Australasian Transport Research Forum 2017 Proceedings
27 – 29 November 2017, Auckland, New Zealand
Publication website: http://www.atrf.info

Accessibility Measures versus Land use Measures in Active Transport Modelling

Tayebeh Saghapour1, Sara Moridpour1, Russell G. Thompson2

1 Civil and infrastructure Engineering Discipline, School of Engineering, RMIT University, Australia
2 Department of Infrastructure Engineering, The University of Melbourne, Australia
Email for correspondence: tayebeh.saghapour@rmit.edu.au

Abstract

The importance of physical activities and its impacts on health not only attracts the attention of practitioners, but it has also turned planners and policy makers towards achieving transportation sustainability through enhancing active travel behaviours. Although many studies have been conducted on active transportation modelling, the importance of accessibility in terms of availability of activities to pedestrians and cyclists has been neglected. Hence, this study used new approaches measuring cycling and walking accessibility measures against land use features in two separate Ordered Logistic Regression (OLR) models to examine how accessibility could affect active transportation. Data used in this study, has been obtained from Victorian Integrated Survey of Travel and Activity (VISTA, 2009). Key findings indicated that more accessible neighbourhoods had more walking and cycling trips; while the model using accessibility measurements showed higher accuracy. Therefore, the results of this study suggest that being aware of levels of accessibility in existing and developing neighbourhoods could provide a better perspective for planners and policy makers to promote active transportation.

Keywords: Built environment, accessibility, active transportation, OLR models

1. Introduction

The recent mobility patterns favouring single-occupancy vehicles and sprawling metropolitan areas bring about many problems including longer unproductive hours spent in traffic, air pollution, and different sort of diseases due to sedentary travel behaviour (Ermagun and Samimi, 2015, Mercier et al., 2016). Sedentary travel behaviours not only affect the quality of citizen's life, but also involves social and economic negative externalities (Mayeres, 2000, Hallgrimsdottir et al., 2016).

The integration of transport and land use planning is extensively recognized as essential requirements of sustainable development, and the concept of accessibility is believed to provide a central framework for this integration (Bertolini et al., 2005, Wang et al., 2011, Silva et al., 2017). There is a variety of concepts and tools to address theoretical and methodological aspects around the definition, and measurement of accessibility (Iacono et al., 2010, Geurs et al., 2015, Shliselberg, 2015, Silva et al., 2017). However, these concepts and tools have not been extensively used in planning practice.

Accessibility can be directly related to both the qualities of the transport system and the land use system such as functional densities and land use mixes. At the same time, it can be directly related to economic and social goals as well as environmental goals in terms of resource-efficiency of the activities and mobility patterns. In other words, shifting from more accessible neighbourhoods to more auto-oriented suburban areas was found to decrease the use of more sustainable travel options such as walking and cycling (Bertolini et al., 2005).

Meanwhile, walking and cycling can make a considerable contribution to sustainable transport goals from which accessibility is the most important one (Tight et al., 2011). According to Bertolini and Le Clercq (2003) accessibility is the basic reason for a transport system to exist. Walking and cycling are also known as 'active transport' which refers to human-powered forms of travel (Cole et al., 2010).

The benefits of active transport, ranging from air quality and sustainability issues to tourism, access and equity, and crime prevention, are now widely acknowledged by researchers (Goodman and Tolley, 2003, Stewart and Wild, 2016). For this reason, the global concerns for issues relating to climate change, sustainability and transport challenges prompt political imperative for making efforts on active transport (Cole et al., 2010). One of the most effective ways to make physical activities into daily routines is through active travel, which not only benefits public health but also can help prevent climate change. Although it is widely agreed that walking and cycling are good for individuals' health (Pucher and Buehler, 2010, Pucher et al., 2010), there is a lack of evidence about what works to promote active travel (McCartney et al., 2012). Besides, despite a noticeable focus on the importance of promoting walking and cycling in many transport related strategies, policies and plans, there is relatively little robust evidence regarding the relationship between accessibility and levels of walking and cycling. There is no single method to determine the success of sustainable transport systems; however, comparing results among different built environment measures can be helpful in finding out the importance of considering the accessibility measures in transport modelling.

Therefore, this paper aims to contribute to the implementation of accessibility in practice, by innovatively integrating accessibility in active transportation modelling. Two new accessibility indexes, which have been developed for Melbourne metropolitan, are used to examine how accessibility could affect the active transportation. Furthermore, accessibility measures are compared to land use measures to explore the importance and applicability of them in transport modelling.

The next section presents the methods of the study which describes dataset, study area and explanatory variables. This debate is followed by an analysis of the perspective of planning practitioners focussed on the usefulness of accessibility measures (Section 3). Thereafter, in Section 4, results of the analysis are discussed, while in the final section, conclusions and future directions of this study are outlined (Section 5).

2. Methods

This study used two new indexes measuring, walking and cycling accessibility along with other built environment measures to examine the importance of accessibility on active transportation. Following describes the data source and study area as well as the calculation process of independent variables.

2.1. Datasets and Study Area

Travel Data

The travel dataset (Transport, 2009) has been provided from the Victorian Integrated Survey of Travel and Activity (VISTA). This was a cross sectional survey conducted from 2009 till 2010. It covers the Melbourne Statistical Division (MSD) as defined by the Australian Bureau of Statistics (ABS), plus the regional cities of Geelong, Ballarat, Bendigo, Shepparton and Latrobe Valley. Data includes demographic, trip information and car ownership from randomly selected residential properties. A total of 16,411 households, comprising 42,002 individuals responded with a response rate of 47%. In this research, only residents within the MSD (22,201 individuals) have been considered. This study used walking and cycling trip stages which are one-way travel movements from an origin to a destination for a single purpose (including change of mode) and by a single mode. The reason behind using the trip stages for analysis is that walking/cycling trips are considered as the shortest trip; while covering all trip purposes even changing transport modes. VISTA dataset contains a total of 18,405 numbers of walking and cycling trip stages.

Spatial Data

A database of Mesh Blocks from the 2011 Census for the Melbourne Region was accessible from Australian Bureau of Statistics (ABS). This data set contains the total usual resident population and total number of dwellings from the 2011 Census of Population and Housing for Mesh Blocks and all other statistical areas, including SA1s. According to the Australia Bureau of Statistics (ABS), the Melbourne region contains 53074 Mesh Blocks, 9510 SA1s, 277 statistical area level 2 (SA2) and 31 local government areas (LGA). Fig. 1 presents the statistical geography areas of the Melbourne region. Mesh blocks are the smallest geographical unit released by the ABS and all other statistical areas are built up from or, approximated by whole Mesh Blocks. In this study, SA1s were chosen as geographical scale for analyses and calculating the built environment factors. SA1s are the second smallest geographic areas defined in the Australian Statistical Geography Standard. Besides, SA1s districts with an average area and population of roughly one km2 and 414, respectively, have the closest conformity to neighbourhood's definition compared to other available geographical units for Melbourne region.

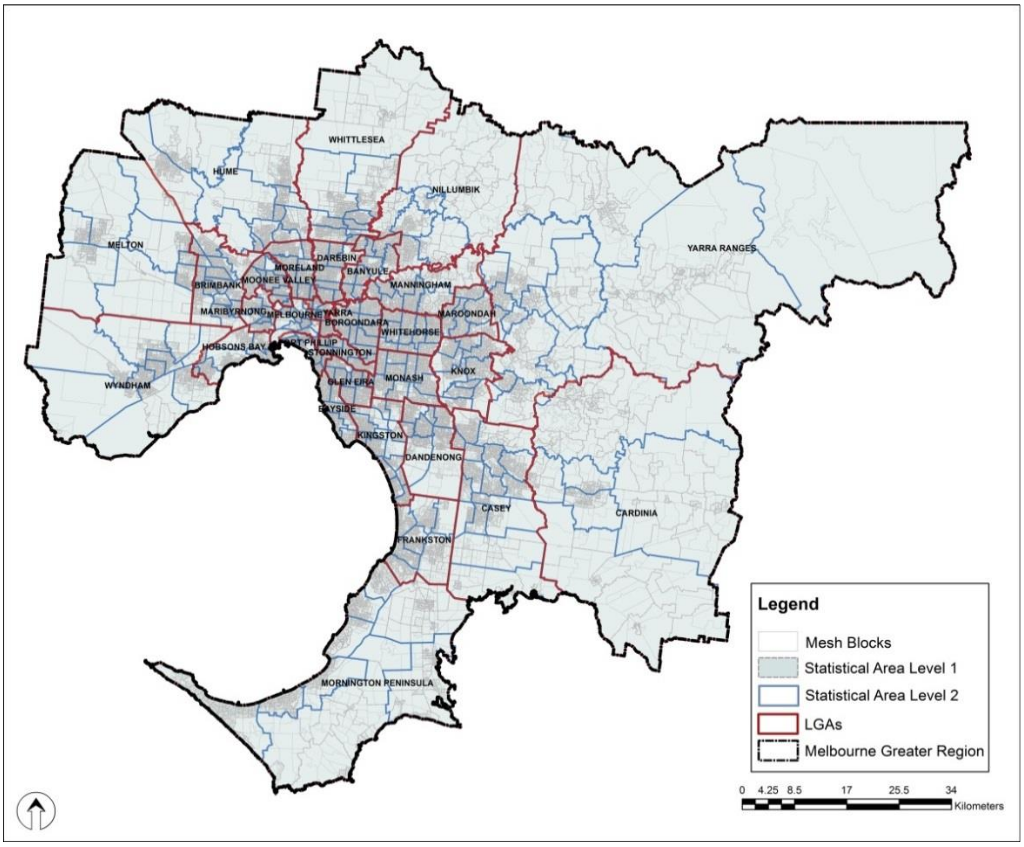

Figure 1: Geographical Areas in Melbourne Region

2.2. Explanatory Variables

Independent variables were mainly considered in two groups of socioeconomic characteristics and built environment measurements. Age, gender, car licence, dwelling type and ownership, work arrangement, household size, household structure, and number of cars as well as bikes in the household were employed as socioeconomic variables (Nilsson and Küller, 2000, Cao et al., 2009, Ewing and Cervero, 2010, Winters et al., 2010, Jun et al., 2012, Lee et al., 2014).
With respect to the built environment measurements, three dimensions of factors were examined: land use, design, and accessibility. Land use included population density and land use mix entropy index; and design covered connectivity and roadway measure while accessibility encompassed cycling accessibility index and walking access index. Using GIS techniques, all built environment measures were calculated for SA1s.

2.2.1 Land use measures

Land-use Mix Entropy Index (LUMIX)
LUMIX is computed when the numerator is normalized by the natural logarithm of the number of land use types. Six developed uses are considered, including residential, commercial, Industrial, transport and infrastructure, community services and sport recreation centres. These categories are defined from ten main uses categories defined by Australian Valuation Property Classification Codes (AVPCC) (Morse-McNabb, 2011). The values vary from 0 to 1, while 1 indicates a perfect balance among different type of land uses and 0 shows the homogeneity. Eq. 1 presents one of the most common approaches for measuring mixed used development within spatial extents (Nilsson and Küller, 2000, Cerin et al., 2007, Duncan et al., 2010, Song et al., 2013, Lee et al., 2014).

$$\mathrm{LUMIX_i} = -\left(\sum_{j=1}^{J} \frac{\mathrm{P_j.lnP_j}}{\mathrm{lnJ}}\right) \qquad \text{Eq. 1}$$

where LUMIXi indicates the entropy index within a buffer i (SA1). Pj represents the proportion of a type of land use j and J is the number of land use categories. Six different Land use categories including residential, commercial, Industrial, transport and infrastructure, community services and sport and recreation centres, have been chosen to calculate LU mix index entropy.

Population Density (PDSTY)
Population density is one of the most important indicators of population distribution which is widely used in urban and transport research (Cole et al., 2010, Ewing and Cervero, 2010, Manaugh and Kreider, 2013, Ewing et al., 2014, Chakhtoura and Pojani, 2016). The concept of the measure is simple and it indicates the number of residents in a given area. It should be noted that, this study calculated the net population density within SA1s.

2.2.2 Design measures

Two design variables related to street patterns were measured in this study including connectivity and roadway measure. Other design measures were not considered mainly due to data unavailability.

Roadway Measure (RDW)
The roadway measure examines how long the network spreads over a buffer area, which is defined as SA1 in this study. It is quantified by total roadway length divided by total area where the distance is normalized by a unit area of 100m2 (Lee et al., 2014).

Connectivity (CON)

The connectivity measure, also called internal connectivity, is defined as the number of intersections divided by total number of intersections and dead ends within a certain area (Song and Knaap, 2004, Knaap et al., 2007, Lee et al., 2014). The Australian Urban Research Infrastructure Network (AURIN) (Sinnott et al., 2011) has been developed the connectivity for areas within the Melbourne, as well. They provide a web-based environment for calculating connectivity for different statistical subdivisions in the Melbourne area. Hence, this study used the environment for calculating the connectivity for SA1s.

2.2.3 Accessibility measures

Cycling Accessibility Index (CAI)

The CAI measures cycling for SA1s and reflects cycling catchments as well as travel impedances between origins and destinations. The weighted centroids of SA1s were defined as origins and distinct categories of activities considered as destination of trips. Destinations were categorized into four groups of activities, including education centres, health and care facilities, retail and recreation centres and community services. For each SA1, the CAI is calculated using the formula shown in Eq.2. The index is a combined measure of Area Ratio (ARi) and the exponential function of Xij given as:

$$\mathrm{CAI_i} = \mathrm{AR_i} + \sum_{j=1}^{4} e^{-X_{ij}} \qquad (\mathrm{Xij} \neq 0) \qquad \text{Eq. 2}$$

where, CAIi is the Cycling Accessibility Index for each SA1, ARi represents the ratio of cycling catchment areas to the area of the corresponding SA1, and Xij is the distance or travel time between origin i and destination j divided by the total length of bicycle paths within the corresponding SA1. Cycling catchment areas were calculated for each activity within each of four categories of destinations: education centres, health and care facilities, retail and recreation centres, and community services. Cut-off values were defined as 15min/4km for education centres, 15min/4km for health and care facilities, 10min/2.5km for retail and recreation centres and 20min/5.3km for community services.

For areas with no bicycle network, the CAI is equal to ARi. The logic for this is that cyclists may share the roads with other modes within those areas. More details and an illustration of calculating the CAI is provided in a study by Saghapour et al. (2017b). The CAI ranges from 0 to 44.7 with an average value of 2.98.

Walking Access Index (WAI)

The WAI is used to measure walkability within the 9510 SA1s in Melbourne (Saghapour et al., 2017a). WAI measures the walking distances to different destinations as one of the main barriers to active transport. Walking distances were calculated as the average distance from a SA1 weighed centroid to all available points of interest (POIs) or destinations within acceptable walking distances (cut-off values). The acceptable walking distances were defined as 1.6 km for primary and secondary schools, 2.4 km for tertiary institutions, 1.6 km for child care centres, 1.6 km for medical centres, 1.6 km for retail and recreation centres and 2.4 km for community services and libraries. These values have been adopted from the Austroads network operation planning framework (Espada et al., 2015, Espada and Luk, 2011); while having consistency with the research conducted by Millward et al. in the United States (Millward et al., 2013), Rattan et al. in Canada (Rattan et al., 2012), Rendall et al. in New Zealand (Rendall et al., 2011).
POIs were categorised into six groups of destinations, including primary and secondary schools, tertiary institutions, child care centres, medical centres, retail and recreation centres, and community services and libraries. The WAI reflects travel impedance in terms

of median desirable[1] and maximum desirable[2] travel time/distance. Eq. 3 presents the formula used to calculate the WAI for SA1s. For each SA1, the index is computed as:

$$\mathrm{WAI}_{\mathrm{SA1}_\mathrm{i}} = \sum_{\mathrm{j}=1}^{\mathrm{m}} \mathrm{N}_i \times \left(\frac{\mathrm{D}_\mathrm{j}^\mathrm{M} - \mathrm{D}_\mathrm{ij}^\mathrm{A}}{\mathrm{D}_\mathrm{j}^\mathrm{D}}\right) \qquad \text{Eq. 3}$$

where, WAISA1 is the Walking Access Index, N_i is the number of destinations available within acceptable walking distance for origin i, $\mathrm{D}_\mathrm{j}^\mathrm{M}$ is the maximum desirable walking distance to destination j, $\mathrm{D}_\mathrm{j}^\mathrm{D}$ denotes the median desirable walking distance to destination j, and $\mathrm{D}_\mathrm{ij}^\mathrm{A}$ represents the average walking distance from a SA1 weighted centroid i to destination j. The new index reflects both the diversity and intensity of land use, while considering the availability of destinations as well as the number of activities. A higher value of WAI indicates a higher level of accessibility. A value of 0 indicates no accessibility in terms of the availability of destinations within the acceptable distance (cut-off values). The WAI ranges from 0 to 222.43 with an average value of 24.08.

3. Data Analyses and Results

As mentioned in previous sections, this study aims at investigating the importance of walking and cycling accessibility on active transportation. For this purpose, two separate OLR models were specified with socioeconomic and built environment factors. M1 presents the results of the model considering all the predictor variables and accessibility measures; while M2 contain the entire variable used in the M1; however, accessibility measures were replaced by land use measures. Walking and cycling trips were defined as an ordered dependent variable. Age, gender, car licence, work arrangement, household size, household structure, number of cars and bicycles, type of dwelling, dwelling ownership, and years lived at address in the household were employed as socioeconomic variables (Ewing and Cervero, 2010, Winters et al., 2010, Jun et al., 2012, Lee et al., 2014). Three groups of variables including accessibility (CAI and WAI), land use measures (PDSTY and LUMIX) and design measures (roadway measure and connectivity), were considered as built environment measures.

3.1. Descriptive Statistics

The VISTA dataset contains trip records of 22,201 individuals within the Melbourne region. This study used walking and cycling trip stages which are one-way travel movements from an origin to a destination for a single purpose (including change of mode) and by a single mode. The reason behind using the trip stages for analysis is that walking/cycling trips are considered as the shortest one; while covering all trip purposes even changing transport modes.

Being able to run the statistical analysis on the VISTA dataset, both the WAI as well as the CAI have combined with the VISTA dataset using the SA1 codes. VISTA dataset contains total number of 18405 walking and cycling trips, from which 17,089 are walking trips and 1316 are reported as cycling trips. Table 1 shows the frequency of walking trips within SA1s which are categorised into 5 groups from very low to very high. Table 2 shows the list of independent variables and their description.

Table 1 Frequency of walking and bike trips

[1] Median desirable walking distance is a value that satisfies half of the travellers.

[2] The maximum desirable walking distance is defined as a value at which a significant percentage of people would find it unfeasible to regularly travel and they may be forced to relocate their residence closer to the destination or find a less suitable destination that is closer.

Walking Trips Categories	Number of Walking & Cycling Trips	Frequency	Percentage	Cumulative Percentage
Very Low	< 8	2261	12.3	12.3
Low	8 - 14	3681	20.0	32.3
Average	15 - 23	3246	17.6	49.9
High	24 - 33	3084	16.8	66.7
Very High	34 - 49	3052	16.6	83.3
Excellent	> 50	3081	16.7	100.0
N/A	Total	18405	100.0	

Table 2: Independent variables and their description

Variables	Description
Socioeconomic Characteristics	
Age	Age of the respondent
Sex	Gender
Licence	Driver licence
Car No.	Number of vehicles in the household
Bike No.	Number of bicycles in the household
HH Size	Usual number of residents in the household
HH Structure	Demographic structure of household
Dwelling Type	Type of Dwelling
Dwelling Ownership	Dwelling Ownership
Years Lived	Years lived at address
Work arrangement	Arrangement of the work
Built Environment Measurements	
Accessibility Measures	
CAI	Cycling Accessibility Index
WAI	Walking Access Index
Design Measures	
RDW	Roadway Measure
CON	Connectivity
Land use Measure	
LUMIX	Land use mix entropy index
PDSTY	Population density

Note: HH structure is converted to five dummy variables: sole person, couple no children, couple with children, one parent and other; work arrangement is converted into five dummy variables: fixed Hours, flexible Hours, rostered shifts, work from Home and other; dwelling type is converted into three dummy variables: separate house, terrace/townhouse, and flat or apartment; dwelling ownership were converted to five category: owned, being purchased, rented, rent free and other, sex and driver licence are defined as binary variables.

Table 3 suggests the descriptive statistics for the variable used in the OLR models. These statistics are calculated for 18,405 records of walking and cycling trip stages. In terms of socio-demographic characteristics, respondents were 37 years old on average and equally distributed according to gender. The average of HH Size shows that respondents were mostly from households with a usual number of about three residents. The average years lived at the address was 10 and households owned more than one car and bicycle.

Table 3: Descriptive Statistics of variables

Variable	Mean	S.D.	Min	Max
Age	36.76	19.06	0.00	90.00
Sex	1.52	0.50	1.00	2.00
Licence	1.29	0.45	1.00	2.00
Car No.	1.57	1.02	0.00	7.00
Bike No.	1.85	1.91	0.00	13.00
HH Size	3.00	1.37	1.00	6.00
HH Structure	2.80	1.13	1.00	5.00
Dwelling Type	1.52	0.80	1.00	3.00
Dwelling Ownership	1.97	0.82	1.00	5.00
Years Lived	9.95	11.21	0.00	77.00
Work arrangement	2.86	1.78	1.00	5.00
CAI	4.01	3.91	0.00	32.75
WAI	32.63	21.63	0.00	212.02
RDW	1.48	0.86	0.00	5.57
CON	5.21	9.17	0.00	92.06
LUMIX	0.45	0.16	0.00	0.87
PDSTY	3706.77	4521.05	0.00	158817.12
Walking & Cycling Trips	28.81	21.91	1.00	110.00

n=18,405 trip stages

3.2. Modelling and Interpretation

Walking and cycling trips in SA1s are defined into six ordered levels from very low, coded as 1, to excellent coded as 6. Having an ordered dependent variable, OLR models were used to explore the effects of socioeconomic characteristics as well as walking and cycling access indexes. OLR models estimate a single equation (regression coefficients) over the levels of the dependent variable. Estimates from the model denote the ordered log-odds (logit) regression coefficients. Interpretation of the ordered logit coefficient is that for a one-unit increase in the predictor, the response variable level is expected to change by its respective regression coefficient in the ordered log-odds scale while the other variables in the model are held constant. Interpretations of the ordered logit estimates are not dependent on auxiliary parameters. Secondary parameters are used to differentiate the adjacent levels of the response variable. The Odds Ratio (OR) which is estimated in this model can be obtained by using the exponential function and the coefficient estimate (i.e. eCoef.). To interpret this, the people who are in groups greater than k are compared to those who are in groups less than or equal to k, where k is the number of the response variable's levels (Andren et al., 1999). A typical model for the cumulative logits is shown in Eq. 6:

$$logit[P(Y \leq j)] = \alpha_j + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n = \alpha_j + \acute{\beta} X \qquad Eq. 6$$

where, j = 1, . . ., c-1; c is the total number of categories; x1, x2, . . ., xn are n explanatory variables; β_1, β_2, . . ., β_n are corresponding coefficients.

An ordered logit regression models is generated for walking and cycling trips. As explained, walking and cycling trips are defined as an ordered dependent variable.

Before running the model, the correlation analysis was applied to examine whether there is any association between the CAI, WAI and other built environment factors (see Table 4). As expected and also explained in previous sections, both defined accessibility measures reflect the diversity and intensity of land uses (land use mix) as well as population density. Hence, we run the two models once using the accessibility measure with design measures, and in the second run replacing accessibility measures by land use measures.

Table 4: Correlation analysis between CAI, WAI and other built environment measures

	LUMIX	PDSTY	RDW	Connectivity
CAI	0.420	0.149	0.142	0.144
WAI	0.468	0.507	0.304	0.227

In order to examine the importance of accessibility on the number of active transport trips two OLR models were estimated. Table 5 presents the results of the OLM models. The accessibility measures (CAI and WAI) along with other variables were employed to run the model M1, likewise, the land use measures in M2. The results indicated that all built environment measures in both models were statistically significant and the active transport was positively associated with built environment measures. However, based on Akaike Information Criterion (AIC) which is a measure of the relative quality of statistical models for a given set of data, M1 were found a better model. Given a series of models for the data, the AIC estimates the quality of each model, relative to each of the other models. Hence, the AIC provides a means for model selection (Aho et al., 2014, Hu, 2007, Boisbunon et al., 2014). In terms of association, as presented in Table 5, number of cars in a household and living as a sole or single person negatively associated with walking and cycling trips. In terms of dwelling type, the log odds of being in a higher level of walking/cycling trips is higher for people who live in a terrace or townhouse rather than flats or apartments.

Meanwhile, built environment features also had significant impacts on the number of walking and cycling trips. CAI, WAI, LUMIX and PDSTY were positively and RDW was negatively associated with walking and cycling trips. For instance, there is an expectation of a 0.31 increase in the log odds of being in a higher level of walking and cycling trips for a unit increase of WAI. In contrast, while the RDW decreased for about 0.15 in M1, the log odds of being in a higher level of walking and cycling trips increased.

Table 5: Outputs of the ordered logit model for walking and cycling trips

Parameter	M1			M2		
	Estimate	S.E.	OR	Estimate	S.E.	OR
Age	-0.0003	0.0010	1.0000	0.0003	0.0010	1.0000
Sex	-0.1078***	0.0275	0.8980	-0.1049***	0.0267	0.9000
Licence	0.0401	0.0393	1.0410	0.0129	0.0380	1.0130
Car No.	-0.1249***	0.0171	0.8830	-0.1513***	0.0166	0.8600
Bike No.	0.0872***	0.0089	1.0910	0.1066***	0.0086	1.1130
HH Size	0.0615	0.0183	1.0630	0.0605***	0.0178	1.0620
HH Structure						
Sole Person	-0.1650**	0.0694	0.8480	-0.1972***	0.0673	0.8210
Couple no Kids	0.0862	0.0549	1.0900	-0.0011	0.0534	0.9990
Couple with Kids	-0.0170	0.0490	0.9830	-0.1322***	0.0477	0.8760
Single Parent	-0.2876***	0.0662	0.7500	-0.5126***	0.0637	0.5990
Dwelling Type						
Separate House	-0.0289	0.0446	0.9710	-0.0488	0.0433	0.9520
Terrace/Townhouse	0.5384***	0.0508	1.7130	0.5285***	0.0492	1.6960
Dwelling Ownership						
Owned	0.5091**	0.2406	1.6640	0.5772**	0.2397	1.7810
Being Purchased	0.4276*	0.2411	1.5340	0.5007**	0.2401	1.6500
Rented	0.7373***	0.2425	2.0900	0.7796***	0.2414	2.1810
Rent Free	0.7715***	0.3042	2.1630	0.8772***	0.3041	2.4040
Years Lived	0.0055***	0.0016	1.0060	0.0077***	0.0015	1.0080
Work arrangement						
Fixed Hours	0.2096***	0.0374	1.2330	0.2568***	0.0361	1.2930
Flexible Hours	0.1855***	0.0458	1.2040	0.2661***	0.0442	1.3050
Rostered Shifts	0.2463***	0.0569	1.2790	0.3017***	0.0547	1.3520
Work from Home	0.4847***	0.1061	1.6240	0.4682***	0.1033	1.5970
Design Measures						
RDW	-0.1494***	0.0254	0.8610	-0.1973***	0.0248	0.8210
CON	0.0145***	0.0017	1.0150	0.0155***	0.0016	1.0160
Accessibility Measures						
CAI	0.1895***	0.0131	1.2090	-	-	-
WAI	0.3128***	0.0101	1.3670	-	-	-
Land use Measures						
LUMIX	-	-	-	0.2433***	0.0120	1.2750

PDSTY	-	-	-	0.6143***	0.0230	1.8480

Note: (1) number of walking and cycling trips are converted to five dummy variables by using level 1(very low): less than 10 trips, level 2 (low): 11-17 trips, level 3 (average): 18- 28 trips, level 4 (high): 29-43 trips, and level 5 (very High): more than 44. Level one was the reference level.
(2)Threshold coefficients for M1: 1|2 → -0.997, 2|3→ -1.981, 3|4→ -2.935; 4|5→ -4.088; for M2: 1|2 → -1.378, 2|3→ -2.402, 3|4→ -3.343; 4|5→ -4.459;
(3) Significance codes: p < 0.001 '***', 0.01 '**', 0.1 '*'.
(4) Overall goodness-of-fit:
AIC_{M1} = 52,666.49, -2 Log L = 52,891.58, SC = 52,608.49;
AIC_{M2}= 56,377.44, -2 Log L = 56,604.23, SC= 56319.44.

4. Discussions

The current study aimed at investigating the impacts of accessibility on active transportation. For this purpose, three sets of built environmental measures including land use measures, design measure and accessibility measures used in two separate OLR models to examine their effectiveness as well as their importance. CAI and WAI were both developed for Melbourne's 9510 statistical areas level one (SA1s). These new indexes formulated in a way that reflects the land use mix developments as well as population density (tested using correlation analysis, see Table 4). Hence, accessibility measures and land sue measures were not used simultaneously in a model. Conversely, accessibility measures along with design measures and socioeconomic characteristics were employed in OLR model 1 (M1); while M2 had the same variables except the accessibility measures which have been replaced by land use measures. Going through the figures of both models, results indicated that both land use measures and accessibility measures had statistical significant impacts on the walking and cycling trips.
Coefficients estimated by models indicate that higher log odds of being in a higher level of walking and cycling trips are expected while there is a one-unit increase in the associated variable compared to its counterparts. Among the socioeconomic characteristics, age, car licence, household size, couples with/without kids, household living in a separate house had no statistical significant impacts on levels of walking and cycling trips. Regarding the built environment measures, although the OR values were estimated slightly higher for land use measure (OR_{LUMIX}=1.28, OR_{DNSY}=1.85; OR_{CAI}=1.21, OR_{WAI}=1.37) in M2; however, comparing AIC, M1 had the lowest AIC (AICM1 = 52,666 < AICM2 = 52,891) and showed a better fit for the data.
The accessibility measures developed in this study can be used to compare neighbourhoods, which are within the same study area, in terms of their walkability and bikeability. Using this approach, planners and policy makers can compare and rank areas already built, and identify the new areas where investment might improve the walking and cycling accessibility. The way urban areas are configured can influence the pedestrian behaviour because it could make the built environment more attractive, safer and more accessible, by bringing together shops and services, and recreation centres (Peiravian et al., 2014). CAI and WAI used in this study, not only reflect the diversity of different land uses, but also consider the intensity of population. Walkable, bikeable communities and active living are quite related to sustainable living. Changes in the physical environment affect urban mobility, particularly in metropolitan areas (Cubukcu, 2013). While, the promise of planning and policy actions to improve active travels is that walking and cycling can be encouraged, by enhancing the quality of the built environment which can affect travel distance, travel time and transport mode choice (Kim et al., 2014). As Randall and Baetz (2001) argue neighbourhoods should be constructed with sustainability concepts in mind. Those providing good pedestrian and cycling environments and more green space could enhance the level of physical activity. All across the urban and transport planning, much effort is currently being put into providing safe environments that encourage walking in cities.

5. Conclusions

The literature commonly reports that built environment features such as density, diversity, and road connectivity could promote walking and cycling trips. This study hypothesised the impacts of accessibility measures on the level of walking and cycling trips; while introducing and using new accessibility measurements. The results of the analysis revealed the fact that people were more likely to walk and cycle when their desired destination is located within the distance thresholds.

A major methodological challenge when working with accessibility measures in land use and transport planning is to find the right measure that is theoretically and empirically complete and it is adequately simple to be usefully employed in practice (Bertolini et al., 2005). The accessibility measures used in this study had simple and straightforward approaches to apply on different databases as well as different geographical scale. Furthermore, they were sufficiently comprehensive to be used in a transport modelling.

In summary, going through the literature, there is a significant gap between the advances in scientific knowledge on accessibility and its application in planning practice. In comparison with the limited previous work on accessibility-based analyses, the analysis presented here is distinctive because it incorporates the impacts of both land-use and accessibility on active transportation. The measurements describe in this study are capable of being used by urban and transport planner as well as policy makers to any given proposed land-use development. Apart from ease of understanding of both measurements, without doubt one of the greatest strengths of these measures is that they reflect the land use features in terms of diversity and intensity of activities.

References

AHO, K., DERRYBERRY, D. & PETERSON, T. 2014. Model selection for ecologists: the worldviews of AIC and BIC. *Ecology,* 95**,** 631-636.

ANDREN, T., FLOOD, L., HANSEN, J., POPA, D. & TASIRAN, A. 1999. Introduction to SAS. *Department of Economics, School of Economics and Commercial Law, Gothenburg University*.

BERTOLINI, L. & LE CLERCQ, F. 2003. Urban development without more mobility by car? Lessons from Amsterdam, a multimodal urban region. *Environment and Planning A,* 35**,** 575-589.

BERTOLINI, L., LE CLERCQ, F. & KAPOEN, L. 2005. Sustainable accessibility: a conceptual framework to integrate transport and land use plan-making. Two test-applications in the Netherlands and a reflection on the way forward. *Transport policy,* 12**,** 207-220.

BOISBUNON, A., CANU, S., FOURDRINIER, D., STRAWDERMAN, W. & WELLS, M. T. 2014. Akaike's information criterion, cp and estimators of loss for elliptically symmetric distributions. *International Statistical Review,* 82**,** 422-439.

CAO, X., MOKHTARIAN, P. L. & HANDY, S. L. 2009. Examining the impacts of residential self-selection on travel behaviour: a focus on empirical findings. *Transport Reviews,* 29**,** 359-395.

CERIN, E., LESLIE, E., TOIT, L. D., OWEN, N. & FRANK, L. D. 2007. Destinations that matter: Associations with walking for transport. *Health & Place,* 13**,** 713-724.

CHAKHTOURA, C. & POJANI, D. 2016. Indicator-based evaluation of sustainable transport plans: A framework for Paris and other large cities. *Transport Policy,* 50**,** 15-28.

COLE, R., BURKE, M., LESLIE, E., DONALD, M. & OWEN, N. 2010. Perceptions of representatives of public, private, and community sector institutions of the barriers and enablers for physically active transport. *Transport policy,* 17**,** 496-504.

CUBUKCU, E. 2013. Walking for sustainable living. *Procedia-Social and Behavioral Sciences,* 85**,** 33-42.

DUNCAN, M. J., WINKLER, E., SUGIYAMA, T., CERIN, E., DUTOIT, L., LESLIE, E. & OWEN, N. 2010. Relationships of Land Use Mix with Walking for Transport: Do Land Uses and Geographical Scale Matter? *Journal of Urban Health,* 87**,** 782-795.

ERMAGUN, A. & SAMIMI, A. 2015. Promoting active transportation modes in school trips. *Transport policy,* 37**,** 203-211.

ESPADA, I., BENNETT, P., GREEN, D. & HATCH, D. 2015. Development of the accessibility-based network operations planning framework.

ESPADA, I. & LUK, J. 2011. *Application of accessibility measures*.

EWING, R. & CERVERO, R. 2010. Travel and the built environment. *Journal of the American planning association,* 76**,** 265-294.

EWING, R., MEAKINS, G., HAMIDI, S. & NELSON, A. C. 2014. Relationship between urban sprawl and physical activity, obesity, and morbidity–Update and refinement. *Health & place,* 26**,** 118-126.

GEURS, K. T., MONTIS, A. & REGGIANI, A. 2015. Recent advances and applications in accessibility modelling. *Computers, environment and urban systems,* 49**,** 82-85.

GOODMAN, R. & TOLLEY, R. 2003. 6 - The decline of everyday walking in the UK: explanations and policy implications. *Sustainable Transport.* Woodhead Publishing.

HALLGRIMSDOTTIR, B., WENNBERG, H., SVENSSON, H. & STÅHL, A. 2016. Implementation of accessibility policy in municipal transport planning–Progression and regression in Sweden between 2004 and 2014. *Transport Policy,* 49**,** 196-205.

HU, S. 2007. Akaike information criterion. *Center for Research in Scientific Computation*.

IACONO, M., KRIZEK, K. J. & EL-GENEIDY, A. 2010. Measuring non-motorized accessibility: issues, alternatives, and execution. *Journal of Transport Geography,* 18**,** 133-140.

JUN, M.-J., KIM, J. I., KWON, J. H. & JEONG, J.-E. 2012. The effects of high-density suburban development on commuter mode choices in Seoul, Korea. *Cities*.

KIM, S., PARK, S. & LEE, J. S. 2014. Meso-or micro-scale? Environmental factors influencing pedestrian satisfaction. *Transportation Research Part D: Transport and Environment,* 30**,** 10-20.

KNAAP, G.-J., SONG, Y. & NEDOVIC-BUDIC, Z. 2007. Measuring patterns of urban development: new intelligence for the war on sprawl. *Local Environment,* 12**,** 239-257.

LEE, J.-S., NAM, J. & LEE, S.-S. 2014. Built environment impacts on individual mode choice: An empirical study of the Houston-Galveston metropolitan area. *International journal of sustainable transportation,* 8**,** 447-470.

MANAUGH, K. & KREIDER, T. 2013. What is mixed use? Presenting an interaction method for measuring land use mix. *Journal of Transport and Land use,* 6**,** 63-72.

MAYERES, I. 2000. The efficiency effects of transport policies in the presence of externalities and distortionary taxes. *Journal of Transport Economics and Policy***,** 233-259.

MCCARTNEY, G., WHYTE, B., LIVINGSTON, M. & CRAWFORD, F. 2012. Building a bridge, transport infrastructure and population characteristics: explaining active travel into Glasgow. *Transport Policy,* 21**,** 119-125.

MERCIER, J., CARRIER, M., DUARTE, F. & TREMBLAY-RACICOT, F. 2016. Policy tools for sustainable transport in three cities of the Americas: Seattle, Montreal and Curitiba. *Transport Policy,* 50**,** 95-105.

MILLWARD, H., SPINNEY, J. & SCOTT, D. 2013. Active-transport walking behavior: destinations, durations, distances. *Journal of Transport Geography,* 28**,** 101-110.

MORSE-MCNABB, E. The Victorian Land Use Information System (VLUIS): A new method for creating land use data for Victoria, Australia. Surveying and Spatial Sciences Conference, 2011. 155.

NILSSON, M. & KÜLLER, R. 2000. Travel behaviour and environmental concern. *Transportation Research Part D: Transport and Environment,* 5**,** 211-234.

PEIRAVIAN, F., DERRIBLE, S. & IJAZ, F. 2014. Development and application of the Pedestrian Environment Index (PEI). *Journal of Transport Geography,* 39**,** 73-84.

PUCHER, J. & BUEHLER, R. 2010. Walking and cycling for healthy cities. *Built Environment,* 36**,** 391-414.

PUCHER, J., BUEHLER, R., BASSETT, D. R. & DANNENBERG, A. L. 2010. Walking and cycling to health: a comparative analysis of city, state, and international data. *American journal of public health,* 100**,** 1986-1992.

RANDALL, T. A. & BAETZ, B. W. 2001. Evaluating pedestrian connectivity for suburban sustainability. *Journal of Urban Planning and Development,* 127**,** 1-15.

RATTAN, A., CAMPESE, A. & EDEN, C. 2012. Modeling walkability. *Arc. User. Winter,* 2012**,** 30-3.

RENDALL, S., PAGE, S., REITSMA, F., VAN HOUTEN, E. & KRUMDIECK, S. 2011. Quantifying transport energy resilience: active mode accessibility. *Transportation Research Record: Journal of the Transportation Research Board***,** 72-80.

SAGHAPOUR, T., MORIDPOUR, S. & THOMPSON, R. 2017a. Measuring Walking Accessibility in Metropolitan Area. *Transportation Research Record: Journal of the Transportation Research Board,* In Press.

SAGHAPOUR, T., MORIDPOUR, S. & THOMPSON, R. G. 2017b. Measuring cycling accessibility in metropolitan areas. *International Journal of Sustainable Transportation,* 11**,** 381-394.

SHLISELBERG, R. 2015. Accessibility and Spatial Interaction. *Transport Reviews,* 35**,** 814-816.

SILVA, C., BERTOLINI, L., TE BRÖMMELSTROET, M., MILAKIS, D. & PAPA, E. 2017. Accessibility instruments in planning practice: Bridging the implementation gap. *Transport Policy,* 53**,** 135-145.

SINNOTT, R., GALANG, G., TOMKO, M. & STIMSON, R. 2011. Australian Urban Research Infrastructure Network.

SONG, Y. & KNAAP, G.-J. 2004. Measuring urban form: Is Portland winning the war on sprawl? *Journal of the American Planning Association,* 70**,** 210-225.

SONG, Y., MERLIN, L. & RODRIGUEZ, D. 2013. Comparing measures of urban land use mix. *Computers, Environment and Urban Systems,* 42**,** 1-13.

STEWART, B. & WILD, C. P. 2016. World cancer report 2014. *World*.

TIGHT, M., TIMMS, P., BANISTER, D., BOWMAKER, J., COPAS, J., DAY, A., DRINKWATER, D., GIVONI, M., GÜHNEMANN, A. & LAWLER, M. 2011. Visions for a walking and cycling focussed urban transport system. *Journal of Transport Geography,* 19**,** 1580-1589.

TRANSPORT, D. O. 2009. *Victorian Integrated Survey of Travel and Activity* [Online]. Vicoria, Australia. Available: http://www5.transport.vic.gov.au/.

WANG, D., CHAI, Y. & LI, F. 2011. Built environment diversities and activity–travel behaviour variations in Beijing, China. *Journal of Transport Geography,* 19**,** 1173-1186.

WINTERS, M., BRAUER, M., SETTON, E. M. & TESCHKE, K. 2010. Built environment influences on healthy transportation choices: bicycling versus driving. *Journal of urban health,* 87**,** 969-993.