urban planning and transportation policy, such exploration was beyond the scope of this study.

TTS does not collect data on travel distance, and instead, reports the straight-line distance between origin and destination of a trip as a proxy measure. For the purpose of this study, we included the proportion of trips originated from a CT that were >5 km in length was used as a proxy measure for trip distance (Table 1). Nearly three-quarter (74%) of all cycling trips in the GTHA were less than 5 km in length, compared to only 46% of all trip which were of that length in 2011 (*4*). Consequently, within the context of this study, we hypothesized that a CT with a higher proportion of shorter trips ≤5km would also demonstrate fewer cycling trips, similar to what has been reported previously (*13*).

## Socio-Demographic and Built Environment Data

Socio-demographic variables came from the 2011 TTS, 2011 Canadian Census, and the 2011 National Household Survey (NHS). Variables include age, marital status, education, family/ household characteristics, labor characteristics, occupied private dwelling characteristics and household income characteristics (Table 1). For the purposes of this study, variables that are potentially related to personal/ rider perceptions of cycling were not considered because they are difficult to measure at an aggregate scale.

The built environment variables came as a result of GIS processes using data from DMTI Spatial©'s road infrastructure datasets and Enhanced Points Of Interests (EPOI) dataset, current to the year 2013. The variables consisted of several density measures (population, business, employment, and road blocks), station access, road speeds and predominant building age (used here as a proxy measure for neighbourhood maturity) (Table 1).

The latest open data for the regional municipal cycling facilities across the study area was used to measure the proportion of streets within a CT with a dedicated cycling facility. Only on-street cycle tracks and bicycle lanes were considered for the analysis (Table 1). A more flexible definition of cycling facility (which would include shared road spaces, sharrows and recreational trails in addition to dedicated facilities mentioned above) was initially considered but was excluded from final analysis because of the lack of statistical significant data. The currency of the cycling infrastructure data, however, could not be confirmed.

**TABLE 1: Variable Descriptions and Summary Statistics (n = 1,321).**

| Variable | Definition |
|---|---|
| *TripCharacteristics* | |
| Cycling trips (commute) | Number of cycling trips for commute (work or school) purposes, originating from a census tract (CT) |
| Mode share of cycling (commute) | Percent of all commute trips in a CT taken using a bicycle |
| Cycling trips to non-work destinations | Number of cycling trips for non-work purposes (ie., to market/ shop or other), originating from a CT. |
| Mode share of cycling (non-work) | Percent of all non-work trips in a CT taken using a bicycle |
| Commute trips > 5 km | Proportion of all work or school trips, starting from a CT, that are > 5km (straight line distance) |
| Non-work trips > 5 km | Proportion of all non-work trips (market/shop or other), starting from a CT, that are > 5km (straight line distance) |
| *Socio-demographic Characteristics* | |
| Household >4 | Percent of families in CT with 4 or more members |
| ≤1 cars in household | Percent of households in CT with one or less cars |
| Median income | The median household income of the CT |
| Single Parent Families* | Percent of households in CT that are single parent families |
| Education* | Predominant level of education in CT. 0 if post-secondary or higher; 1 if high school; 2 if no high school. |
| Sex* | Percent of population identified as Female |
| Age* | Percent of the CTs population that is ≤ 40 years of age |
| *Neighbourhood Characteristics* | |
| Population density | Number of people (,000) per square km in a CT |
| Population change | Population change in CT between 2006 and 2011 |
| Neighborhood age | Predominant age of the buildings in a CT. 0 if built after 2000; 1 if built between 1960 and 2000; 2 if built before 1960. |
| Household Rooms* | Number of rooms in a Household – which also includes bedrooms |
| Blocks density | Number of road blocks per sq km of area within CT |
| Employment <5km | All employment opportunities within 5 km from the centre of a CT |
| commercial density | Number of commercial addresses per sq km in a CT not including office addresses |
| Transit access* | A CT with a subway or regional rail station within 2 km. 0 if false; 1 if true. |
| Major roads | Operating Speed of the majority (>50%) streets in a CT. 0 if ≤40 km.hr; 1 if >40 km/ hr. |
| Cycling facility | Percent of all roads in a CT with dedicated cycling facilities, including on street bike lanes and cycle tracks |
| Other people cycling | Number of cyclists aged 15-64 years within 5 km from the centre of a CT |

*Variables excluded from the final multivariate analysis due to lack of statistical significance at α= 0.1

Finally, recent research has emphasized that cycling behaviour is "local" and may be influenced by the presence of a strong bicycling culture in local communities (*8*, *13*). To account for this potential influence, we included a spatial auto-correlation term in our multivariate analysis. In its simplest form, an auto-correlation can be expressed by the number of other people who are cycling nearby a CT. This approach is widely used in the field of environmental ecology (*31*), and was adopted here as a proxy to represent localized cycling culture (Table 1).

After accounting for missing data and extreme outlier, data relating to 1,321 CTs were included in multi-variate statistical analysis.

**Statistical Analysis and Mapping**

Preliminary analysis of the TTS data relating to CT-level cycling counts across the GTHA indicated that they were unevenly dispersed and not normal. Additionally, there are an abundance of CTs with zero recorded cycling trips (61% of CTs had zero reported commute trips, and 72% of CTs had zero reported non-work trips, on bicycles). As a result, a set of negative binomial regression models were estimated. These models are similar in nature to a Poisson regression, and are generally used to explore count data. A negative binomial regression (instead of a Poisson regression) was appropriate in this context, as these models are better suited to analyze overly dispersed data, which was the case in this study (Table 1) (*32*,*33*). Furthermore, the total number of trips were not uniform across all CT (i.e., the potential opportunities for a cycling trips or the "exposure" was different across CTs). As a result, an offset variable was introduced in the model. This offset variable represents the log of exposure, with coefficient constrained to be 1.

The coefficient ($\beta_{x1}$) of a negative binomial model represents the correlation between a variable $x_1$ and the log of expected change in cycling count, controlling for the total number of trips in a CT. In this paper, the results are also reported in terms of $e^{\beta_{x1}}$ or the "Incident rate ratio (IRR)", which represents the expected change in cycling count, per trip originated within a CT, in response to a one-unit change in variable $x_1$.

A propensity map was then created to explore the geographical distribution of the model results (i.e., the influences on cycling incidence rates), informed by Mitra & Buliung (*15*) and Yoon et al. (*16*). The values of each statistically significant correlate were first standardized into Z-scores (binomial variables were re-scaled to -3 (reference) and +3 (response)). The standardized values were then multiplied by their corresponding IRR, producing the propensity of high versus low cycling rates, relating to each statistically significant independent variable included in the model, by CTs across the GTHA. Additive propensities (grouped into socio-demographic and built environment variables) were mapped at the CT level to identify cycling-friendly versus un-friendly communities.

## RESULTS AND DISCUSSION

Cycling behaviour relating to both commute and non-work trips, for 1,321 CTs in the GTHA, was explored using the 2011 TTS data. The preliminary descriptive statistics presented in Table to illustrate the problem identified in the study design- both cycled commute trips and cycled non-work trips have comparatively low counts to total trips of all modes. Additionally, Table 2 indicates that the majority of trips in the GTHA are >5 km, however, 38% of all commute trips are ≤5 km, and thus potentially cyclable. Alternatively, the proportion of non-work trips that are ≤5 km is much higher (70%), indicating, at least theoretically, a higher potential for cycling for non-work trips if evaluated solely based on travel distance.

The majority of households in the GTHA have access to ≤1 privately owned automobile (53%) leaving 47% of all households owning two or more cars. In addition, 33% of all households are families with four or more members, which represents a socio-demographic group that is negatively correlated with cycling rates (*10*). The median household income for the region is relatively high at > $75,000. Of all GTHA residents aged 15-64 years, 51% are ≤40 years of age (Table 2).

In terms of the built environment, it is worth noting that only 2% of all road space within the GTHA has dedicated on-street cycling facilities, which include either a cycle track or a painted bicycle lane (Table 2).

**TABLE 2: Descriptive Statistics**

| **Variable** | **Mean (Std. Dev)** | **%** |
|---|---|---|
| *Trip Characteristics* | | |
| Cycling trips (commute) | 27(66) | |
| Mode share of cycling (commute) | | 1 |
| Cycling trips to non-work destinations | 19(61) | |
| Mode share of cycling (non-work) | | 1 |
| Commute trips > 5 km | | 62 |
| Non-work trips > 5 km | | 30 |
| *Socio-demographic Characteristics* | | |
| Household >4 | | 33 |
| ≤1 cars in household | | 53 |
| Median income | $75,863($26,868) | |
| Single Parent Families* | | 18 |
| Education* | | a |
| Post-secondary or higher | | 57 |
| High school | | 26 |
| No high school | | 17 |
| Sex* | | |
| Female | | 48 |
| Male | | 52 |
| Age* | | |
| ≤40 years | | 47 |
| >40 yeas | | 53 |
| *Neighbourhood Characteristics* | | |
| Population density | 4.8(5.2) | |
| Population change | 104(1931) | |
| Neighborhood age | | |
| Mostly built after 2000 | | 12 |
| Mostly built between 1960 and 2000 | | 58 |
| Mostly built before 1960 | | 30 |
| Household Rooms* | 6(1.3) | |
| Blocks density | 22(14.7) | |
| Employment 5km | 1029(680) | |
| commercial density | 166(527) | |
| Transit access* | | |
| Major transit <2 km | | 48 |
| Major transit >2 km | | 52 |
| Major roads | | |
| Majority of roads ≤40 km/ hr | | 11 |
| Majority of roads >40 km/ hr | | 89 |
| Cycling facility | | |
| Cycle tracks or bicycle lanes | | 2 |
| No cycling facility | | 98 |
| Other people cycling | 63(151) | |

*Variables excluded from the final multivariate analysis due to lack of statistical significance at $\alpha$= 0.1

The results from the negative binomial regression is summarized in Table 3. The omnibus chi-square tests for both the Commute and Non-work models returned significant results at $p<0.001$. Variables such as age, sex, single parent families, education, nearest station, and number of rooms in a household were excluded from the final multivariate analysis due to lack of statistical significance at $\alpha= 0.1$ during preliminary analysis.

## Correlates of Cycling Incidence

In our multi-variate analysis, travel distance was analyzed as percent of trips in a CT that were over 5 kilometers. The results confirmed findings from existing literature and suggested a strong negative correlation between travel distance and cycling rate, for both commute and non-work trips. More specifically, we found that for every 1% increase in the work trips greater than 5 km, the incidence rate ratio or IRR (i.e., the number of expected cycling trips, per trip within the census tract) would decline by a factor of 0.12 units (Table 3). A similar effect was also observed for non-work trips, although travel distance appear to have an effect of smaller magnitude (IRR= 0.42) on the rate of non-work cycling trips.

**TABLE 3: Negative Binomial Regression of Cycling (n = 1,321)**

| | Cycling for Commute Trips | | | | Cycling Rate for Non-work Trips | | | |
|---|---|---|---|---|---|---|---|---|
| Variable Name | Coef. | S. E. | *IRR* | *p* | Coef. | S. E. | *IRR* | *p* |
| *Trip Characteristics* | | | | | | | | |
| Work trips > 5 km | -1.86 | 0.33 | 0.12 | 0.001 | - | - | - | - |
| Non-work trips > 5 km | - | - | -- | - | 0.87 | 0.42 | 0.42 | 0.039 |
| *Socio-demographic Characteristics* | | | | | | | | |
| Household >4 | -1.87 | 0.47 | 0.12 | <0.001 | -3.29 | 0.47 | 0.04 | <0.001 |
| ≤1 cars in household | 1.8 | 0.28 | 6.01 | <0.001 | 1.14 | 0.26 | 3.1 | <0.001 |
| Median income | 0.02 | <0.01 | 1.02 | <0.001 | .005 | <0.01 | 1.01 | <0.001 |
| *Neighbourhood Characteristics* | | | | | | | | |
| Population density | 0.03 | 0.01 | 1.03 | 0.004 | 0.018 | <0.01 | 1.02 | 0.026 |
| Population change | <0.01 | <0.01 | 0.99 | 0.021 | - | - | - | - |
| Neighbourhood age (< 1960) | 1.21 | 0.13 | 3.3 | <0.001 | 1.09 | 0.12 | 3 | <0.001 |
| Neighbourhood age (1960 – 2000) | 0.50 | 0.12 | 1.6 | <0.001 | 0.24 | 0.10 | 1.3 | <0.000 |
| Blocks density | 0.01 | <0.01 | 1.01 | 0.001 | - | - | - | - |
| Employment <5km | <0.01 | <0.01 | 1.01 | <0.001 | - | - | - | - |
| commercial density | - | - | - | - | <0.001 | <0.01 | 1.01 | <0.001 |
| Major roads | -0.25 | 0.11 | 0.78 | 0.019 | - | - | - | - |
| Cycling facility | 2.83 | 0.84 | 16.99 | 0.001 | - | - | - | - |
| Other people cycling | <0.01 | <0.01 | 1.01 | <0.001 | 0.004 | <0.01 | 1.01 | <0.001 |
| (Intercept) | -6.26 | 0.42 | <0.01 | 0.004 | -5.89 | 0.27 | <0.001 | 0.005 |
| Goodness of Fit | | | | | | | | |
| Chi-sq (df) | 1864.97 (13) | | | | 1802.31(9) | | | |
| *P* | <0.000 | | | | <0.000 | | | |
| AIC | 8433.55 | | | | 8187.26 | | | |

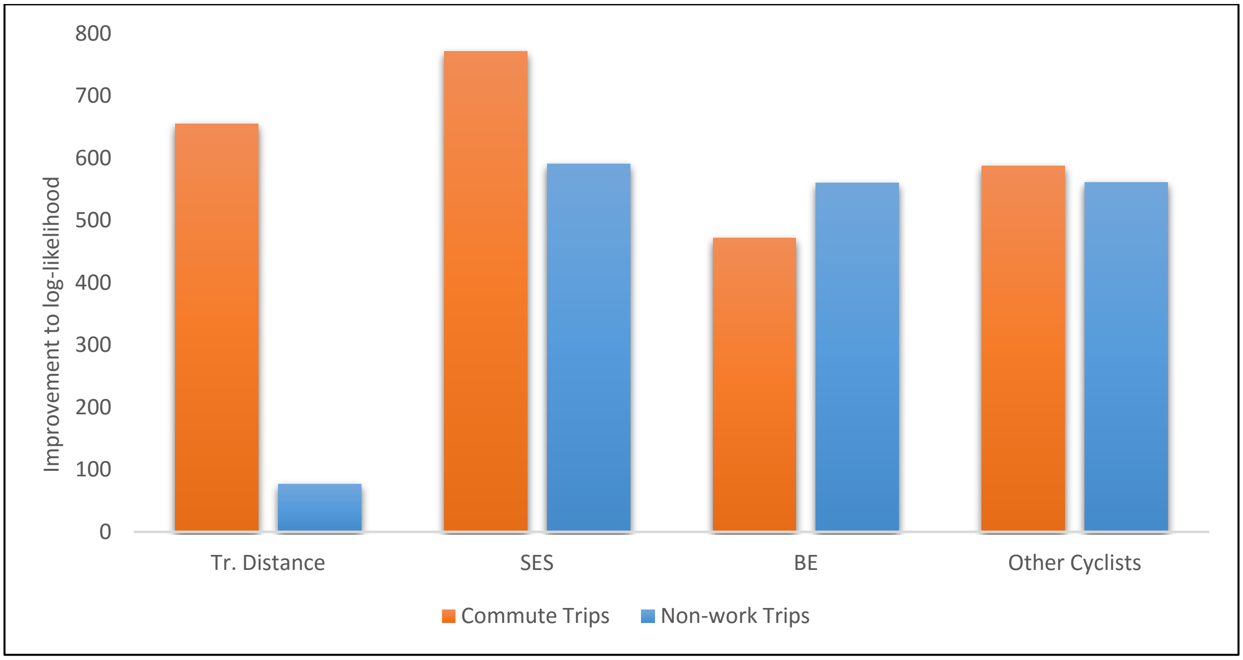
Three variables relating to the socio-demographics in the GTHA were included in the multivariate analysis, and they all produced results that support current literature. Similar to what has been reported in previous research (e.g., *10*), family size was negatively associated with cycling; a one percent increase in households with >4 members in a CT was correlated with 0.12 times decline in the cycling IRR for commute trips, and 0.04 times decline for non-work trips. Access to private automobiles was correlated with cycling, again supporting previous research that indicated statistical association between high car ownership and low cycling rates (e.g., *22, 25*). In the context in the GTHA, the median household income of a CT was positively correlated with cycling, indicating that incidences of cycling would be higher in higher income neighbourhoods (Table 3). When compared between commute and non-work trips, it appears that the effect of household size was stronger (i.e., greater difference in IRR) for non-work trips, while car ownership had a potentially stronger influence on commute trips by bicycle. The IRRs relating to neighbourhood-level household income were similar across the two trip types.

With regard to the built environment characteristics, the model results indicated a strong association between the presence of cycling facilities and expected incidences of cycling trips for commuting purpose (Table 3). A one percent increase in streets with cycling facilities was correlated with 16.99 times increase in the IRR for commute trips. Unfortunately, the amount of dedicated facilities was not a significant correlate in the non-work trip model, and as a result was excluded from our final analysis. The presence of other people cycling nearby would also influence a nearby CT cycling incidence rate, for both trip types.

Among the other neighbourhood characteristics, population density was associated with cycling for both commute and non-work trips, and the IRRs were similar across the two trip types. Neighbourhood age was also associated with both types of trips. In the context of the GTHA older neighbourhoods would have higher incidence of cycling, compared to neighbourhoods that were developed after 2000 (Table 3). Some differences in the correlates of cycling, across commute and non-work trips, was also evident. For example, a range of built environment characteristics, including population change in the neighbourhood, density of residential blocks and concentration of employments within 5 km of a CT were positively associated with cycling incidence rate, while CTs where the majority of roads had an operating speed of >40 km would produce lower IRR, when compared to a CT where the predominant vehicle operating spend is ≤40 km (Table 3). None of these variables were significant predictors of cycling for non-work trips. On the contrary, density of commercial uses within a CT was positively correlated with non-work cycling trips; the variable did not influence IRR for cycling trips to work or school. Findings from this paper, then, generally confirms  previous research has reported the potential influence of population density and mixed land use on cycling (*11, 22*), while at the same time, emphasizes that the correlates of cycling can be different across trip purpose.

Figure 1 further explores the relative influences of various dependent variables on commute versus non-work trips. The figure shows improvement to the log-likelihood relating to broad groups of independent variables. In general, the socio-demographic characteristics and neighbourhood built environment potentially had the largest influences in explaining cycling incidence rates, while the impact of travel distance was relatively moderate. However, when compared between variables, it appears that the built environment has the largest influence among all types of variables used in our model, in explaining cycling for commute purposes. In contrast, for non-work trips, the impact of socio-demographic variables were the highest (Figure 1). Trip distance (i.e., % commute trips >5 km) was also an important indicator of cycling for commute purposes in a CT. In contrast, the impact of travel distance (i.e., % non-work trips >5 km) had only a trivial effect on model fit in our non-work cycling model.

**FIG 1: Relative Impact of Variables on Commute and Non-work Cycling**



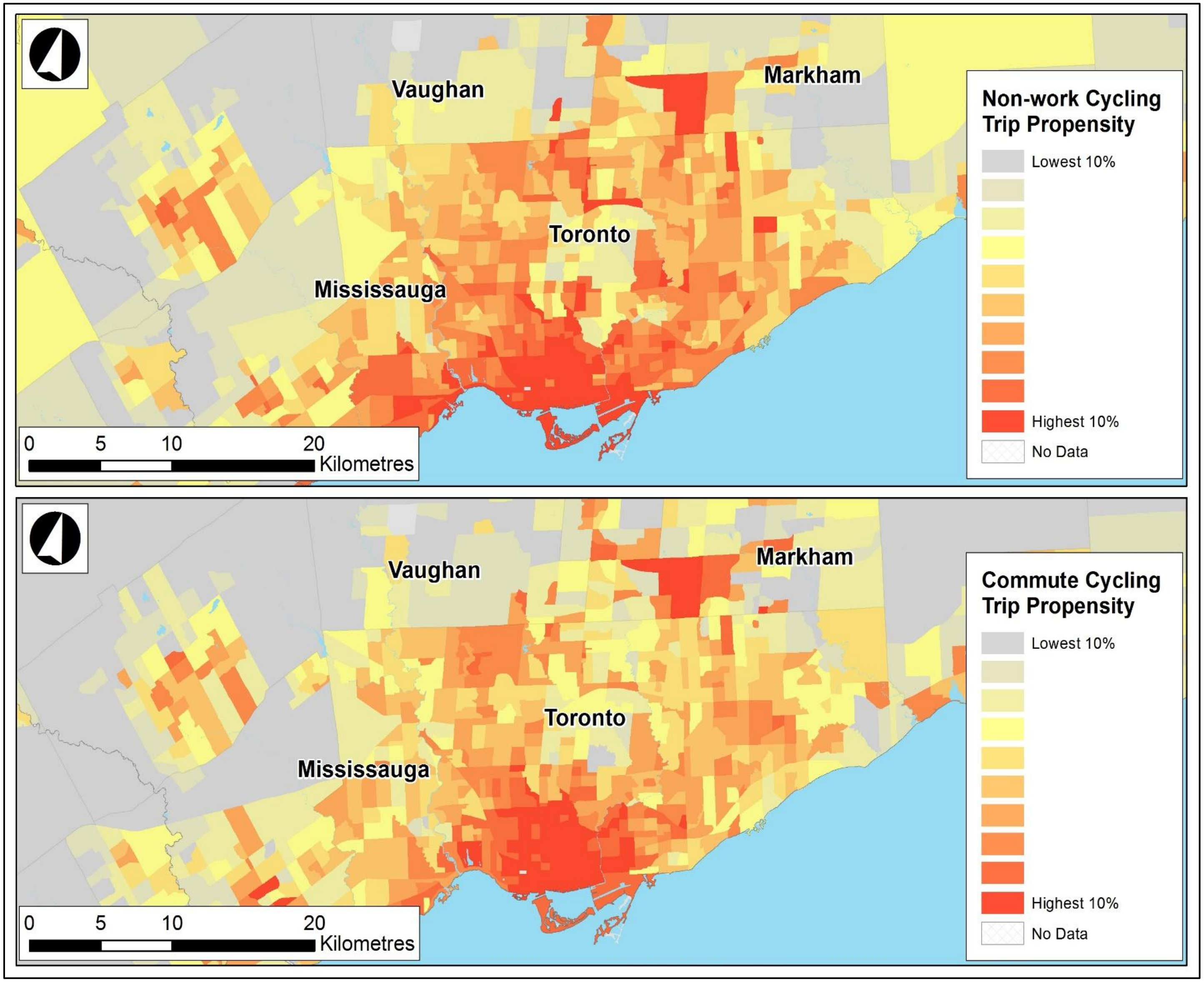

NOTE: SES = Socio-demographic characteristics; BE= Neighbourhood built environment characteristics; Tr Distance = Travel Distance; Other Cyclists = Number of other cyclists in nearby census tracts.

In summary, it appears that cycling trip rates for commute purposes (i.e., to work or school) is influenced more by modifiable factors such as the neighbourhood environment and/or access to opportunities leading to a reduction in travel time, a finding that is encouraging for policy and planning practice around cycling. On the other hand, cycling for non-work purposes is influenced more by socio-demographic characteristics, and may warrant a different policy perspective focusing largely on education and encouragement. Interestingly, the prevalence of nearby cyclists had a comparably large impact on cycling incidence rates for both commute and non-work trips. While this result may be indicative of the influence of localized cycling culture or advocacy (*8, 13*), such findings could also suggest that there are more unexplained correlates that impact cycling counts. Further exploration of this topic, however, was beyond the scope of this study.

## Cycling Propensity across Space

The propensities of cycling for commute and non-work purposes, estimated based on the model results, are mapped in Figure 2. When examining Figure 2, we can identify clustering of CTs with very high propensity (i.e., the highest 10%) in the downtown core of Toronto. Alternatively, we can see low propensities in suburban communities around Toronto, including Mississauga, Markham and Vaughan. The differences between the neighbouring municipalities can be attributed to the differences in the built environment and socio-demographic characteristics between the CTs. In this case, Mississauga, Markham and Vaughan, despite having high populations, have a very different built environment in comparison to the tight, urban form found in the downtown of Toronto. Distinctions can even be made within the City of Toronto, where the downtown core has high propensities and the neighbourhoods to the East along the lake have lower propensities.

1 **FIG 2: Commute vs Non-work Cycling Trip Propensity Comparison**




2

The propensity map for non-work cycling trips echoes the spatial distribution of commute cycling trip propensity, with some differences. For example, the Southern CTs of Mississauga have higher propensities for non-work cycling trips compared to commuting cycling trips. Additionally, in the Northern CTs in Toronto also have higher propensities for non-work cycling trips compared to commuting cycling trips.

In summary, this methodical approach enabled a more policy-relevant exploration of cycling behaviour, across the regional landscape. Comparing neighbourhood-level cycling propensity within municipalities and regions can reveal significant clustering of favourable and un-favourable conditions for cycling, and as a result can inform policy that may systematically target these areas with programs or capital investments. Additionally, our results indicate that areas that are amenable to cycling for commute trips may not necessarily demonstrate high propensity of cycling for non-work trips. This distinction between commute and non-work trips with regard to the geographical distribution of cycling potential is critically important, and may enable planners to undertake targeted programs focusing on specific trip types

Many different approaches, both qualitative and quantitative methods, cross-sectional and longitudinal, case studies as well as statistical analyses, have been used in previous research to improve our understanding of cycling behaviour. One of the key goals of this body of research is to generate evidence that can inform public policy (*34*). This research, and in particular the methods employed to model and map regional-level travel behaviour data can be an important part of the decision making tool for regional transportation agencies, such as Metrolinx in the GTHA (www.metrolinx.com). The findings can assist agencies such as Metrolinx in understanding key topical areas where current and future planning and programming can focus on, but more importantly help identify municipalities and/ or specific hot spots that are more or less amenable to cycling so that targeted programming can be designed to improve cycling, with a larger goal of improving cycling rate at the regional level. The Regional Transportation Plan for the GTHA (i.e., The Big Move) sets out a target active transportation mode share of 20% by 2035 (*27*). In the context of a current mode share of 6% (5% walking and 1% cycling) (*4*), clearly a lot remains to be done in order to meet these planning and policy goals. Findings from this study may inform a strategic investment of limited resources.

## CONCLUSION

In the context of a limited literature that has focused on exploring cycling behaviour at a regional scale, this study examined the correlates of incidences of cycling for the GTHA, which is one of the largest metropolitan regions in North America, and the largest in Canada. Differences in cycling behaviour for commute and non-work trips were also emphasized through this research. A set of negative binomial regressions identified several sociodemographic, built environment and trip characteristics correlated with cycling rates in the GTHA. In terms of socio-demographics, our findings have echoed similar findings in previous studies, further reinforcing the importance of understanding and addressing traveler characteristics. Moreover, this study concluded that neighbuorhood built form potentially has an important influence on cycling rates for commuting purposes. In general, the results indicated that the neighbourhood environment and travel distance (which directly relates to access to work/school) had a more important influence on commute trips, in contrast, their potential influence on non-work trips were relatively moderate. Furthermore, the presence of other cyclists had an important influence on the expected incidences of cycling, the causal implications of which, could not be confirmed in this study.

Several methodical limitations of this study, however, may influence the generalizability of the results reported here. Due to some limitations in data collection method, the TTS may underreport cycling trips. In other words, the true rates of cycling in CTs across the GTHA might be higher than what the data indicated. Furthermore, the analysis focused on travel data aggregated at the CT level, in the absence of data on individual travelers across the region. The results from our analysis, then, while they provide insights into the rates of cycling in small geographic areas (i.e, CTs, which typically consists of between 2500 and 8000 people), do not directly explain how individual travellers may behave in the GTHA. However, the scale of analysis adopted here is more relevant for policy, and it enabled further exploration of cycling propensity across space with a large metropolitan region.

Despite being one of the most populous urban region in North America, cycling behaviour in the GTHA remains less known. In this context, our research makes an important contribution by providing a case study and comparison to existing international research on cycling behaviour. It also offers an easy-to-implement analytical framework for exploring cycling behaviour and potential for cycling growth at a regional scale. Our findings related to commute trips and non-work trips can influence future policy and strategic investments in the GTHA region, which may include the construction of new cycling facilities in some municipalities to improve cycling for commuting purposes, or undertaking targeted educational programmings to improve cycling for non-work destinations. If our regions and municipalities are serious about cycling as a healthier and environmentally sustainable transportation alternative, then it is critical that policy and programs are directed to specific population groups and specific locations where they can be most successful. It is our hope that the methods applied in this research as well as the findings would inform the development of such policy.

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