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Neighbourhood Attributes towards Active Transportation

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Abstract

Over the past decades, automobile-oriented development along with a huge increase in car ownership has encouraged people to have fewer active travels and spends more times traveling by private cars. The negative consequences of this kind of travel behaviour have been highlighted in metropolitan areas such as Melbourne, Australia. Since suggestions on how active commuting behaviour incorporated in daily trips can be provided by understanding the current active transport network; this paper aims to investigate whether built environment features in neighbourhoods could enhance the odds of active transportation. The present study used a new index measuring public transport accessibility (PTAI) as well as other built environment factors such as land use mix entropy index, and roadway measure investigating mode choice behaviour. Data used in this study, has been obtained from Victorian Integrated Survey of Travel and Activity (VISTA, 2009). Multinomial Logit (MNL) regression model is applied to investigate the impacts of explanatory variables on transport mode choice. Findings indicated that high rates of active travel are consistently associated with more diverse used areas with higher levels of public transport accessibility.

1. Introduction

In recent years, transport investments have been directed towards forming physical environment with strong connectivity to improve active travel modes like walking and cycling (Sallis et al., 1998). Built environment factors such as land use mix development, population density, employment density, dissimilarity index as well as connectivity were found to have an influence on individuals' transport mode choice and in turn on their level of physical activity (Lee et al., 2014). In this regard, active travel strategies can be achieved through land-use zoning policies. These strategies mainly include density regulations and mixed-use developments (De Nazelle et al., 2011). Transport policies and investments from one side and built environment from the other side can affect active travel behaviour. As Dannenberg claims (2003) the way we design and build the environment through the proximity of different facilities and services affect physical activity.

The link between the built environment and travel behaviour has received considerable research attention in recent decades (Handy et al., 2002, Wang et al., 2011). The arrangement and distribution of land use activities in the surroundings of living areas is one of the main factors found to influence urban transport patterns. Providing services and utilities for residents in their neighbourhoods is a way to minimize the need to travel long distances and increase the chance of walking and cycling. There is a long tradition of investigation about the association between the built environment and travel behaviour, however, from the late 1970s, researchers have focused on travel behaviour and policies (Lee et al., 2014, Boarnet, 2011).

As claimed by Pratt et al. (2004) as long as automobiles and roads are available and fuel is cheap, urban housing will be developed in outer suburbs, a considerable distance to workplaces. This phenomena means that auto-oriented transport is needed for regular trips, such as travelling to work, school and shopping. In this regard, the increased time spent in cars is passive travel, behaviour replacing active forms of transport. The way in which cities and transport corridors are designed has been found to be an important contributor to physical inactivity (Saelens et al., 2003, Ewing and Cervero, 2010, Pratt et al., 2004). According to the Australian Government Department of Health and Ageing (2009) “A well designed neighbourhood will assist in enhancing the health and wellbeing of a community by encouraging people to be more physically active and engaged in the community”.

Results of previous studies demonstrate that sprawling urban areas and low-density land use patterns increase the odds of residents being overweight or obese (Ewing et al., 2014, Lopez, 2004). Also, some built environment features such as net residential density and connectivity were negatively associated with obesity (Bodea et al., 2009). Based on a literature review by Ewing and Cervero (2010), proximity to different activities from one’s home increases the probability of walking and transit use. Density and land use diversity have also been found to be related to shorter trip distances and more non-motorized trips (Wang et al., 2011, Friedman et al., 1994, Cervero and Duncan, 2003, Khattak and Rodriguez, 2005). A substantial body of research has examined factors that affecting walking.

Zoning has been defined as designating land for different uses such as residential, commercial and industrial. By making changes in zoning policies, existing patterns of land use as well as new ones may be affected (MAV, 2012). In traditional Euclidean zoning residential areas were segregated from commercial and other uses within each zone. This strategy discourages walking and cycling trips for residents. To address this problem, multidisciplinary experts were called to change existing zoning regulations into pedestrian-friendly and more liveable neighbourhoods (Schilling and Linton, 2005). Modernization of zoning policies allowing reasonable mixes of various uses could support higher level of physical activity. While zoning regulations can encourage people to be more car independent, it may act as a major obstacle to develop active environments (Mineta, 2002).

Therefore, land use policies and zoning strategies influence individuals’ travel mode choice by locating different uses in various urban scales. A mix of destinations and proximity has been found to be strongly associated with walking for transport. McCormack (2014) argued that higher levels of physical activities will be achieved when there is more diversity of destinations.

The public transport system has been considered as a sustainable as well as social means of transportation (Lei and Church, 2010), which may lead to liveable and sustainable cities (Mamun, 2011). Public transportation provides long-term sustainability in terms of reducing highway congestion and transferring large numbers of people within considerable distances (Armstrong-Wright and Thiriez, 1987). This enhances systemic mobility, while decreasing the economic and environmental burdens of increasing private motorized traveling. Furthermore, improved public transport system provides mobility to those who do not access to automobiles (Mamun, 2011). In other words, Use of public transport is somehow considered within the definition of active transport as it often involves some walking or cycling to get connected to origins and destination of trips (Taniguchi et al., 2013). Findings of other studies have indicated that density, land use mix, and accessibility to subways negatively affects motorized trips while distance from CBD to the workplace or home are positively related to automobile usage. As well, mixed use developments with more diversity have a large share of active internal trips and less traffic impacts. Walkable areas with good levels of public transport accessibility have a significant share of walking/public transport trips. Centrally located mixed use developments both in small and large scale generate fewer motorized trips (Ewing et al., 2011; Jun et al., 2013).

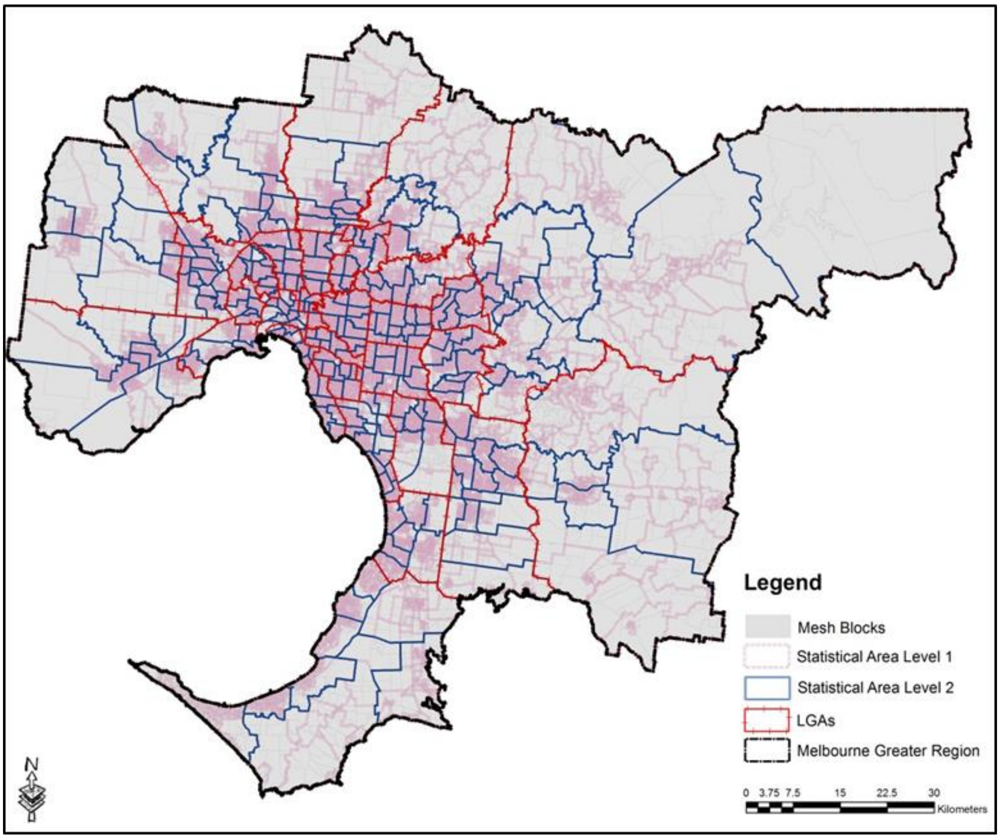
This study investigated the influence of built environment factors including land use mix entropy index, roadway measure and public transport accessibility along with socioeconomic factors on transport mode choice. The following sections discuss study area and dataset, methods, results, discussion and conclusion.

This study investigated the influence of built environmental factors including land use mix entropy index, roadway measure and walkability index along with socioeconomic factors on active transportation. The following sections discuss dataset, explanatory variables, method, results, discussion and conclusion.

2. Study Area and Data

Melbourne is the capital and most populous city in the state of Victoria, Australia with the approximate area of 9,900 km2. Based on Australian Statistical Geography Standard (ASGS), Melbourne has been divided into 53057 mesh blocks, 9510 statistical area level 1 (SA1), 277 statistical area level 2 (SA2) and 31 local government areas (LGA). SA1 can be defined as neighborhood scale and SA2 almost cover the suburbs. In this study, built environmental factors have been calculated based on SA1 level boundaries. Figure 1 shows the Melbourne greater region with geographical subdivisions.

Figure 1: Geographical subdivision in Melbourne region



Data has been provided from Victorian Integrated Survey of Travel and Activity (VISTA, 2009). It was a cross sectional survey conducted from 2009 till July 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. Randomly selected residential properties, data have been collected regarding demographic, trip information and car ownership. Based on response rate of 47%, there were 16411 households (42002 individuals) responding. In this research, only residents within MSD (22201 individuals) have been considered (www.dtpli.vic.gov.au/ transport). The VISTA recorded travel in the form of trip stages where a “trip stage” is a segment of travel with a single purpose and mode. The data contained the details information of 93902 trips stages of 80353 numbers of trips made by 22184 individuals in Melbourne region. There were 93,902 commuting trips in the VISTA data (Table 1). Approximately 68% made by private cars, 11% by non-motorized modes and one-fifth of total trips (19.5% of total trips) were taken by public transport.

Table 1: Number and Percent of trips made by different modes in the Melbourne region

Transport Modes	Frequency	Percent	Cumulative Percent
Vehicle Driver	42989	45.8	45.8
Vehicle Passenger	21073	22.4	68.2

Motorcycle	174	.2	68.4
Private Motorized	64236	68.4	-
Walking	9625	10.3	78.7
Bicycle	1340	1.4	80.1
Non-Motorized	*10965*	*11.7*	-
Public Bus	3230	3.4	83.5
Train	11095	11.8	95.3
Tram	3999	4.3	99.6
Public Transport	*18324*	*19.5*	-
Other	377	.4	100
Total	93902	100.0	

3. Methods

Methodology used in this study is Multinomial Logistic regression (MNL) Model using SPSS V.22. This model examines the likelihood of using different transport mode considering socioeconomics and built environments factors. Odds Ratio (OR), calculating in this model, shows the probability that individuals may go for specific mode of transport in comparison to the reference category. In this study four modes of private cars, walking, cycling and public transport is considered for analysis. In followings, explanatory variables used in this study are described.

3.1. Land use mixed entropy index (EI)

Variables were mainly considered in two groups, socio-economic variables, including age, gender, employment type, household income and number of vehicles in households; and built environment factors includes roadway measure, land use mix entropy and public transport access. Land use mix entropy index was calculated using Equation (1) (Lee et al., 2014). The values vary from 0 to 1, while 1 indicates a perfect balance among different type of land uses and 0 shows the homogeneity.

$$EI_i = -\left(\sum_{j=1}^{J} \frac{P_j . \ln P_j}{\ln J}\right) \quad (1)$$

where EIi 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 centers, have been chosen to calculate LU mix index entropy. These categories are defined from ten main uses categories defined by Australian Valuation Property Classification Codes (AVPCC) (Morse-McNabb, 2011).

3.2. Roadway Measure (RM)

Roadway measure considered as another built environmental factor which examines how long the network spreads over an area. It is quantified by total roadway length divided by total area where the distance is normalized by $100m^2$.

3.3. Public transport accessibility index (PTAI)

Public transport accessibility calculated using Public Transport Accessibility Index (PTAI) (Saghapour et al., 2016). PTAI measuring the levels of public transport access is built for the Melbourne's 9510 SA1. This approach computes the level of access by public transport for points of interest. The PTAI provides a 6 level rating scale of public transport accessibility which includes measures such as access walk time, service frequency and waiting time as well as population density ratio in walking catchments and SA1s as shown in equation (2).

$$PTAI_{SA1} = \sum_{j=1}^{J}\sum_{i=1}^{I}\left(\frac{D_{B_{ij}}}{D_{SA1}}\right) * WEF_{SA1} \tag{2}$$

Where $PTAI_{SA1}$ denotes the level of access to public transport; D_{Bij} presents the population density of walking buffer i for public transport mode j; D_{SA1} denotes the population density of the SA; and WEF_{SA1} is the weighted equivalent frequency in the SA1. In this approach, accessibility is calculated for the spatial coverage of each SA1 which is covered by walk buffers to public transport stops/stations and also their frequencies. The index also counts the overlapped buffer areas. For instance, where there is a place within possible walking distance to a both bus and tram stop, measurements are double counted, which indicates that those areas have a higher level of accessibility to public transport. A higher value of the PTAI indicates a higher level of accessibility. The index can be allocated to 6 categories of accessibility levels where category 1 represents a very poor level and level 6 represents an excellent level of accessibility. A value of 0 indicates that there is either no accessibility or population in a specified SA1.

4. Analysis and Results

Analysis of variance (ANOVA) is carried out to compare the descriptive statistics for travel time by spent on different modes of transport in dataset. Results are presented in Table 2, as shown average travel time spent on trips by public transport has been 22.41 minutes and average travel time for walking trips has been 9.92 minutes. This number is reported as 23 minutes for bicycle trips.

Table 2 Compare means of travel time spent in different transport modes

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
Private Motorized Vehicle	65154	18.68	17.846	.070	18.54	18.82
Walking	19711	9.92	8.363	.060	9.80	10.03
Cycling	1437	23.19	19.520	.515	22.18	24.20
Public Transport	7441	22.41	16.163	.187	22.04	22.77
Total	93743	17.20	16.673	.054	17.10	17.31

Contents of the Table 3 show the descriptive analysis of variables. Average age was 38 years and household income was mostly between third and fourth categories varied from 1100 to 2499 ($/week). Average number of vehicles recorded in households is about 2. Among built environment factors, the average for EI, RM and PTAI were 0.4, 1.3 and 36.1, respectively. The mean value for EI represents that there was average distribution of different uses among the study area.

Table 3 Descriptive statistics of sample

Factors	Mean	Std. Deviation	Min	Max	Skewness	Kurtosis
Age	37.77	19.98	0.00	97.00	0.03	-0.74
Gender	1.53	0.49	1.00	2.00	-0.12	-1.98
Employment Type	2.88	1.78	1.00	5.00	0.18	-1.76
Household income	3.63	1.33	1.00	5.00	-0.57	-0.89
Car ownership	1.95	1.02	0.00	9.00	1.02	2.84
EI	0.40	0.15	0.00	0.87	0.79	0.45
RM	1.33	0.77	0.00	6.37	1.22	2.93
PTAI	36.15	491.62	0.00	11012.50	21.95	486.07

* Employment status categories: full time, part time, casual, not-working and other.
** Household income ($/week): less than 650, 650-1099, 1100-1649, 1650-2499 and more than 2500)

MNL model was applied for trip stages undertaken by four modes of transport (private cars, walking, cycling and public transport). As explained in the previous section, this model presents the odds ratio (OR) for variables. OR>1 and OR<1 show the more and less likelihood for a mode to be chosen by individuals with respect to a specific characteristic. The odds ratio of a coefficient indicates how the probability of the outcome falling in the comparison group compared to the probability of the outcome falling in the referent group changes with the changes in variables in the model. In general, if the odds ratio < 1, the outcome is more likely to be in the referent group and vice versa. Reference category has defined as private motorized vehicles, and each mode has been compared to the reference category (Hosmer Jr et al., 2013).

Table 4 shows the model fitting summary. This is the probability getting a likelihood ratio (LR) test statistic being as extreme as, or more so than the observed statistic under the null hypothesis; the null hypothesis is that all of the regression coefficients in the model are equal to zero. As shown in Table 5, the small p-value from the LR test, <0.001, would lead us to conclude that at least one of the regression coefficients in the model is not equal to zero. In other words, the results show that the model was fitted significantly on the data ($\chi 2$ = *129062.73, $p<0.001$*).

Table 4 Model Fitting Information

Model	Model Fitting Criteria	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	140643.365			
Final	129062.729	11580.636	33	.000

Table 5 presents the estimated multinomial logistic regression coefficients for the models. An important feature of the multinomial logit model is that it estimates m-1 models, where m is the number of levels of the outcome variable. Private cars' category is treated as the referent group and therefore, a model was estimated for walking, cycling and public transport mode relative to the private cars separately. Thus, since the parameter estimates are relative to the referent group, the standard interpretation of the multinomial logit is that for a unit change in the predictor variable, the logit of outcome m relative to the referent group is expected to change by its respective parameter estimate (which is in log-odds units) given the variables in the model are held constant. Flexible working hours has no significant impact on choosing the bicycle as a mode of transport. Between built environment factors RM had a significant impact on choosing public transport modes. Furthermore, walking trips have not been significantly influenced by working from home types of employment.

ORs in Table 5 are the exponentiation of the coefficients. If age were to increase by one point, the multinomial log-odds for preferring walking to the private cars would be expected to decrease by 0.002 units while holding all other variables in the model constant. In contrary, by the one-point increase in the level of household income, the likelihood of preferring the walking to the private cars would increase by 0.063 units. These two variables have the same effect on cycling trips as well.

Table 5 MNL Model for Transport Modes*

	Walking			*Cycling*			*Public Transport*		
Factors	**Coe.**	**Wald test**	**OR**	**Coe.**	**Wald test**	**OR**	**Coe.**	**Wald test**	**OR**
Intercept	-2.46	1650.62[a]	-	-5.81	1228.22[a]	-	-0.89	370.05[a]	-
Age	-0.002	13.04[a]	0.99	-0.01	61.63[a]	0.98	-0.01	781.43[a]	0.98
Gender (Male)	-0.09	15.77[a]	0.91	1.20	39.84[a]	3.34	0.79	165.40[a]	2.22
Household Income	0.06	42.91[a]	1.06	-0.54	224.90[a]	0.58	-0.62	2943.57[a]	0.53
Car Ownership	-0.44	953.89[a]	0.64	0.33	256.11[a]	1.38	0.15	727.44[a]	1.17
Employment Type									
Fixed Hours	-0.49	311.70[a]	0.61	0.19	6.93[a]	1.21	0.45	421.96[a]	1.57
Flexible Hours	-0.42	140.81[a]	0.65	0.14	2.62	1.16	0.26	91.09[a]	1.30
Roistered shifts	-0.29	36.33[a]	0.74	0.67	41.08[a]	1.97	0.66	373.39[a]	1.94
Work from home	-0.08	1.34	0.92	0.41	5.29[a]	1.51	-0.39	26.10[a]	0.67
EI	1.85	583.59[a]	6.35	0.13	16.56[a]	1.14	0.07	46.21[a]	1.08
RM	0.16	138.63[a]	1.18	0.20	64.97[a]	1.22	-0.001	0.02	0.99
PTAI	0.13	327.86[a]	1.14	0.82	197.21[a]	2.28	0.03	3.75[b]	1.03

* Reference Category is Private car
[a] Significant at 99% level
[b] Significant at 95% level.

5. Discussions and Conclusions

In this paper, we examined different socioeconomic and built environment factors influencing transport mode choice. Socioeconomic variables included age, gender, employment status, car ownership and household income along with the built environment variables were used to investigate their possible impacts on transport mode choice. The built environment factors were defined as land use mix entropy index, roadway measure and accessibility to public transport. For measuring the access levels to public transport the PTAI (Saghapour et al., 2016) has been used. This index quantifies the accessibility within geographical areas incorporating population density. PTAI originally introduced for Melbourne region; however, as long as equation elements are available, the index is straightforward to apply to other geographical areas.

Both groups of variables had significant impacts on transport mode choice. As presented in table 6, except home office working types other factors significantly influenced walking trips.

However, for trips made by public transport modes, RM had no significant impacts. The key findings of the analysis can be summarized as follows:

- As number of vehicles in households increase the probability of walking trips (OR=0.64, p<.001) decreased;
- Individuals with full time careers are more likely to go for public transport (OR=1.168, p<.001), while people with part time or casual jobs are less likely to go for walking (respectively, OR=.709, p<.001 and OR=.835, p<.001);
- Males are more likely to go for cycling (OR=3.34, p<.001) or public transport (OR=2.22, p<.001);
- As income level increases people are less likely to go for walking (OR=0.58, p<.001) as well as public transport (OR=0.53, p<.001);
- Individuals living in the areas with more diversity of uses, are more likely to go for walking (OR=6.35, p<.001), cycling (OR=1.14, p<.001) and public transport (OR=1.03, p<.001);
- As roadway measure increased the probability of walking (OR=1.18, p<.001) and cycling increased (OR=1.22, p<.001);
- Individuals living in the areas with higher accessibility to public transport, are more likely to go for walking (OR=1.14, p<.001), cycling (OR=2.28, p<.001) and public transport (OR=1.03, p<.001).

Hence, it can be concluded that in neighbourhoods with higher diversity in uses and higher levels of access to public transport, the level of physical activities can be higher. However, cultural and social factors as Cairns et al., (Cairns et al., 2014) argued may affect travel behaviors, as well. Another limitation of the study is that the road measure was calculated in terms of density regardless of how well the roads are connected. Future studies may consider those factors as well as neighborhood design factors to have a better understanding of travel behaviors.

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