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# Evaluation of Neighbourhood Characteristics and Active Transport Mode Choice

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***Abstract*—**One of the common aims of transport policy makers is to switch people's travel to active transport. For this purpose, a variety of transport goals and investments should be programmed to increase the propensity towards active transport mode choice. This paper aims to investigate whether built environment features in neighbourhoods could enhance the odds of active transportation. The present study introduces an index measuring public transport accessibility (PTAI), and a walkability index along with socioeconomic variables to investigate mode choice behaviour. Using travel behaviour data, an ordered logit regression model is applied to examine the impacts of explanatory variables on walking trips. The findings indicated that high rates of active travel are consistently associated with higher levels of walking and public transport accessibility.

***Keywords*—**Active transport, public transport accessibility, walkability, ordered logit model.

## I. Introduction

PROVIDING efficient walkable neighbourhoods is one of the main objectives of policy makers and planners throughout the world. In recent decades, automobile-oriented developments along with the increase in car ownership have encouraged people to have more passive travels. High level of car dependency is not only affecting quality of life, but critically threatening people's health. On the other hand, the growing use of private motorized vehicles has resulted in critical issues such as traffic congestion and environmental impacts. These phenomena mean 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 sedentary travel behaviour replacing active forms of transport. The way in which cities and transport corridors are designed and developed has been found to be an important contributor to physical inactivity [1]-[3]. Australia has been categorized among countries with highest car ownership [4] and particular groups of people such as youth, seniors, low-income households and aboriginals have found to encounter difficulties in accessing work, education and social or cultural activities [4]-[6].

This paper presents a review of previous researches in this area. There are numerous studies focusing on measuring walkability. However, there are limited works which consider the walking distances to different destinations as one of the main barriers of active transport. Therefore, the current study describes a new concept to measure walking accessibility followed by an implementation of the new index in metropolitan Melbourne, Australia. The paper is also presenting the results of a comparison of the new index with one of the most common approaches measuring walking accessibility. The following section provides background information. The methodology section describes the approach of the computation for the index, analysis and results of the application of the WAI in the Melbourne region, along with a comparison of the results between the new index and existing approaches is also presented. Discussions and conclusions summarize the key findings of the research, and lastly, the limitations of the study and future research direction are outlined.

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## II. Background

The link between the built environment and travel behaviour has received considerable research attention in recent decades [7], [8]. The arrangement or 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 active travels. 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 [9], [10]. Transport and urban planners, as well as health practitioners have recently turned towards promoting physical activity by environmental solutions.

Low density, less mixed-use and less walkable neighbourhoods and suburbs in metropolitan areas intensify automobile dependency amongst residents. In 2012, Lee et al. conducted a study to examine the impact of the built environment on individuals' mode choice. The results of their research indicated that built environment features including population density, entropy index, and connectivity significantly influenced an individual's mode choice depending on the trip destinations and trip purposes [9].

The present study aims at investigating whether areas with more walkable neighbourhoods with higher levels of access to public transport stops/stations would have higher rates odds of active transportation.

## III. Methods

### A. Study Area

A database of Mesh Blocks from the 2011 Census for the Melbourne Region was accessible from the Australian Bureau of Statistics (ABS) [1]. 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 ABS [1], 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 other words, these statistical areas are completely nested within each other.

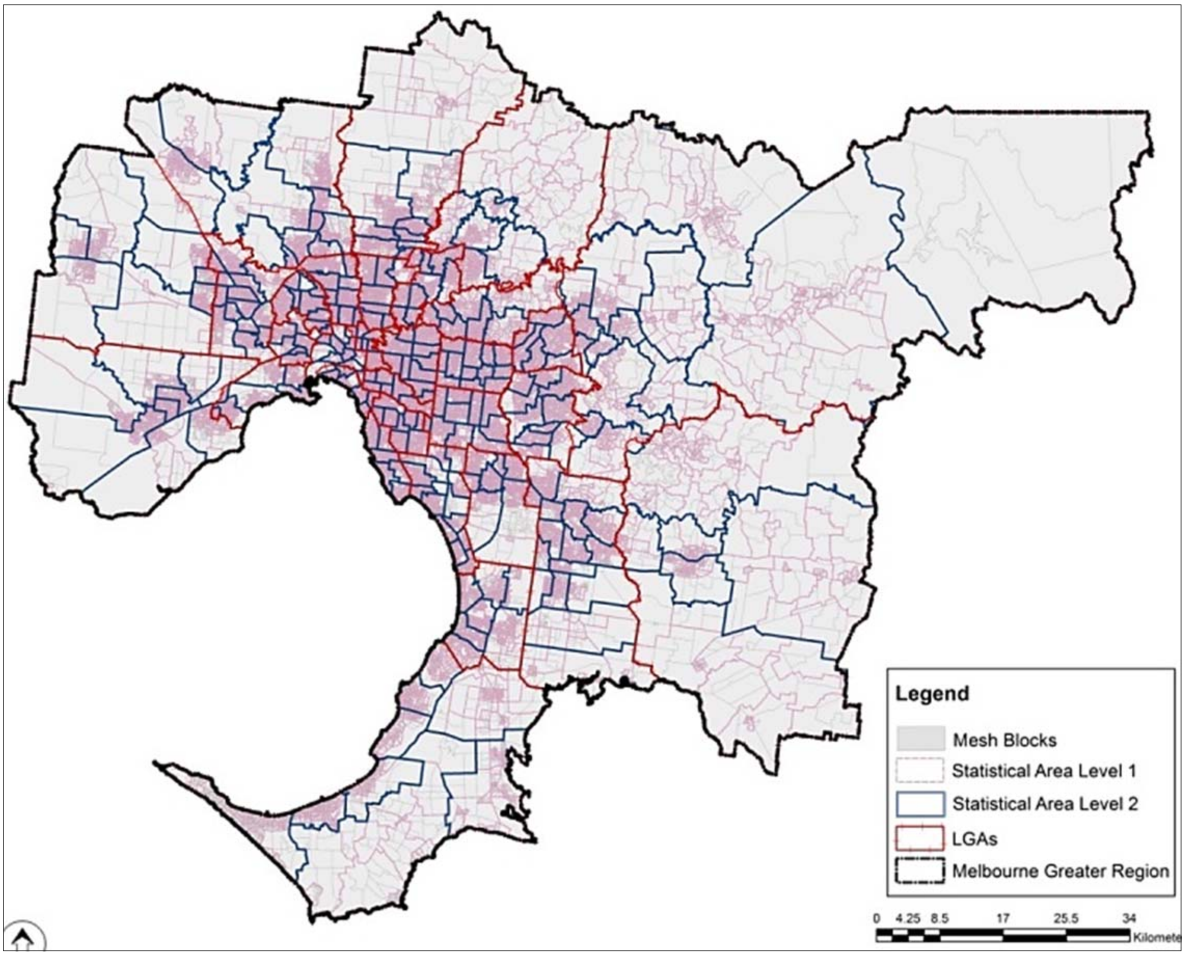


Fig. 1 Geographical Areas in Melbourne Region [1]

### B. Dataset

The Victorian Integrated Survey of Travel and Activity (VISTA) data set [11] was adopted to assess and evaluate the index. The VISTA is a cross-sectional survey conducted from 2009 until 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. A stratified random sampling technique was used to select residential properties. Data were collected regarding demographic, trip information and car ownership. A total of 16,411 households (42,002 individuals) responded, with a response rate of 47%. This paper only considered responses within the MSD (22,201 individuals). 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. Hence, the dataset contains the details of 93,902 trips stages made by 22,184 individuals in the MSD.

### C. Built Environment Variables

1. Public Transport Accessibility Index (PTAI)

Public transport accessibility is calculated using the PTAI [12], [13]. PTAI measuring the levels of public transport access is built for Melbourne's 9510 SA1. This approach computes the level of access by public transport for points of interest. The PTAI provides a six-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 (1).

$$\text{if } D_{B_{ij}} = 0\,;\;\; PTAI_{SA1} = \sum_{j=1}^{3}\sum_{i=1}^{I}\left(1+\frac{D_{B_{ij}}}{D_{SA1_i}}\right) * WEF_{SA1_i}$$

$$\text{if } D_{B_{ij}} \neq 0;\;\; PTAI_{SA1} = \sum_{j=1}^{3}\sum_{i=1}^{I}\left(\frac{D_{B_{ij}}}{D_{SA1_i}}\right) * WEF_{SA1_i} \qquad (1)$$

where PTAISA1 denotes the level of access to public transport; DBij presents the population density of walking buffer i for public transport mode j; DSA1 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 six 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 no population in a specified SA1. In areas with no population or non-residential uses, the PTAI is equal to $WEF_{SA1}$.

Fig. 2 illustrates the distribution of PTAI categories in the Melbourne region. As explained above, the PTAI is categorized into six bands. The first category represents a very poor accessibility, while the last category corresponds to an excellent level of accessibility to public transport. The first and last categories have been further sub-divided into sub-levels to provide better clarity. High levels of accessibility from good to excellent are mostly concentrated in the inner parts of the Melbourne region. As shown, outer Melbourne, where public transport is mainly provided by public buses have lower levels of accessibility in comparison to the inner parts and the CBD.

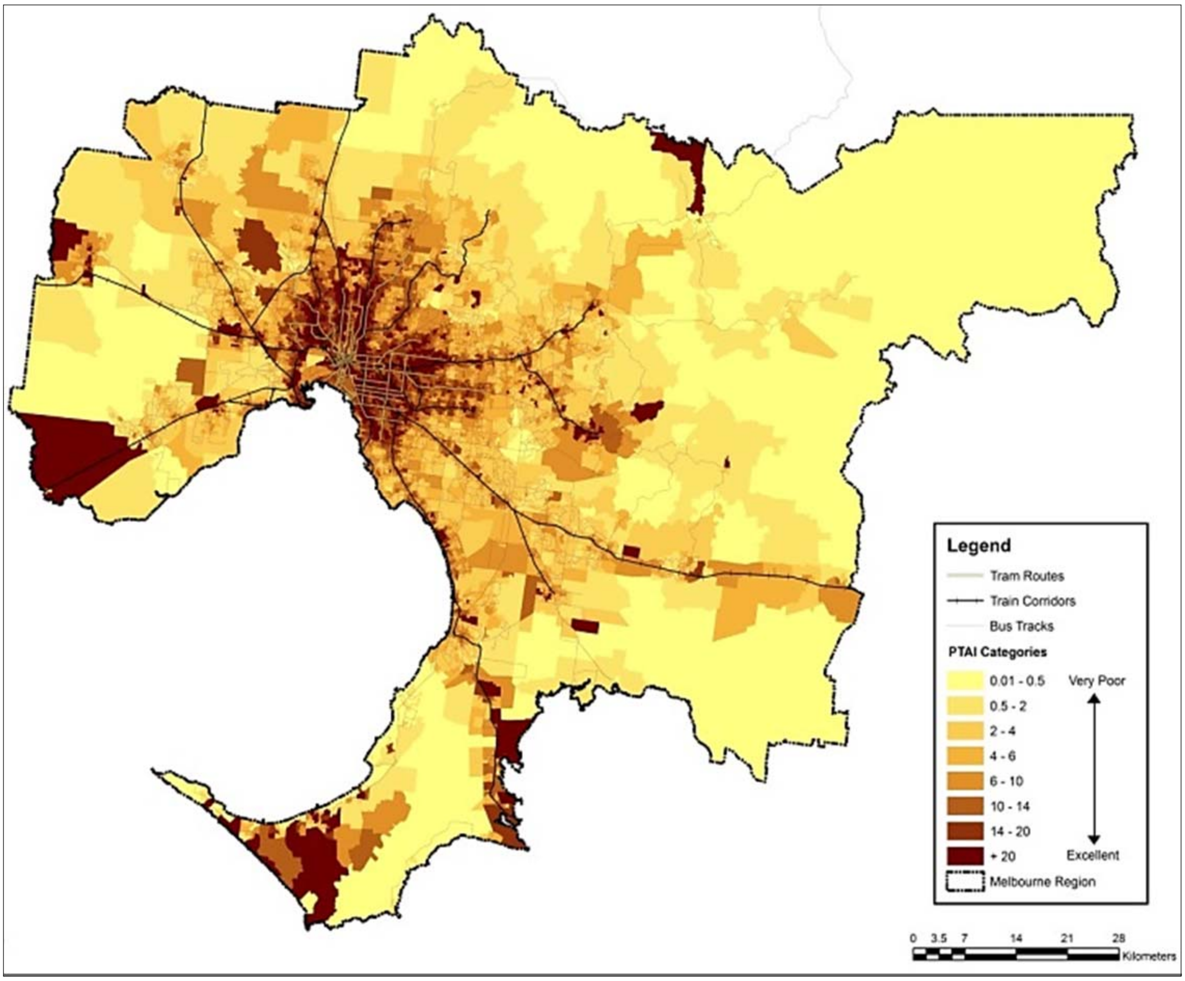


Fig. 2 Distribution of PTAI categories in Melbourne region

2. Walkability Index (WI)

As explained, the WI is one of the most common approaches used in calculating walkability [14]-[20]. The typical form of the WI expression is as:

$$WI = (\text{Zscore}_{\text{LUMIX}}) + \left(\text{Zscore}_{\text{Residential}_{\text{Density}}}\right) + \left(\alpha \text{Zscore}_{\text{Connectivity}}\right) \tag{2}$$

The walkability index (WI) for each SA1 is calculated as the sum of the z-scores for the three components included in the index, i.e. residential density (ratio of residential units to the residential area), street connectivity (intersection density), and land use mix. Land use mix, or entropy score (LUMIX), indicates the degree to which a diversity of land use types are present. Six different land use categories including residential, commercial, industrial, transport and infrastructure, community services and sport and recreation centres, have been chosen to calculate the entropy index, using (3). These categories are defined from 10 main land use categories defined by the Australian Valuation Property Classification Codes (AVPCC) [21].

$$\mathrm{LUMIX} = -\left(\sum_{\mathrm{j}=1}^{\mathrm{J}} \frac{\mathrm{P_j . lnP_j}}{\mathrm{lnJ}}\right) \quad (3)$$

where, LUMIXi indicates the entropy index within a buffer i; Pj represents the proportion of land use type j, and J is the number of land use categories. Values are normalised between 0 and 1, with 0 being single use and 1 indicating a completely even distribution of the six uses. WIs were computed for SA1s, using (2). Finally, the z-score of the connectivity shows the intersection density within SA1s.

The Australian Urban Research Infrastructure Network (AURIN) [22] has been developed the WI for areas within the Melbourne Region using the above equation. They provide a web-based environment for calculating WIs for different statistical subdivisions in the Melbourne area. This study applies the same method for calculating the WIs for SA1s. It should be noted that different studies consider different values for $\alpha$ as the coefficient for normalized values of connectivity. However, AURIN has defined $\alpha$ to equal 1. The calculated WIs for SA1s vary from -1.8 to +50.8.

### D. Modelling and Interpretation

Ordered Logit regression models were used to explore the correlations of PT trips and socioeconomic characteristics, as well as built environment factors. 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. Interpretation of the ordered logit estimates is not dependent on auxiliary parameters. Secondary parameters are used to differentiate the adjacent levels of the response variable. ORs are the proportional odds ratios. They can be obtained by using the exponential function with the coefficient estimate, (i.e. $e^{Coef.}$). The interpretation OR is that for a one-unit change in the predictor variable, the odds for cases in the level of the outcome that is greater than k versus less than or equal to k, where k is the level of the response variable are the proportional odds times larger [23]. A typical model for the cumulative logits is shown in (4): 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.

$$logit[P(Y \le j)] = \alpha_j + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n = \alpha_j + \acute{\beta} X \quad (4)$$

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.

## IV. Data Analysis

Socioeconomic characteristics including age, gender, car licence, car ownership, employment type, household (HH) size and household (HH) structure along with PTAI and WI as built environment indicators were employed to run an ordered logit regression models on VISTA dataset. Table I shows the explanatory variables and their definitions.

The number of walking trips is defined as ordered dependant variables in the model. The VISTA dataset contains 17,089 walking trips in the form of trip stages. The reason behind using the trip stages for analysis is that walking trips are considered as the shortest one; while covering all trip purposes even changing transport modes. Table II shows the frequency of walking trips within SA1s which are categorised into five groups from very low to very high.

TABLE I
EXPLANATORY VARIABLES AND DEFINITIONS

| Variables | Description |
|---|---|
| *Socio-demographic* | |
| Age | Age of the respondent |
| Sex | Gender |
| Licence | Driver licence |
| Employment Type | Type of the work |
| HH Size | Usual number of residents in the household |
| HH Structure | Demographic structure of household |
| Car No. | Number of vehicles in the household |
| *Built Environment* | |
| PTAI | Public Transport Accessibility Index |
| WI | Walkability Index |

Note: HH Structure is converted to five dummy variables: sole person, couple no kids, couple with kids, one parent and other; employment type is converted into three dummy variables: Full time, part time and other; sex and driver licence are defined as binary variables.

TABLE II
FREQUENCY OF WALKING TRIPS

| Walking Trips Categories | Walking Trips* | Frequency | Percentage |
|---|---|---|---|
| Very Low | 1 - 9 | 2,973 | 18.05 |
| Low | 9 - 14 | 3,420 | 20.76 |
| Average | 15 - 23 | 3,314 | 20.12 |
| High | 24 - 39 | 3,348 | 20.32 |
| Very High | 40+ | 3,419 | 20.75 |
| N/A | Total | 16,474 | 100.00 |

*Outliers were removed from analysis.

Table III suggests the descriptive statistics for the variable used in the ordered logit models. These statistics were calculated for 77,020 trip stages records. In terms of socio-demographic characteristics, the respondents were 38 years old on average and equality distributed in terms of gender. The average of HH Size shows that respondents were almost all from households with a usual number of about three residents.

In order to evaluate the impacts of explanatory variables on the number of walking trips, an ordered logistic regression model was estimated. In terms of association, as presented in

Table IV, being a single parent, the number of cars in a household and being a male are negatively associated with public transport trips. Considering the built environment measures a larger increase in the log odds of being in a higher level of walking trips is expected, while PTAI and WI increase.

TABLE III
DESCRIPTIVE STATISTICS

| Variable | Mean | S.D. | Min | Max |
|---|---|---|---|---|
| Walking Trips | 26.80 | 20.09 | 1.00 | 108.00 |
| Age | 36.88 | 19.31 | 0.00 | 90.00 |
| Gender | 1.54 | 0.50 | 1.00 | 2.00 |
| Licence | 1.29 | 0.45 | 1.00 | 2.00 |
| HH Size | 3.00 | 1.37 | 1.00 | 6.00 |
| Employment | 2.89 | 1.78 | 1.00 | 5.00 |
| HH Structure | 2.80 | 1.13 | 1.00 | 5.00 |
| Car No. | 1.78 | 0.85 | 1.00 | 4.00 |
| PTAI | 13.01 | 9.94 | 0 | 49.7 |
| WI | 0.61 | 1.76 | -1.78 | 12.42 |

n=16474 walking trips

TABLE IV
OUTPUTS OF THE ORDERED LOGIT MODEL FOR WALKING TRIPS

| Parameters | Estimates | S.E. | ORs | *p*-value |
|---|---|---|---|---|
| Age | -0.0006 | 0.0009 | 0.999 | 0.5553 |
| Gender (Male)** | -0.0718 | 0.0301 | 0.931 | 0.0171 |
| License (Yes)** | 0.1159 | 0.0467 | 1.123 | 0.0131 |
| HH Size** | 0.1128 | 0.0184 | 1.119 | <.0001 |
| *Employment Type* | | | | |
| Full Time* | 0.0767 | 0.0406 | 1.08 | 0.0588 |
| Part Time** | 0.1313 | 0.0497 | 1.14 | 0.0083 |
| Casual** | 0.1502 | 0.0622 | 1.162 | 0.0158 |
| Unemployed* | 0.2100 | 0.1195 | 1.234 | 0.0788 |
| *HH Structure* | | | | |
| Sole Person | -0.1009 | 0.0822 | 0.904 | 0.2196 |
| Couple with kids | 0.0457 | 0.0624 | 1.047 | 0.4642 |
| Couple without kids | 0.0259 | 0.0528 | 1.026 | 0.6238 |
| Single parent*** | -0.3384 | 0.0724 | 0.713 | <.0001 |
| Car No.*** | -0.132 | 0.0200 | 0.876 | <.0001 |
| WI*** | 0.1758 | 0.0096 | 1.192 | <.0001 |
| PTAI*** | 0.412 | 0.0104 | 1.51 | <.0001 |

Note: (1) number of walking trips are converted to five dummy variables by using level 1 (very low): less than 9 trips, level 2 (low): 9-16 trips, level 3 (average): 17- 26 trips, level 4 (high): 27-41 trips, and level 5 (very High): more than 42. Level one was the reference level. (2) Threshold coefficients: 1|2 → -0.467, 2|3→ -1.615, 3|4→ -2.579; 4|5→ -3.727; (3) Significance codes: $p$ < 0.001 '***', 0.01 '**', 0.1 '*'. (4) Overall goodness-of-fit: AIC = 44,105.2; -2LogL = 44,069.2; SC= 44,241.61.

## V. DISCUSSIONS AND CONCLUSIONS

Overall, accessibility can be considered as a measure of locational disadvantage, particularly from a social perspective planning. As Kim et al. [24] argued, the promise of the planning and policy actions to improve walkability is that walking can be encouraged, by enhancing the quality of the built environment which can affect travel walking distance, walking time and transport mode choice. On the other hand, the use of public transport is considered within the definition of active transport, as it often involves some walking or cycling to get connected from the origin to destination of trips [25]. In this regard, providing high levels of accessibility for public transport systems with good connectivity can promote active transport and sustainability.

As Peiravian et al. argued [15] neighbourhoods in which improvements in the built environment are supported and encouraged can produce safe walkability and improve living conditions due to increased economic activity. Moreover, Lamíquiz et al. [26] claimed how as an urban area is configured influencing the pedestrian needs, because it makes the built environment more attractive, safer and closer, by influencing and bringing together the location of shops and services, etc.

This paper presented the results of research aimed to examine the impacts of built environment attributes of neighbourhoods on active transportation. PTAI and WI as accessibility measurements along with a series of socioeconomic variables employed to evaluate the impacts of explanatory variables on walking trips. VISTA dataset used to run an ordered logit model on the selected variables.

Key findings of the study indicated that residents who live in more walkable areas (OR = 1.2, p<.001) with higher levels of accessibility to public transport stops/stations (OR = 1.5, p<.001) are more likely to have more walking trips. In addition, people from a bigger family size are more likely to have more walking trips.

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