

1 **The missing middle: Filling the gap between walkability and observed walking behavior**

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**ABSTRACT**

Many fields of study recognize the interdependent health, environmental and economic benefits of walking. To promote walking in entire populations, measures such as Walk Score® have been developed to classify the walking-friendliness or ‘walkability’ of places. Yet, high walkability is not always equated with increased walking. We investigate this discrepancy using survey data on pedestrian behavior, a variety of GIS-derived land use and built environment measures of Montreal neighborhoods, and socio-economic characteristics obtained from the 2011 National Household Survey. A descriptive analysis of walking behavior and neighborhood characteristics reveals that some neighborhoods with higher walking rates are characterized by a lower presence of parking lots/setbacks and a greater proportion of on-street tree canopy. Linear regressions predicting walking rates confirm these associations after adjusting for Walk Score® and neighborhood socio-economic characteristics. These findings suggest that more work is needed for nuancing walkability measures, and offers particular insight for health professionals, planners, and engineers looking to promote walking as an alternative and healthier mode of transport. Reducing open space such as parking lots and setbacks and increasing street-level tree canopy are two ways that the urban built environment can be modified to support walking especially in areas with high Walk Score® and low walking rates.

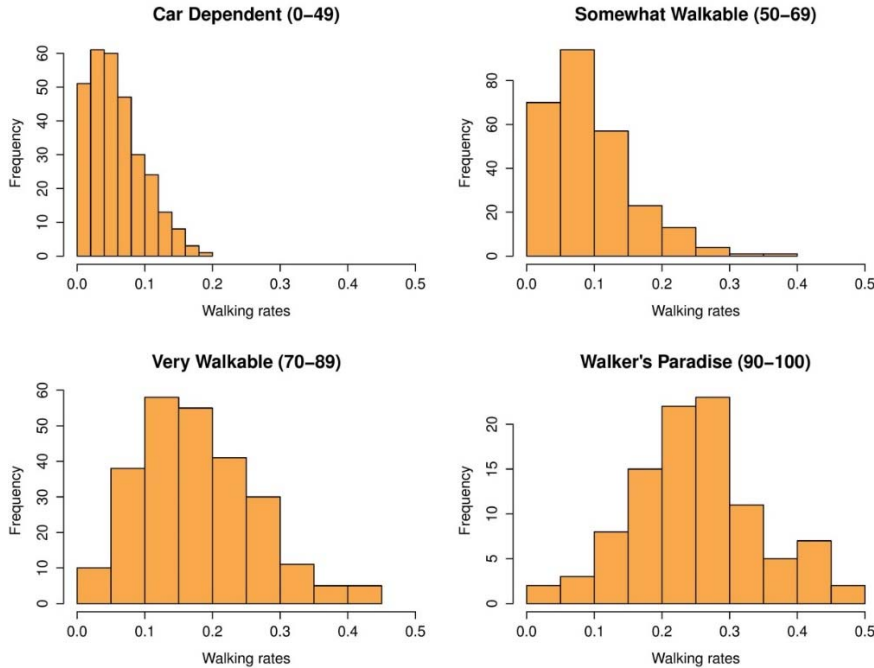
*Keywords:* walkability, walkability measures, Walk Score, land use, parking lots, setbacks, tree canopy

## 1 INTRODUCTION

2           Increasing awareness of the environmental, health and economic benefits of walking has  
3 generated interest across disciplines in identifying built environment factors that facilitate  
4 walking. These factors are often referred to collectively as ‘walkability’, and include elements  
5 related to amenity density (e.g., number of shops or jobs in an area), land use, and street  
6 connectivity. Due to the number of factors considered when attempting to quantify walkability,  
7 many researchers have begun developing indices to capture these elements in a single measure  
8 (1). Most existing walkability indices consider mixed land use, accessibility (i.e.: number of  
9 destinations reachable on foot), street connectivity, and presence of pedestrian infrastructure as  
10 indicators of higher walkability (2). One such index is Walk Score® (www.walkscore.com), a  
11 proprietary web-based algorithm that assigns a score from 0 (low walkability) to 100 (high  
12 walkability) for any address. Walk Score measures street connectivity, population density, and  
13 block length, as well as proximity to thirteen types of amenities (e.g., grocery stores, restaurants,  
14 bars, schools, parks, etc.). A distance decay function assigns weights to these amenities, in which  
15 destinations within 0.25 miles (0.40 kilometers) are assigned full weight, and less weight is given  
16 to more distant amenities up to 1.5 miles (2.4 kilometers) (3-5). Walk Score data is easily  
17 accessible and thus widely used among researchers (6; 7). Although Walk Score makes much of  
18 its data available for free on its website, the exact parameters of its index are not public given the  
19 proprietary nature of some of Walk Score’s services.

20           While Walk Score provides an accessible and mostly free resource for researchers to use,  
21 it might not fully capture every element of walkability. In Montreal, we find many areas with  
22 similar Walk Scores that vary substantially in terms of walking rates. Figure 1 shows the  
23 distribution of census tracts’ walking rates calculated from survey data, within the same range of  
24 Walk Scores using data from Montreal, Canada. The distributions reveal that while Walk Score  
25 is generally associated positively with walking rates, there is still a high degree of variation in  
26 recorded pedestrian activity between census tracts within the Walk Score categories. Given  
27 increasing interest from researchers and policy makers in walkability and walkability indices,  
28 and the discrepancies found between Walk Score and walking rates, the aim of this paper is to  
29 identify land use characteristics that are associated with higher rates of walking at the  
30 neighborhood-level. We focus on identifying walkability factors not included in the Walk Score  
31 that might explain the discrepancy between walking rates and Walk Scores. Our hypotheses are  
32 that: (1) parking lots/setbacks will be associated with lower walking rates, while on-street tree  
33 canopy cover will be associated with higher walking rates; and (2) Walk Score does not fully  
34 account for these neighborhood characteristics. To achieve our research objective, we identify  
35 census tracts with a Walk Score and walking rate divergence using a cluster analysis, and then  
36 assess the discrepancies in parking lots/setbacks and tree canopies coverage. We then estimate  
37 linear regression models predicting walking rates as a function of Walk Score, parking  
38 lots/setbacks, on-street tree canopy cover and control variables. As this study focuses on the  
39 influence of the built environment on walking, we choose to perform a neighborhood-level  
40 analysis as opposed to an individual-level analysis. Accordingly, the findings of this study may  
41 be used to improve neighborhood walkability metrics and suggest built environment  
42 improvements for increasing walking rate for entire populations.

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1

2 **FIGURE 1 Distribution of Walking Rates by Walk Score Interval in Montreal**

3

4 **LITERATURE REVIEW AND RESEARCH CONTEXT**

5 Walking is recognized across several disciplines for its interdependent health,  
 6 environmental, social, and economic benefits. Starting in the 1990s, health officials in the United  
 7 States began recommending walking as a form of exercise to combat the onset of chronic illness  
 8 related to physical inactivity (8-10). While personal characteristics such as age and motivation  
 9 affect walking frequency and intensity (11), research indicates that certain elements of the built  
 10 environment influence walking behavior and improve physical health (12). In light of these  
 11 findings, urban planners now advocate for more compact and less auto-dependent development  
 12 patterns that facilitate walking (13). Planners cite these ‘walkable’ compact environments as  
 13 beneficial not only for health, but also for more cost-efficient allocation of transportation  
 14 infrastructure investments, and lower ecological footprints (14; 15).

15 Walk Score is easily accessible and its use in research is now widespread. In health  
 16 research, for instance, Walk Score has been used to analyze association between obesity (BMI)  
 17 and neighborhood built environment (16; 17) and to measure walking rates and physical activity  
 18 levels in socially disadvantaged populations (18). In the field of urban planning, research using  
 19 Walk Score has been used for policy goals, such as integrating higher density land uses near  
 20 transit (19) and simulating travel behavior and carbon footprint impacts of proposed  
 21 developments (20). While Walk Score has been validated as a general measure of neighborhood  
 22 walkability (6; 21), other research has found gaps in its predictability of walking rates.  
 23 Koschinsky et al. (22) find that the association between Walk Score and walking is less strong in  
 24 low-income than high-income neighborhoods (22). Weinberger and Sweet (23) validate Walk  
 25 Score as a predictor of walking, but they point out that sensitivity between the Walk Score and

1 walking rates differs by trip type. Accordingly these discrepancies deserves attention and  
2 requires further investigation in research.

3

#### 4 **DATA AND METHODOLOGY**

##### 5 **Data**

6 We examined the relationship between features of the built environment and walking rates for  
7 466 of 477 census tracts (11 census tracts lacked data) in the City of Montreal. Three types of  
8 variables were collected in addition to the Walk Score data: (1) measures of walking behavior,  
9 (2) neighborhood characteristics, and (3) neighborhood socio-economic characteristics. A  
10 summarized description of these variables is provided in Table 1.

##### 11 *Walking rates and Walk Score*

12 Walking rates were measured as the ‘pedestrian modal share’. These rates are determined  
13 from the 2013 Montreal Origin-Destination (O-D) Survey (Table 1). The O-D survey is a phone-  
14 based survey conducted once every five years during the fall by the *Agence métropolitaine de*  
15 *transport* (AMT) (24). Respondents provide demographic information about their household,  
16 characteristics of individual persons taking trips, and disaggregate characteristics of each trip  
17 taken by individuals during the previous day. Trip information, including trip mode, purpose,  
18 origin and destination, is collected for 5% of households in the metropolitan area and our  
19 analyses are based on home-based trips for 51,547 adults (age 18-65) (25). For this analysis, any  
20 trip where both the origin and destination was reached by walking was considered a pedestrian  
21 trip. The walking rate, therefore, reflects the percentage of all trips that were pedestrian trips. A  
22 walk-to-work rate was also calculated by finding the percentage of all trips made for commuting  
23 to work that were pedestrian trips. The shortest path walking distance for all pedestrian trips was  
24 calculated in a GIS using a pedestrian street network (i.e., one with highways removed by on-  
25 street paths included). Using expansion factors provided by the AMT, the data is aggregated to  
26 the census tract level to calculate the walking rates. While many studies examine walkability by  
27 using trip origin or destination coordinates (4; 26), other studies have used Walk Score at a  
28 similar neighborhood-level of analysis (22; 27).

29 The Walk Score is a continuous variable between 0 (lowest possible walkability) and 100  
30 (highest possible walkability). Walk Scores were downloaded at the postal code level. In Canada,  
31 postal codes are smaller than census tracts: approximately the size of one side of a city block.  
32 The 39,648 Walk Scores for each postal code were aggregated to the 466 census tracts by  
33 determining the centroid of each postal code and averaging Walk Score values for postal code  
34 centroids within each census tract. The average number of points aggregated to the census tract  
35 level was 78. The average standard deviation for Walk Score points within census tracts was  
36 4.90.

##### 37 *Land use measures: Parking lots/setbacks and tree canopy*

38 Parking lots and setbacks were determined using Clutter Data from DMTI Spatial (28).  
39 The Clutter Data consists of raster datasets at a 30 meter resolution and ten values representing  
40 different land use classifications. Most of the land uses are based on data from the National

1 Topographic Database (NTDB), which is itself a database of delineations of different terrains,  
2 forest cover, populated places, and industrial infrastructure collected by Natural Resources  
3 Canada at the 1:50,000 scale. ‘Open land’ is one of ten land use classifications included in  
4 Clutter Data. Open land refers to areas where the NTDB has no mapped features. These areas  
5 contain neither natural terrains (e.g., rivers, lakes, forest, wetlands, etc.) nor built features (e.g.,  
6 buildings, pipelines, dams, etc.). Satellite imagery reveals that most open land use in urban  
7 settings are human-manipulated areas, such as parking lots and other forms of setbacks, such as  
8 driveways, and lawns. The Clutter Data does not classify parks as open space. A neighborhood  
9 with a large park, therefore, will not necessarily have a large proportion of open space, but a  
10 neighborhood with more space between buildings will have more open space. The percent of  
11 each census tracts’ parking lots and setbacks is calculated by converting the raster pixels to  
12 vector centroids in GIS, and calculating the percentage of open land centroids as a total of all  
13 land class centroids for each census tract. We expect that open land use (herein, parking lots and  
14 setbacks) will depress walking rates, as parking lots and setbacks reduce dwelling densities.

15 We assess on-street tree canopy cover from a shapefile containing polygon features of  
16 each tree in the City of Montreal, which was downloaded from the City’s website (29). The tree  
17 canopy shapefile was created by the City in 2007 and made available online in 2013. A central  
18 assumption of using the tree canopy data is that only trees near streets will correlate positively  
19 with walking rates. Only trees with a majority of their area within 10 meters of the street  
20 centerline were included. This assumption is consistent with research which suggests that on-  
21 street trees provide a more favorable walking environment (30). Our on-street tree canopy  
22 variable represents the percentage of the area of the ten meter street buffer that is covered by the  
23 tree canopy in each census tract. The average census tract in Montreal has an 18.98% tree cover  
24 surrounding its streets, with a standard deviation of 11.06 across the sample.

25 *Auto-dependency controls: Paid parking and distance from highway*

26 Two variables measured auto-dependency: the presence of on-street metered parking  
27 (herein, ‘paid parking’) in the census tract, and distance from the centroid of the census tract to  
28 the nearest limited-access highway. The geocoded location of parking meters was taken from the  
29 Stationnement de Montréal (local parking authority) website. We expected that paid parking  
30 would be positively associated with walking rates as paid parking is generally implemented in  
31 areas with lower car ownership (3), whereas free parking is associated with higher rates of  
32 automobile-oriented investment and use (31). The distance from a highway variable is calculated  
33 by measuring the distance in meters between the centroid of the census tract and the nearest  
34 highway segment using shapefiles provided by DMTI Spatial. Distance from highway is  
35 expected to be positively associated with walking rates, as highways often represent physical  
36 barriers in the environment that correlate with lower walking rates (32).

37 *Socio-demographic controls: Median household income and percent immigrant*

38 The socio-demographic profile of the census tracts is thought to influence walking  
39 behavior (33). Median household income and the percentage of immigrants (i.e., people who  
40 immigrated to Canada at any time) was calculated for each census tract from 2011 National  
41 Household Survey (NHS) data. In Canada, major urban centers host substantial immigrant  
42 populations whose travel behaviors may differ from Canadian-born individuals. In the Montreal

- 1 CMA, for instance, 48.6% of recent immigrants commuted to work by public transit compared to
- 2 20.9% of Canadian-born commuters (34).

1 TABLE 1 Description of variables

	Variables	Description	Source
<b>Walking Behavior Measures</b>	Walking rates	Proportion of all trips where the primary reported mode is walking	Montreal O-D Survey (AMT, 2013)
	Mean walk trip distance	Mean distance in meters of all walk trips originating in the census tract assuming shortest path calculations	Montreal O-D Survey (AMT, 2013)
	Walk-to-work rate	Percent of all work trips where the primary reported mode is walking	Montreal O-D Survey (AMT, 2013)
<b>Walk Score</b>	Walk Score	Average of all Walk Scores in the census tract (0-100), with 0 indicating lowest possible walkability, and 100 indicating highest possible walkability	Walk Score
<b>Land Use Measures</b>	Parking lots and setbacks	Proportion of total area characterized by the absence of buildings, water or natural environments (e.g.: lawns, parking lots, cropland)	DMTI Spatial
	On-street tree canopy cover	Proportion of the total area of trees within the 10 meters of the street and the total area of a buffer of 10 meters within the street centerline	City of Montreal
<b>Controls: Auto-dependency</b>	Paid parking	Binary variable indicating the absence (0) or presence (1) of metered parking	Stationnement de Montréal
	Distance from highway	Distance in meters from the nearest (grade-separated, limited access) highway.	DMTI Spatial
<b>Controls: Socio-demographic</b>	Median household income	Median household income reported in 2010	Statistics Canada (National Household Survey 2011)
	Percent immigrant	Percent of neighbourhood population that is an immigrant to Canada (i.e.: not Canadian-born)	Statistics Canada (National Household Survey 2011)

2

3 **Methodology**

4 A cluster analysis (k-mean approach) was performed to identify census tracts with a  
5 Walk Score and walking rate divergence. A descriptive analysis then compared walking behavior  
6 (walking rate, walk-to-work rate, and average walk trip distance) and neighborhood  
7 characteristics (Walk Score, median household income, parking lots and setbacks, on-street  
8 canopy cover, and population density) between the different clusters.

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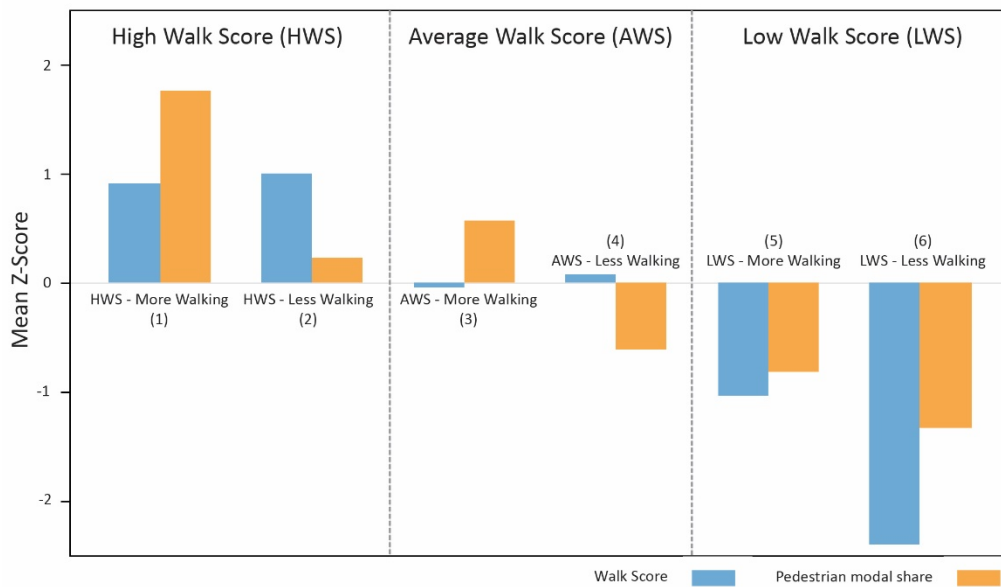
1 Three linear regression models of walking rates were then estimated. Each of the three  
 2 models use walking rate as the independent variable, four control variables (paid parking,  
 3 distance from highway, median household income, and percentage of immigrant population), and  
 4 different sets of predictor variables. The first model considers the relationship between walking  
 5 rate and the land use measures of interest (parking lots and setbacks and the on-street tree  
 6 canopy), while the second model examines the relationship between the pedestrian modal share  
 7 and Walk Score. The third model uses both Walk Score and the land use measures of interest  
 8 (parking lots and setbacks and the on-street tree canopy) as independent variables. The working  
 9 assumption is that these two variables will remain significant when adjusting for Walk Score.

10 Independent variables were tested for multicollinearity in each regression model. The  
 11 multicollinearity between each independent variable and the dependent variable was determined  
 12 by finding the Variable Inflation Factor (VIF). The highest VIF found of any independent  
 13 variable in any model was 2.290 (Walk Score). Walk Score, in fact, was the only variable that  
 14 had a VIF above 2. Often, variables are eliminated on the basis of multicollinearity if the VIF  
 15 exceeds 10 (35). The VIFs of our independent variables were well below this common threshold.

16 **RESULTS AND ANALYSIS**

17 **Cluster Analysis**

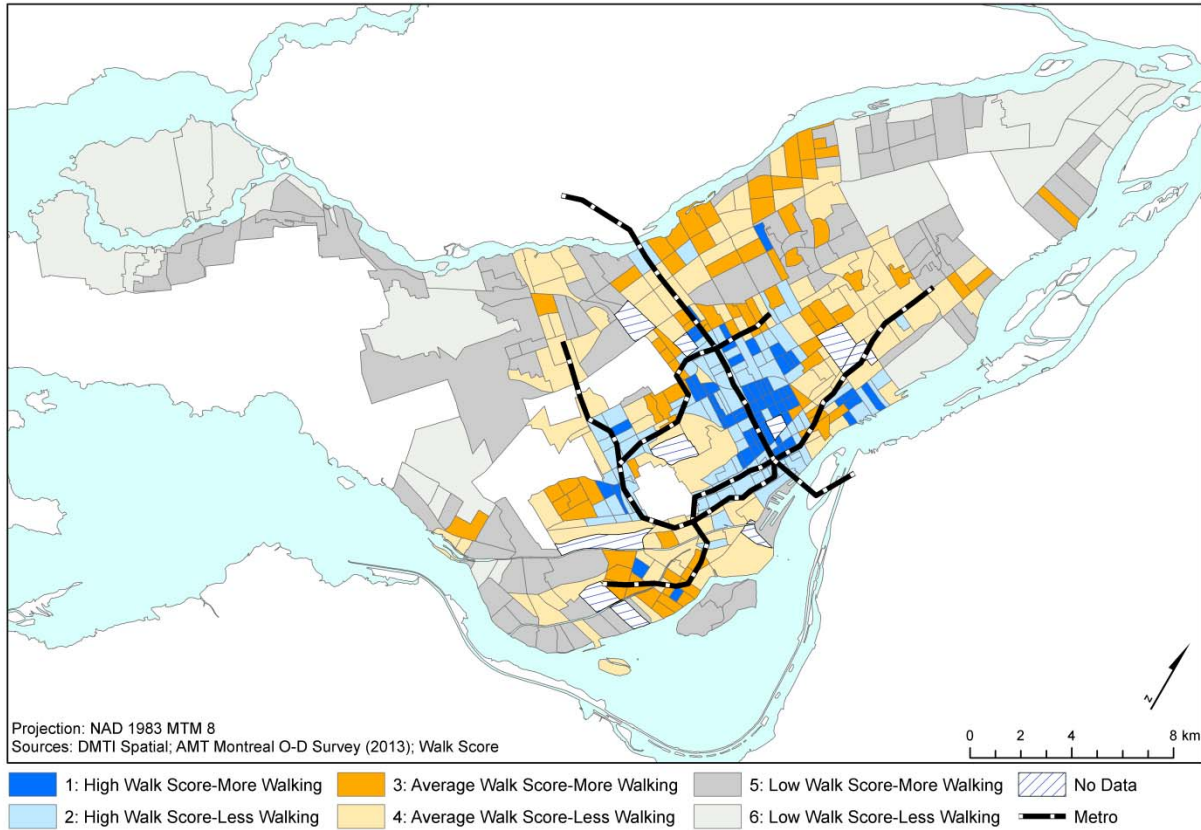
18 Six clusters displayed the least redundancy and most variation across groups (Figure 2).  
 19 Clusters 1 and 2 had above average (high) Walk Scores (HWS), clusters 3 and 4 had average  
 20 Walk Scores (AWS), and clusters 5 and 6 had below-average (low) Walk Scores (LWS), when  
 21 compared to the city-wide sample. Clusters 1 and 2 have above average Walk Score but cluster 2  
 22 exhibits a much lower walking rate, only slightly above the average. With respect to clusters 3  
 23 and 4, with average Walk Scores, cluster 3 has an above average walking rate whereas cluster 4  
 24 has a below-average rate.



25

26 **FIGURE 2 Cluster Analysis of Montreal census tracts (n=466) using Walk Score and Walking Rate**

1 Walk Scores and walking rates gradually decrease away from the central area of the city  
2 (Figure 3). The distinct colors represent different Walk Score pairs: clusters 1-2 (blue) with high  
3 Walk Scores, clusters 3-4 (orange) with average Walk Scores, and clusters 5-6 (grey) with low  
4 Walk Scores. Each shade signifies where the walking rates are higher or lower than the other  
5 cluster within that pair, revealing the variation between census tracts within the same Walk Score  
6 classification and in similar geographic location.



7  
8 **FIGURE 3 Geographic Distribution of Clusters of Walk Score and Walking, Montreal Census Tracts**

9 Despite their comparable Walk Scores (75 and 76), the walking rate of cluster 3 (23%) is  
10 nearly double that of cluster 4 (12%) (Table 2). The walk-to-work rate of both clusters is the  
11 same (6%), suggesting that non-commuting trips (such as shopping trips, trips to visit a friend,  
12 etc.) are driving higher walking rates in cluster 3. These groups are very similar  
13 socioeconomically, suggesting that elements of the built environment, and not personal or socio-  
14 economic characteristics, are influencing the difference in walking behavior between these  
15 clusters. Similar patterns are observed in the High Walk Score pair (clusters 1 and 2). Despite  
16 similar Walk Scores (90 and 91), walking rates are much higher in cluster 1 (35%) than in cluster  
17 2 (20%). As in the Average Walk Score cluster, the socio-economics and walk-to-work rates of  
18 clusters 1 and 2 are similar.

19 Descriptive statistics reveal that the land use characteristics of interest in higher walking  
20 rate clusters follow the expected direction. For High and Average Walk Score cluster pairs, the  
21 cluster with the lowest walking rate also has the highest proportion of parking lots and setbacks.

1 In cluster 3, the proportion of land used devoted to parking lots and setbacks (14%) is lower than  
 2 in cluster 4 (26%). Conversely, in the same pair, the cluster with the highest walking rate has a  
 3 highest on-street canopy cover: cluster 3 has a larger proportion of land as on-street tree canopy  
 4 (26%) than cluster 4 (20%). In the High Walk Score pair, the cluster group with more walking  
 5 also follows the expected pattern: there are fewer parking lots and setbacks (6% vs. 14%) and  
 6 more trees (28% vs. 22%) in cluster 1 where walking rates are 35% when compared to cluster 2  
 7 where walking rates are 20%.

8 **Table 2 Descriptive statistics of the six clusters**

	High Walk Score		Average Walk Score		Low Walk Score	
	High Walking (1)	Low Walking (2)	High Walking (3)	Low Walking (4)	High Walking (5)	Low Walking (6)
<b>Sample Size</b>	63	96	79	110	91	27
<b>Walk Score (0-100)</b>	90.02	91.34	74.84	76.45	58.88	37.06
<b>Median Household Income</b>	\$43,493	\$41,068	\$42,245	\$42,107	\$54,586	\$67,763
<b>Parking lots and setbacks (average)</b>	6%	14%	14%	26%	28%	41%
<b>On-Street Canopy Cover (average)</b>	28%	22%	26%	20%	15%	15%
<b>Walking rate</b>	35%	20%	23%	12%	10%	5%
<b>Walk-to-work rate</b>	17%	15%	6%	6%	4%	2%
<b>Population Density (per sq. km.)</b>	14,020	10,616	9,895	7,751	5,319	2,548
<b>Average Walk Trip Distance (m)</b>	856	942	813	1,019	975	1116

9

## 10 Regression Models

11 The results of the regression models are reported in Table 3. The first model explains  
 12 46.1% of the variation in walking rate, with parking lots and setbacks driving the model strongly:  
 13 for each 10% increase in the proportion of parking lots and setbacks, a 1.7% decrease in walking  
 14 rate is expected (Table 3). Conversely, the presence of a larger on-street tree canopy is shown to  
 15 be positively associated with walking rates; for each 10% increase in tree canopy, a 0.7%  
 16 increase in the walking rate is predicted. Model 2 examines the relationship between walking  
 17 rates and Walk Scores. We observe that the Walk Score term is significant and positively  
 18 associated with walking rates, and the model explains a similar amount of variation in walking  
 19 rates ( $R^2= 44.1\%$ ) as Model 1. When Walk Score, parking lots/setbacks, and tree canopy are  
 20 modelled together in Model 3, the model fit ( $R^2= 50.4\%$ ) is better compared to Models 1 or 2.  
 21 The comparative assessment of Model 1 and Model 3 reveals that the proportion of parking  
 22 lots/setback and on-street canopy remain significant when Walk Score is included in the model.  
 23 Also, including our new land use variables (parking lots and setbacks, and on-street tree canopy),  
 24 in addition to the Walk Score variable, increases the explanatory power of the model.

25 In terms of the other explanatory variables, presence of paid parking and distance to  
 26 highway are positively associated with walking rates in all models, as expected. The paid parking

1 variable, in particular, is highly predictive of walking rates. For example, in Model 1, walking  
 2 rates are found to be 6% higher in the census tracts with paid parking versus those without it.  
 3 Finally, census tracts with higher proportions of immigrants and higher median incomes are  
 4 negatively associated with walking rates in all three models.

5 **Table 3 Regression coefficients predicting walking rate at the census tract level (n=466)**

	<b>Model 1</b>	<b>Model 2</b>	<b>Model 3</b>
<b>(Constant)</b>	0.250** [0.219 0.280]	-0.015 [-0.071 0.042]	0.083** [0.023 0.142]
<b>Walk Score</b>	-	0.003** [0.002 0.003]	0.002** [0.001 0.002]
<b>Parking Lots and Setbacks</b>	-0.169** [-0.209 -0.129]	-	-0.130** [-0.171 -0.090]
<b>On-street Tree Canopy</b>	0.073** [0.032 0.114]	-	0.057** [0.017 0.096]
<b>Paid parking</b>	0.062** [0.047 0.076]	0.035** [0.017 0.052]	0.031** [0.015 0.048]
<b>Distance from Highway</b>	0.010** [0.004 0.017]	0.016** [0.009 0.023]	0.011** [0.005 0.018]
<b>Median Household Income (in ten thousands)</b>	-0.014** [-0.018 -0.010]	-0.005* [-0.010 -0.001]	-0.008** [-0.012 0.003]
<b>Percent immigrant</b>	-0.100** [-0.148 -0.052]	-0.092** [-0.141 -0.044]	-0.098** [-0.144 -0.052]
<b>Model Fit (R<sup>2</sup>)</b>	0.461	0.441	0.504

6

7

\* Significant (p<0.05) \*\* Significant (p<0.01)

8 **DISCUSSION**

9 Neighborhoods with similar levels of walkability may ‘produce’ very different levels of  
 10 walking rates in their populations. The cluster analysis confirms our preliminary findings that  
 11 there is considerable variation in walking rates among census tracts with similar Walk Scores.  
 12 We find three pairs of cluster groups with similar Walk Scores and similar socio-economics, but  
 13 substantial differences between the groups within the pairs in terms of walking rates and land  
 14 uses. The descriptive statistics associated with each cluster group highlight that in the higher  
 15 walking rate clusters, the presence of parking lots/setbacks is lower whereas the proportion of  
 16 on-street tree canopy is greater, as hypothesized. These associations follow both within and  
 17 between each cluster pair.

18 The regression models validate the trends observed in our cluster and descriptive  
 19 statistics analysis after adjusting for neighborhood socio-economic characteristics. The presence  
 20 of parking lots and setbacks was found to be negatively associated with walking rates, even when  
 21 controlling with Walk Scores. Conversely, the presence of an abundant on-street tree canopy was

1 found to be associated favorably to walking rates in neighborhoods, over and above the influence  
2 of the overall walkability of a neighborhood as measured by the Walk Score.

3 Our finding on the relationship between walking rates and the presence of parking lots  
4 and setbacks is complementary with many conventional measures of walkability. Since the  
5 presence of parking lots and setbacks denote the absence of buildings, it is reasonable to assume  
6 that areas with higher amounts of parking lots and setbacks will also have lower dwelling  
7 densities. As low dwelling densities decrease local accessibility of destinations and presence of  
8 parking lots increases access to destinations by car (36), areas with more parking lots and  
9 setbacks simultaneously discourage walking trips and incentivize car travel. Parking lots and  
10 setbacks may also impede street connectivity, especially in urban areas where they are associated  
11 with larger industrial footprints (37). Areas with large industrial setbacks have also been found to  
12 increase pedestrian crash frequency (38), which could discourage walking. While some of these  
13 effects are accounted for by Walk Score or similar walkability measures, our study highlights  
14 that not all of them are not fully captured by Walk Score.

15 We also found that census tracts with a larger street tree canopy had higher rates of  
16 walking, independent of Walk Score. This contradicts a similar study conducted in the Twin  
17 Cities, which did not find a significant difference between the presence of trees and walking rates  
18 for transport (39). Nevertheless, the positive influence of the street tree canopy on walking can  
19 be explained by the fact that it offers a more aesthetically pleasing walking experience (40; 41).  
20 It also influences the comfort of walking in warmer weather by providing shade and cooling  
21 from evapotranspiration (42; 43). These effects may encourage walking, as opposed to areas  
22 with less trees but more parking lots and setbacks.

23

## 24 **Study Limitations**

25

26 While the Walk Score values used in this analysis are relatively recent (2013), Walk  
27 Score has since changed its methodology. Beginning in 2014, Walk Score began using street  
28 network buffers to derive neighborhood walkability measures; the older Walk Score values used  
29 for this analysis used Euclidean distance buffers instead (4). Accordingly, our models may  
30 slightly underestimate the association between Walk Score and walking rates. Within the scope  
31 of this study, it was not feasible to obtain more recent Walk Score values at the level of analysis  
32 desired. Nonetheless, our findings identify environmental and land use factors with strong  
33 associations to walking rates that have never been used by Walk Score.

34

35 Secondly, given the methodology used by the Agence métropolitaine de transport for the  
36 2013 Montreal Origin-Destination survey, we cannot guarantee that all walking trips that occur  
37 in the Montreal CMA were surveyed evenly at our level of analysis (census tracts). Nonetheless,  
38 each census tracts contain at least thirty trips of any travel mode, and the sample size of the  
39 survey (5% of households in the Montreal CMA) is substantial.

40

41 Lastly, due to the neighborhood level of this analysis, the results of this analysis are  
42 subject to some generalization and smoothing, especially as some data was aggregated at the  
43 census tract level. The effects of these externalities are mitigated by using the smallest  
44 aggregation geography available (census tract). The analysis is intended to understand broad

1 patterns of walking behavior at the population level and not determinants of an individual's  
2 walking behavior.  
3

#### 4 **CONCLUSION**

5 This paper examined areas where the strength of association between Walk Score and  
6 walking rates was less strong than expected. Our cluster analysis reveals substantially different  
7 walking rates between clusters with similar Walk Score means. Based on our findings in the  
8 regression analysis, we can confirm that consideration of parking lots and setbacks, and on-street  
9 tree canopies would improve the predictive power of Walk Score. In areas where the association  
10 between Walk Score and walking rates diverged, this is often explained by the presence of  
11 parking lots and setbacks and absence of trees, as these areas neither increases amenity density  
12 (as buildings do), nor improve the aesthetics or comfort of the pedestrian environment (as trees  
13 do). Therefore, it is important for researchers to consider this balance between neighborhood  
14 land use and greenness when using, interpreting, and designing walkability metrics.

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