JOURNAL OF ADVANCED TRANSPORTATION
J. Adv. Transp. 2016; **50**:1785–1801
Published online 21 November 2016 in Wiley Online Library (wileyonlinelibrary.com). DOI: 10.1002/atr.1429

Modeling access to public transport in urban areas

Tayebeh Saghapour[1]*, Sara Moridpour[1] and Russell G. Thompson[2]

[1]*Department of Civil, Environmental and Chemical Engineering, RMIT University, Melbourne, Australia*
[2]*Department of Infrastructure Engineering, The University of Melbourne, Melbourne, Australia*

SUMMARY

It is important to measure public transport accessibility to help improve the sustainability of transport systems in metropolitan areas. Although many studies have defined different approaches for measuring public transport accessibility, there have been limited methods developed for measuring accessibility levels that incorporate spatial aspects. Population density is an important distributional indicator that has also been ignored in previous methods developed for quantifying accessibility. This paper outlines the research context for measurement of public transport accessibility and then describes a methodology developed as well as an application the Public Transport Accessibility Index in Melbourne area, Australia. Using the Victorian Integrated Survey of Travel and Activity dataset, we applied separate-ordered logit regression models to examine how the new index performs with a series of predictor variables compared with two existing approaches. Key findings indicate that there is a higher probability of public transport patronage in areas with higher levels of accessibility. Furthermore, it was found using statistical modelling that the new index produces better results compared with previous approaches. Copyright © 2016 John Wiley & Sons, Ltd.

KEY WORDS: PTAI; accessibility; ordered logit model; population density

1. INTRODUCTION

Public transport (PT) is considered to improve sustainability as well as being a more social means of transportation [1], which may lead to increasing the liveability and sustainability of cities [2]. Public transportation provides long-term sustainability in terms of reducing highway congestion and moving large numbers of people over considerable distances [3]. This enhances systemic mobility, while decreasing the economic and environmental burdens of increasing private motorized travel. Furthermore, an improved PT system provides mobility to those who do not have access to automobiles [2]. In other words, use of PT is somehow considered within the definition of active transport as it often involves some walking or cycling to connect to trip origins and destinations [4].

A number of research studies have identified that persons living in many suburban areas within Australian metropolitan areas are significantly disadvantaged by current transport services [5–7]. More recently, research has indicated that increasing auto fuel prices and home loan interest rates has intensified the transport difficulties experienced by persons living in the fringe areas of Australian cities [8]. However, improving PT accessibility in terms of service coverage and availability may result in a more reliable transport system as a whole [2].

A substantial body of research has been conducted relating to measuring PT accessibility. Nevertheless, there is limited research on quantifying the PT accessibility incorporating spatial factors. Moreover, the importance of population density within geographical areas and its influence on the level of accessibility has largely been ignored. Hence, this study presents a new approach for measuring PT accessibility within geographical areas that integrates population density.

*Correspondence to: Tayebeh Saghapour, Department of Civil, Environmental and Chemical Engineering, RMIT University, Melbourne 3001, Australia. E-mail: tayebeh.saghapour@rmit.edu.au

This paper presents the results of a study aimed at objectively measuring PT accessibility by considering population density in the metropolitan area of Melbourne, Australia. The study contains four main parts. The first part after a review of previous research describes the calculation process for estimating the accessibility index. The following section presents the methodology, analysis and results of the models. The final section discusses the key findings and the implications of the approach.

2. BACKGROUND

Accessibility measures have been generally categorized into three groups, access to PT stops, duration of journeys by PT modes and access to destinations by PT modes [9]. A large number of studies measuring accessibility have focused on the proximity to a PT stop/station [10–13]. Some of these studies have measured accessibility levels by considering an administrative division to a PT stop. Currie [11] claimed that using an administrative division as an alternative for homes of all residents within a selected boundary can bias the results. To address this problem, some studies have measured accessibility from dwelling units to PT stops [10, 14, 15]. A key component in modelling access to PT stops is the walking distance. Typically, the maximum acceptable walking distance is considered as 400 and 800 m for PT stops or stations [7, 11, 16].

Although physical access to PT stops is important, the time taken to travel between an origin and destination by PT modes can be considered as another significant factor [1]. Along with studies that focus on access to PT stops, some studies focus on the duration of a journey undertaken by PT modes [17, 18]. O'Sullivan *et al.* [17] measured PT accessibility generating maps of accessible areas with the same travel time. In another study, Cheng and Agrawal [19] introduced an accessibility measurement tool that calculates a PT service area considering travel time. Yigitcanlar *et al.* [20] introduced a Geographic Information System (GIS)-based Land Use and Public Transport Accessibility Index. This approach measures accessibility based on both PT travel time and walking distances utilizing GIS analysis techniques. They used an origin-based accessibility and destination-based GIS technique and applied the index to two pilot studies in the Gold Coast, Australia. Their findings indicated that the Land Use and Public Transport Accessibility Index could easily be applied to a range of different of land use categories.

Access to a destination using PT modes is another technique of measuring accessibility [21]. Huang and Wei [22] measured access via PT using business and industrial land parcels. They computed the distance between census tracks, as the origin points, and those parcels using a PT network.

Service frequency is a critical aspect of accessibility, which varies in different commuting times [9]. Several studies conducted using service frequency as a complement in their approach or as an independent measure. Service frequency-based measurements have been categorized into two general groups Mavoa *et al.* [9]. For the first group, a minimum service frequency standard has been adopted. This approach excludes the PT that does not meet the standard [21]. The second group includes all PT stops while using service frequency. For instance, using the number of trips per week for each stop or station [11] or category, the service frequency is measured by how often a PT mode arrives [20]. A needs-gap approach used by Currie [7] identified spatial gaps in terms of PT supply in Hobart, Australia. A more recent version of that approach was developed for metropolitan Melbourne [11]. These studies used a combined measure of service frequency and access distance, which was calculated for each census collector district (CCD). Among a series of service frequency methodological developments within this area, the PT accessibility level (PTAL) is a UK approach that measures the level of accessibility. The PTAL provides a six-level rating scale of PT accessibility, which includes measures such as access walk time, service frequency and waiting time. This approach calculates the level of access by PT to points of interest [11, 23].

A major weakness of existing approaches is that they assign a level of accessibility to areas without considering the population distribution within those areas. Therefore, the current study focuses on measuring access to PT stops while considering population levels in conjunction with walk time and service frequency. The following section presents the methodology, which describes the computation of the index.

3. METHODOLOGY

This study presents a method for measuring PT accessibility as well as modelling the number of trips undertaken by PT modes. In the first step, the Public Transport Accessibility Index (PTAI) is introduced that is an index for measuring the level of accessibility to PT in Melbourne's 9510 statistical areas level 1 (SA1s), the second smallest geographic area defined in the Australian Statistical Geography Standard [24, 25]. In order to define the index two factors, a weighted equivalent frequency (WEF) and the ratio of population density in SA1s and buffer areas (walking catchments of each PT stops/stations) are calculated. To calculate the PTAI, we adopted the following datasets.

3.1. Public transport stops/stations

Three modes of PT including public buses, trams and trains are considered. A database of bus and tram stops, train stations and PT routes and corridors were obtained from the Victorian Government's open data sources [26]. According to the database, the Melbourne region is covered by approximately 17 800 bus stops, 1700 tram stops and 240 train stations. These include almost 300 bus routes and a train system comprising 16 lines servicing the Greater Melbourne area (Figure 1) and suburban regions [27].

3.2. Public transport service frequency

Service frequency data are calculated from the timetable of each mode during the morning peak hours (7.00 to 9.00 hours). Timetables are accessible through the Public Transport Victoria website [28]. Based on the dataset, average walk times from POIs to the closest tram stops, bus stops and train

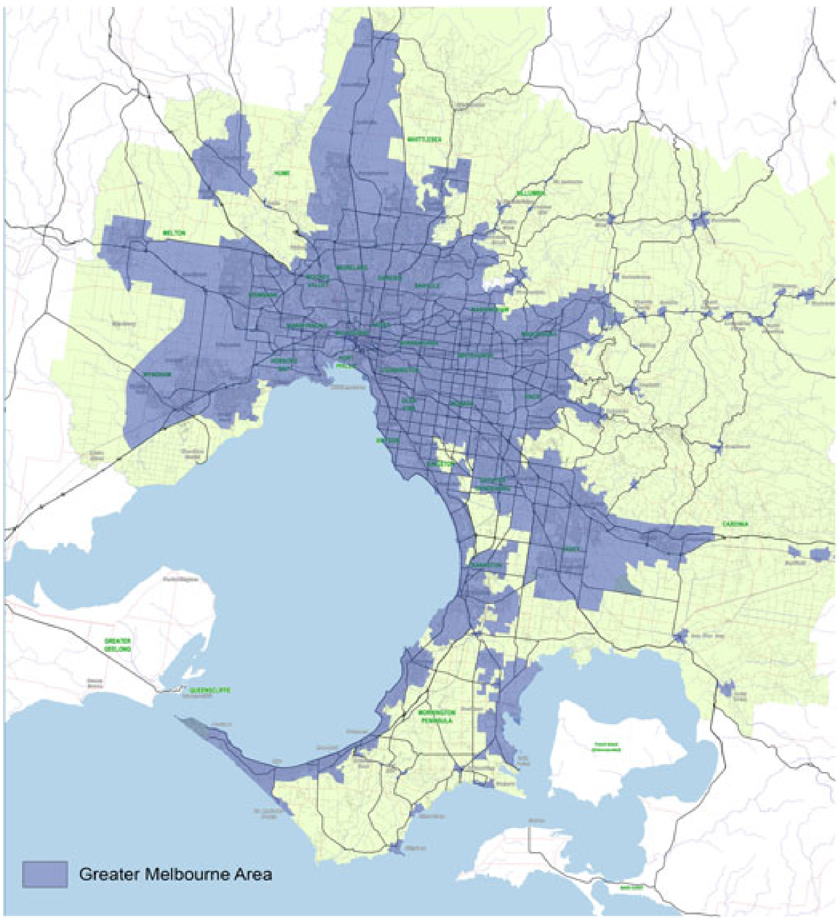

Figure 1. Greater Merbourne area.

DOI: 10.1002/atr

stations were 1, 5 and 7 min, respectively. Also, the average waiting time (AWT) for desired services from selected POI was 8, 2 and 5 min, correspondingly to the closest tram stops, bus stops and train stations.

3.3. Points of interests

A database of points of interests (POIs) was obtained from Australian Urban Research Infrastructure Network. This included urban centres, significant buildings, landmarks, public spaces, community facilities and indigenous locations, consisting of 15 588 points. Figure 2 shows the distribution of POIs and PT stops/stations.

3.4. Geographical areas

A database of Mesh Blocks from the 2011 Census for the Melbourne Region was accessed from Australian Bureau of Statistics (ABS). This dataset 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 ABS, the Melbourne region contains 53 074 Mesh Blocks, 9510 SA1s, 277 statistical area level 2 (SA2) and 31 local government areas (LGAs). Figure 3 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.

3.5. Victorian Integrated Survey of Travel and Activity dataset

The Victorian Integrated Survey of Travel and Activity (VISTA) dataset [29] has been provided from the VISTA. This was a cross-sectional survey conducted from 2009 till July 2010. It covers the Melbourne Statistical Division (MSD) as defined by the ABS, plus the regional cities of Geelong, Ballarat, Bendigo, Shepparton and Latrobe Valley. Data were collected regarding 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 trip stages undertaken

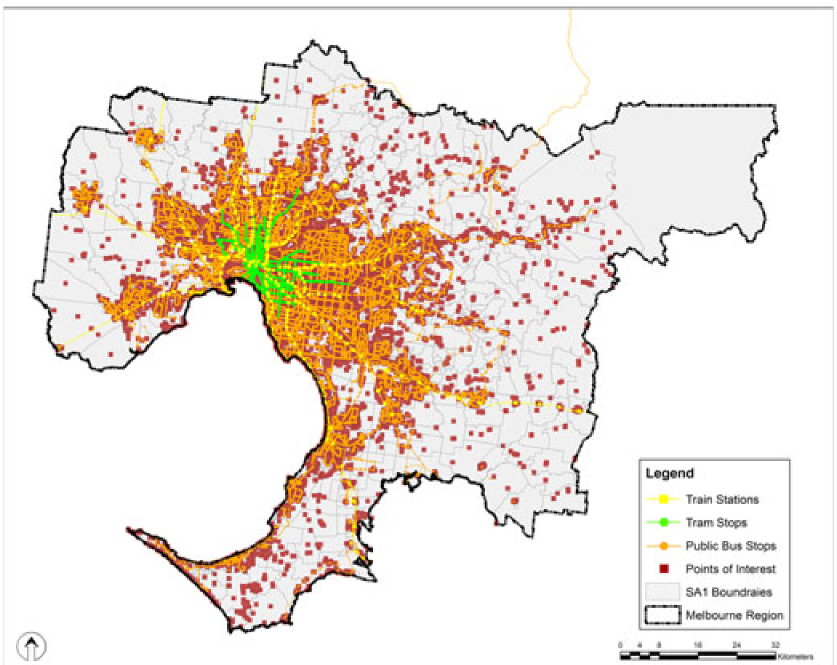

Figure 2. Distribution of points of interest (POIs) and public transport stops stations in Melbourne region.

DOI: 10.1002/atr

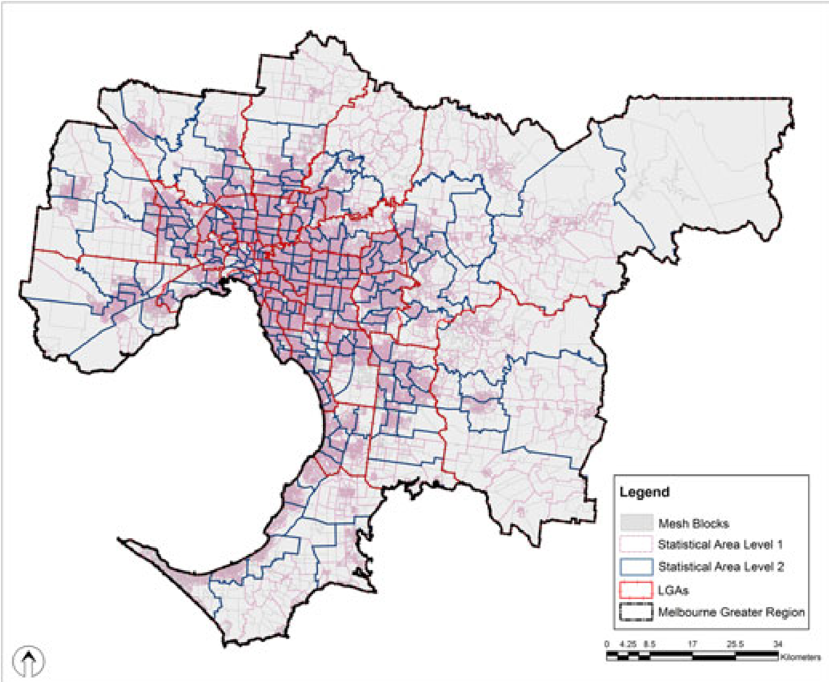

Figure 3. Geographical areas in Melbourne region.

by PT for assessing the index. According to VISTA definitions, trip stages are one-way travel movements from an origin to a destination for a single purpose (including change of mode) and by a single mode.

3.6. Approach

The current study aims to measure the level of accessibility for each SA1. The index measures the accessibility of a selected POI from the PT network considering walk time and service frequency, which reflects the estimated doorstep frequency. The PTAI also incorporates the share of population density in PT mode service areas and SA1s.

As mentioned, there are roughly 20 000 PT stops within the Melbourne region. This area is covered by about 16 000 POI including community services and facilities, landmarks, non-residential and buildings. In some SA1s, with two or more stops/stations, service areas have been merged using the same break value. Network analysis was conducted separately for each PT mode. For instance, considering a shopping centre as a selected POI, the distance of the nearest public bus stop has been measured. Thereafter, the same process was applied for the closest tram stop and train station. In other words, the following steps were calculated for all three modes. In terms of determining the service frequency for a POI, network analysis of closest facility was applied. The process of computing the accessibility index can be broken into the several stages from measuring the walking distances and times to estimating population densities in service areas of PT modes. The following sections describe the formulation of the index. The calculation of the WEF extends the approach used in measuring PTALs in London [30].

3.7. Walk time

The walking time was the first component calculated from a specified POI to the closest PT stops. Distances from the POI were converted to a measure of time assuming an average walking speed of 4.8 km/h or 80 m/min [30]. Walk distance, using network analysis by ArcGIS 10.2, was calculated from a particular POI to the closest PT stop/station, including bus stops, tram stops and train stations.

DOI: 10.1002/atr

3.8. Average waiting time

The AWT is the average time between arriving at a stop/station and the arrival time of the desired services. For each selected route, the AWT was considered as the interval between services. For instance, for a PT mode running services every 5 min or 12 frequencies per hour, the AWT would be 2.5 min. The AWT is estimated as half the headway (i.e. the time interval between services) as shown in Equation (1).

$$AWT_{ij} = 0.5^{*}\left(60/F_{ij}\right)\ i = 1, 2, 3, \ldots, n\ j = 1, 2, 3 \tag{1}$$

where AWT_{ij} is the AWT (min) at the closest stop/station to POI i for PT mode j and F_{ij} is the frequency of mode j (defined as the number of services per hour) at the closest stop/station to POI i.

3.9. Total access time

After calculating the WT and AWT, the total access time (TAT) of a selected POI to the nearest PT stop/station is calculated. This includes walking times from the POI to the stop/station and AWTs. TAT, as shown in Equation (2), comprises WT and AWT.

$$TAT_{ij} = WT_{ij} + AWT_{ij}\ i = 1, 2, 3, \ldots, n\ j = 1, 2, 3 \tag{2}$$

where *TATij* is the total access time (min) of PT mode j at the closet stop/station to POI i. WT_{ij}, as explained earlier, is the walk time (min) from POI i to the closest stop/station of PT mode j.

3.10. Equivalent frequency

Total access times were converted to an equivalent frequency (EF) using Equation (3). This measures the doorstep availability of a route at the specified POI. The EF as presented in Equation (3) is calculated as 30 min divided by the TAT. This treats access time as a notional AWT as though the route was available at the 'doorstep' of the selected POI [23, 30–32].

$$EF_{ij} = \frac{30}{TAT_{ij}}\ i = 1, 2, 3, \ldots, n\ j = 1, 2, 3 \tag{3}$$

where EF_{ij} is the EF for PT mode j at the closest stop/station to the POI i.

3.11. Weighted equivalent frequency

The WEF is calculated as the summation of the EFs of PT modes with a weighting in favour of the most dominant mode (Equation (4)).

$$WEF_{ij} = aEF_{id} + \beta\sum_{i}\sum_{j \neq d} EF_{ij}\ i = 1, 2, \ldots, n\ j = 1, 2, 3 \tag{4}$$

WEF_{ij} i s the WEF for PT mode j at the closest stop/station to the POI i, EF_{id} is the equivalent frequency of the most dominant PT mode at the closest stop/station to POI i, α and β are the coefficients considered for the equivalent frequency of the most dominant PT mode and all other PT modes. In the current study according to the average weekly service level of the PT modes reported by Public Transport Victoria [33], α and β were assigned 1 for the train (the dominant mode) and 0.5 for the two other modes.

3.12. Weighted equivalent frequencies for statistical areas level 1

The WEFs calculated for POIs were transferred to the SA1s. For this purpose, spatial joining (using ArcGIS 10.2) was used based on the criteria of closeness to the boundary of SA1s. Hence, considering any POI, the WEF has been transferred from the one which had the minimum distance to the boundary of its surrounding SA1s. The reason behind this was that SA1 boundaries are completely nested within roads, so, the closer POI to a SA1 boundary has the shorter distance to the road as well. This may make that particular POI more accessible than its counterparts.

3.13. Population density

Population density was used as an indicator of the spatial distribution of the population in calculating the index. Population density was calculated for both buffer areas and SA1s. Based on typical walk catchments for PT modes, 400 m was considered for access to bus and tram stops and 800 m assumed for access to train stations. Thereafter, service areas of PT modes overlapped with SA1s, using a GIS to calculate the share of population density for each SA1 considering the assumption of a homogeneous distribution of population with a SA1. To avoid duplication, the residential population was transferred to buffer catchments considering the proportion of overlapping areas, assuming that 20% of a specified SA1 was covered by a walk catchment of a selected stop/station. In this case, the population calculated for that walk catchment would be 20% of the total population of the SA1. Table I presents information about the population and areas of SA1s and walking catchments of PT modes. As indicated, SA1s have a mean population of 414 persons with the average area of 0.93 km^2.

3.14. Public Transport Accessibility Index

For each SA1, the PTAI is calculated using the formula given in Equation (5). The index is a combined measure of WEF and population density ratio given as

$$\text{if } D_{B_{ij}} = 0 \tag{5}$$

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

$$\text{if } D_{B_{ij}} \neq 0;$$

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

where $PTAI_{SA1}$ denotes PTAI for a given $SA1$ and D_{Bij} is the population density of buffer i for PT mode j. D_{SA1} is the population density of the $SA1$. and WEF_{SA1} is the WEF calculated for the corresponded $SA1$.

In this approach, accessibility is calculated for the spatial coverage of each SA1 that is covered by walking buffers to PT stops/stations as well as their frequencies. The index also counts the overlapping buffer areas. For instance, where there is a place within possible walking distance to a both bus and tram stop, the measurements are double counted, which indicates that those areas have a higher level

Table I. Population and areas of SA1s and walking catchments of public transport stops/stations.

	Population				Area (km^2)			
Categories	Mean	Standard deviation	Min	Max	Mean	Standard deviation	Min	Max
SA1s	414	209.5	0	6427	0.93	10.2	0.002	854.3
Walking buffers for tram stops	31	41.3	0	724	0.10	0.19	0.01	1.50
Walking buffers for train stations	66	55.6	0	1286	1.50	0.54	0.50	3.20
Walking buffers for bus stops	26	35.1	0	869	0.14	0.20	0.01	2.50

SA1s, statistical areas level 1.

DOI: 10.1002/atr

of accessibility to PT. A higher value of the PTAI indicates a higher level of accessibility. The index is allocated to six categories of accessibility levels, where category 1 represents a very poor level and level 6 represents an excellent level of accessibility (Table II). 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}.

Table II presents the ranges and categories of the PTAI. The index was grouped into six main categories including very poor, poor, moderate, good, very good and excellent plus a zero group. The classification method used for PTAI categories are based on quantiles because they are known as one of the best methods for simplifying comparison as well as aiding general map reading [34]. Zero accessibility was calculated for 16 243 residents or 0.55% of total population. Very poor areas were mostly located in outer Melbourne. Overall, around 50% of total population have zero to moderate accessibility to PT.

Figure 4 illustrates the distribution of PTAI categories in the Melbourne region. As explained earlier, 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 PT. First and last categories have been further subdivided into sublevels to provide better clarity. High levels of accessibility from good to excellent are mostly concentrated in the inner parts of Melbourne region. As shown, outer Melbourne, where PT is mainly provided by public buses have lower levels of accessibility in comparison to the inner parts and the central business district (CBD).

Table III presents a summary of the descriptive statistics of the index components. This shows that there was on average 414 residents in each SA1 with an average area of 0.93 km^2. The average number of stops/stations per SA1 was 2.1, which receive a total of 9.6 services during peak times. The average WEF per SA1 was 5.5, and the average value of the PTAI per SA1 was 9.7. On average, 28% of the Melbourne area is covered by the walking catchments of bus stops. This proportion is 4% and 3% for train station and tram stop walking buffers, respectively.

3.15. Existing measures

Public Transport Accessibility Index extends the more recent and common approaches, including the UK approach [30] measuring PTAL and Supply Index (SI) introduced by Currie [11]. PTAL measures accessibility using local indicators and accessibility modelling. It uses a six-level scale to rate PT service access, which includes measurements such as walk time, waiting time and service frequency. The index developed in this paper calculates the sum of equivalent doorstep frequency of all different PT modes. SI is a supply index calculated for Melbourne's 5839 CCDs. The index is a combined measure of service frequency (number of PT vehicle arrivals per week) and access distance.

Both indexes, PTAL and SI, were calculated for SA1s as presented in Table IV. Based on the PTAL about 50% or about 2 M residents have zero to moderate access to PT modes. While considering SI, these figures rise to 67% or 2.6 million residents.

Table II. PTAI ranges and categories.

	PTAI categories	Number of SA1s		Population	
		No.	Percent	No.	Percent
0	N/A	52	0.55	16 243	0.41
<2	Very poor	1331	14.00	538 536	13.66
2–3.5	Poor	1607	16.90	671 449	17.04
3.5–6	Moderate	1791	18.83	751 327	19.06
6–12	Good	1969	20.70	801 520	20.34
12–20	Very good	1480	15.56	623 111	15.81
>20	Excellent	1280	13.46	539 025	13.68
Total	N/A	9510	100.00	3 941 211	100.00

PTAI, Public Transport Accessibility Index; SA1s, statistical areas level 1.

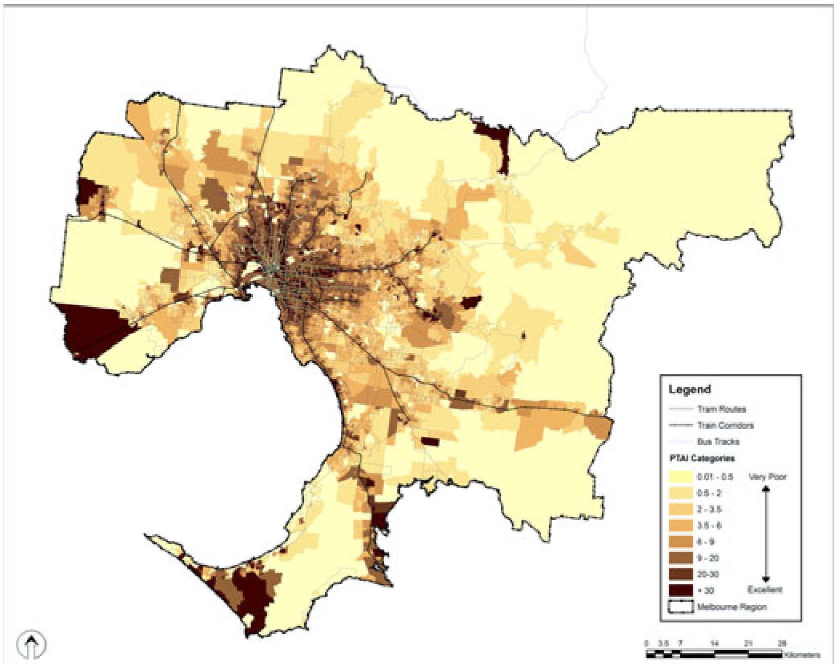

Figure 4. Distribution of Public Transport Accessibility Index (PTAI) categories in Melbourne region.

4. DATA ANALYSIS

Built environment factors, as well as PT access measurements, were combined with the VISTA dataset using the SA1 codes. The VISTA dataset contains trip record information for 22 184 individuals who were randomly selected from 1822 SA1s. The following sections present the results of the models applied to the data while comparing the new index with the previous measurements.

4.1. Modelling and interpretation

Ordered logit regression models were used to explore the correlations of PT trips and socio-economic 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

Table III. Descriptive statistics of indicators in each SA1.

Indicators	Mean	Standard deviation	Minimum	Maximum
Area (km^2)	0.93	10.2	0.002	854.3
Population	414	209.5	0	6224
Frequency of bus services	2.2	1.5	0	20
Frequency of tram services	2.9	4.1	0	12
Frequency of train services	4.5	2.6	0	7
Number of public transport stops/stations per SA1	2.1	2.5	0	60
WEF	5.5	8.6	0	659.7
PTAI	9.7	10.9	0	98.2

PTAI, Public Transport Accessibility Index; SA1, statistical area level 1; WEF, weighted equivalent frequency.

DOI: 10.1002/atr

Table IV. PTAL and SI for SA1s.

PTAL/SI categories	PTAL		SI	
	Number of SA1s	Population (%)	Number of SA1s	Population (%)
Zero access/supply	52	16 243 (0.4)	267	96 585 (2.5)
Very poor/very low	1370	560 271 (14.2)	2117	837 018 (21.2)
Poor/low	1398	604 059 (15.3)	2014	843 374 (21.4)
Moderate/below average	1857	773 731 (19.6)	2069	876 429 (22.2)
Good/above average	1415	582 554 (14.8)	1032	431 338 (10.9)
Very good/high	1624	670 184 (17.0)	1000	416 642 (10.6)
Excellent/very high	1794	734 169 (18.6)	1011	439 825 (11.2)
Total	9510	3,41 211 (100.0)	9510	3,41 211 (100.0)

PTAL, Public Transport Accessibility Level; SA1s, statistical areas level 1; SI, Supply Index.

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 [35]. A typical model for the cumulative logits is shown in Equation (6):

$$\mathrm{logit}[P(Y \le j)] = \alpha_j + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n = \alpha_j + \beta' X \quad (6)$$

where $j = 1, \ldots, c - 1$; c is the total number of categories; $x_1, x_2, \ldots, x_n$ are n explanatory variables; and $\beta_1, \beta_2, \ldots, \beta_n$ are corresponding coefficients.

Three separate ordered logit regression models were specified with socio-economic and built environment factors. M1 presents the results of ordered logit models considering all the predictor variables and the PTAI as the PT accessibility measure. M2 and M3 contain the entire variable used in the M1; however, SI and PTAL are used for PT accessibility measures, respectively. PT trips are defined as an ordered dependent variable. Age, gender, car licence, employment type, household size, household structure and a number of cars in the household were employed as socio-economic variables [36–39]. Built environment factors include roadway measure (RDW), Land Use Mix Entropy Index (LUMIX) and PT accessibility measurements (PTAI/SI/PTAL). RDW examines how long the network spreads over an area. It is quantified by total roadway length divided by the total area where the distance is normalized by 100 m^2. LUMIX was calculated using Equation (7) [36]. The values vary from 0 to 1, while 1 indicates a perfect balance among different types of land uses and 0 represents homogeneity.

$$\mathrm{LUMIX} = -\left(\sum_{j=1}^{J} \frac{P_j.\ln P_j}{\ln J} \right) \quad (7)$$

where LUMIX indicates the land use mix entropy index within buffer i (SA1s). Pj represents the proportion of a type of land use j, and J is the number of land use categories. Six different land-uses categories, including residential, commercial, industrial, transport and infrastructure, community services and sport and recreation centres, have been chosen to calculate LUMIX. These categories are defined from 10 main use categories defined by Australian Valuation Property Classification Codes [40]. Table V shows the list of independent variables and their description as well as hypothesized relationship with the dependent variable.

As mentioned, in the VISTA dataset travels is reported 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 trips stages made by 22 184 individuals in the MSD. Table VI shows the frequency of PT trips which categorized into five groups from very low to very high ranges of PT trips generated in SA1s.

Table VII 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, respondents were 38 years old on average and equality distributed in terms of gender. The average of

Table V. Independent variables and their hypothesized associations with PT trips.

Variables	Description	Hypothesized relationship
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	+
SI	Supply Index	+
PTAL	Public Transport Accessibility Level	+
RDW	Roadway measure	−
LUMIX	Land Use Mix Entropy Index	+

HHstructure 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.
PT, public transport.

Household size (HH size) shows that respondents were almost all from households with a usual number of about three residents.

In order to examine the applicability of the new index compared with existing approaches, three ordered logistic regression models were estimated. All the variables were considered constant in the models except the PT accessibility measures. The PTAI along with other variables were employed to run the model M1, likewise, the SI in M2 and the PTAL in M3 (Table VIII). The coefficient values for PT measurements are different in the models and the PTAI in M1 has the highest value. This can be interpreted as when the PTAI increases by one unit, the odds of being in the higher levels of PT trips increases, given that all other variables in the model are held constant. Furthermore, M1 has the lowest Akaike information criterion (AIC) that is a measure of the relative quality of statistical models for a given set of data. 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 [41–43]. In terms of association, as presented in Table VIII, age, number of cars in a household and being a male are negatively associated with PT trips.

Meanwhile, built environment features also have a significant impact on the number of PT trips. LUMIX and PT access measures are positively and RDW negatively associated with PT trips. For instance, there is an expectation of a 0.16 increase in the log odds of being in a higher level of PT trips for a unit increase of LUMIX. In contrast, while the RDW decreases for about 0.1 in M1, the log odds of being in a higher level of PT trips. This figure is 0.05 in M3. With regards to PT access measurements, a larger increase in the log odds of being in a higher level of PT trips is expected with the PTAI in the model.

Table VI. Frequency of PT trips.

PT trips categories	PT trips	Frequency	Percent	Cumulative percent
Very low	1–9	15 169	19.7	19.7
Low	9–14	13 965	18.1	37.8
Average	15–23	15 585	20.2	58.1
High	24–39	15 974	20.7	78.8
Very high	40+	16 327	21.2	100.0
N/A	Total	77 020	100.0	

Analysis has been run on records related to SA1s with non-zero PT trips.
PT, public transport.

DOI: 10.1002/atr

Table VII. Descriptive statistics.

Variable	Mean	SD	Min	Max
PT trips	25.04	19.57	1.00	106.00
Age	37.55	19.76	0.00	96.00
Sex	1.53	0.50	1.00	2.00
Licence	1.24	0.42	1.00	2.00
HH size	3.25	1.35	1.00	6.00
Employment type	2.05	0.93	1.00	3.00
HH structure	2.86	0.99	1.00	5.00
Car no.	1.90	0.95	0.00	4.00
PTAI	33.26	360.30	0.00	7235.57
SI	17 191.58	17 132.71	0.00	222 037.92
PTAL	16.40	174.80	0.00	3482.64
RDW	1.36	0.79	0.00	5.57
LUMIX	0.42	0.15	0.00	0.87

$n = 77\,020$ trip stages.
LUMIX, Land Use Mix Entropy Index; PT, public transport; PTAI, Public Transport Accessibility Index; PTAL, Public Transport Accessibility Level; RDW, roadway measure; SD, standard deviation; SI, Supply Index.

After estimating and comparing the three ordered logit models, the standard difference-of-means test (Equation (8)) was also used to test the statistical differences in the estimated coefficients obtained from the ordered logistic regression models. The reason behind this was to investigate whether there are any significant differences between the coefficients estimated by three models.

Table VIII. Outputs of the ordered logit model for public transport trips.

	M1			M2			M3		
Parameter	Coefficient	SE	OR	Coefficient	SE	OR	Coefficient	SE	OR
Age***	−0.001	0.000	0.999	−0.002	0.000	0.998	−0.002	0.000	0.998
Sex (male)**	−0.038	0.014	0.963	−0.030	0.014	0.971	−0.031	0.013	0.97
Licence (yes)	0.000	0.021	1	0.015	0.021	1.015	0.014	0.021	1.014
HH size***	0.044	0.008	1.045	0.029	0.008	1.029	0.031	0.008	1.031
Employment type									
Full time***	0.077	0.016	1.08	0.071	0.016	1.073	0.086	0.016	1.09
Part time	−0.002	0.022	0.998	−0.003	0.022	0.997	0.021	0.022	1.021
HH structure									
Sole person***	−0.159	0.037	0.853	−0.197	0.037	0.821	−0.193	0.037	0.825
Couple no kids***	−0.099	0.029	0.906	−0.142	0.029	0.868	−0.148	0.029	0.862
Couple with kids***	−0.087	0.024	0.917	−0.110	0.024	0.896	−0.133	0.024	0.876
Single parent***	−0.277	0.033	0.758	−0.346	0.033	0.707	−0.357	0.033	0.7
Car no.***	−0.180	0.008	0.836	−0.185	0.008	0.831	−0.223	0.008	0.8
LUMIX***	0.164	0.012	1.178	0.145	0.012	1.156	0.252	0.012	1.287
RDW***	−0.091	0.012	0.913	−0.096	0.012	0.908	−0.052	0.012	0.949
PTAI***	0.307	0.004	1.36						
SI***				0.260	0.004	1.297			
PTAL***							0.179	0.004	1.196

Public transport trips are converted to five dummy variables by using level 1 as the reference level (very low): less than 9 trips, level 2 (low): 9–14 trips, level 3 (average): 15–23 trips, level 4 (high): 24 to 40 trips and level 5 (very high): more than 40 trips. Threshold coefficients for M1: 1|2 → 0.447, 2|3 → −0.511, 3|4 → −1.387; 4|5 → −2.443; M2: 1|2 → 0.707, 2|3 → −0.248, 3|4 → −1.115; 4|5 → −2.158 and M3: 1|2 → 0.811, 2|3 → −0.130, 3|4 → −0.986; 4|5 → −2.015; (3)
Overall goodness-of-fit:
M1: log likelihood = 7451.69; AIC = 240 282.51.
M2: log likelihood = 6536.15; AIC = 241 198.06.
M3: log likelihood = 4732.28; AIC = 243 001.92.
AIC, Akaike information criterion; LUMIX, Land Use Mix Entropy Index; OR, odds ratio; PTAI, Public Transport Accessibility Index; PTAL, Public Transport Accessibility Level; RDW, roadway measure; SE, standard error; SI, Supply Index.
***Significance codes: $p < 0.001$.
**$p < 0.01$.

DOI: 10.1002/atr

$$t = \frac{\hat{\beta}_i - \hat{\beta}_j}{\mathrm{SE}\left|\hat{\beta}_i - \hat{\beta}_j\right|} \tag{8}$$

where $\hat{\beta}_i$ is the estimated coefficient of a built environment variable, i; SE denotes the standard error [44, 45]. The estimated coefficients from the models were compared with each other, and results are presented in Table IX. The t-statistics results indicated that there is a significant difference between the coefficients of PT accessibility measurements estimated by the three models.

4.2. *Tests of associations*

Ordinal and interval tests of association were applied to compare the relationship between the PT accessibility measures and the number of PT trips. Somers' D, Gamma and Spearman test are asymmetric measures of association between two variables, which plays a central role as a parameter behind rank or nonparametric statistical methods [46]. Moreover, in terms of linear association, PTAI had a higher value ($r = 0.350$, $p < 0.001$). Table X presents the results of the test. As shown, the PTAI has a better association in comparison with existing approaches.

Figure (5) shows the average number of PT trips undertaken by train, tram and public bus within PTAI categories. It can be seen that the more accessible areas are, the more PT trips are generated. All the three modes had a similar trend; however, train usage shows a sharper upward increase in good to excellent levels of accessibility.

Table IX. Outputs of the ordered logit model for public transport trips.

Measurements	Coefficient (SE)	*t.diff*
PTAI	0.3072 (0.00445)	—
SI	0.2598 (0.00419)	—
PTAL	0.1787 (0.00397)	—
M1/M2	—	182.3077***
M1/M3	—	267.7083***
M2/M3	—	368.6364***

PTAI, Public Transport Accessibility Index; PTAL, Public Transport Accessibility Level; SE, standard error; SI, Supply Index.
***Significance codes: $p < 0.001$.

Table X. Test of associations between public transport trips and public transport measurements.

Test of associations		PTAI		SI		PTAL	
		Value	p-value	Value	p-value	Value	p-value
Ordinal by ordinal	Somers' D	0.255	0.000	0.219	0.000	0.203	0.000
	Gamma	0.257	0.000	0.244	0.000	0.205	0.000
	Spearman	0.309	0.000	0.296	0.000	0.208	0.000
Interval by interval	Pearson's r	0.350***	0.000	0.287***	0.000	0.214***	0.000
No. of valid cases		77 020					

PTAI, Public Transport Accessibility Index; PTAL, Public Transport Accessibility Level; SE, standard error; SI, Supply Index.
***Significance codes: $p < 0.001$.

DOI: 10.1002/atr

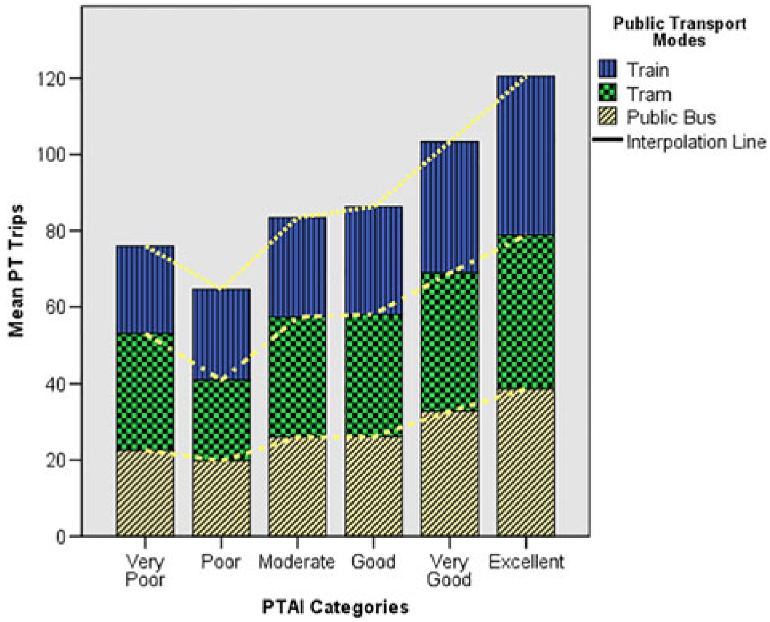

Figure 5. Average numbers of public transport (PT) trips for different modes within Public Transport Accessibility Index (PTAI) categories.

5. DISCUSSION

This paper introduced a new approach measuring PT accessibility. The PTAI defines and extends existing PTAIs by including PT modes' service frequency and population density. It is an applicable measurement for examining the level of accessibility of PT, and also it provides the ability to investigate accessibility at a variety of geographical scales. Hence, the index could be useful for neighbourhood level to regional studies. The transit frequency component provides a useful complement to the PTAI and makes it more representative of real access than either alone. This index allowed the level of accessibility in Melbourne region to be explored. Results indicate that 0.5% of SA1s have zero accessibility to PT. From this percentage, 1.74% of SA1s have no population and 52 SA1s representing 0.4% of Melbourne residents had no access to PT. About 30% of residents had very poor or poor access to PT. Those PTAI categories mainly belong to the outer parts of the Melbourne region (Figure 4). However, these levels of accessibility were not exclusive to outer areas. In the Greater Melbourne area, about 50% of residents have zero to moderate levels of accessibility when outer Melbourne has only 17% of residents have above-average levels of accessibility. As discussed, approximately 30% of Melbourne region is covered by PT walking catchments. This includes about 17 800 bus stops, 1700 tram stops and 240 train stations with an average frequency of 2.2, 2.9 and 4.5 (per hour), respectively. Although public buses have the highest catchment coverage and frequency during the peak hours, it is used less than the train (by 8.3%) and tram (by about 1%).

Two recent and common approaches, SI and PTAL, have been explained and also built for SA1s, in the Melbourne region. The new index showed much consistency with the existing approaches. All the three indexes along with a series of socio-economic characteristics and built environment factors were applied in three separate ordered logit models. The M1 model included the PTAI along with other predictor variables, while the M2 and M3 models used SI and PTAL as the measures of PT accessibility, respectively. Comparing the results, M1 had the lowest AIC ($AIC_{M1} = 240\,282 < AIC_{M2} = 241\,198 < AIC_{M3} = 243\,001$) and showed a better fit for the data. The estimated coefficient for PTAI in M1 ($\beta_{PTAI} = 0.307$) was higher than coefficients estimated for SI ($\beta_{SI} = 0.260$) and PTAL ($\beta_{PTAL} = 0.179$) in M2 and M3, respectively. This figure indicates that higher log odds of being in a higher level of PT trips are expected, while there is a one-unit increase in PTAI compared with its counterparts.

DOI: 10.1002/atr

Tests of association have also applied to examine whether there is a stronger relationship between the new index and number of trips made by PT modes. These findings show that association values for PTAI both in ordinal and interval tests were higher than existing measurements. Thus, PTAI was evaluated as a valid means of measuring PT mode use in Melbourne region based on the VISTA database.

This study's results show much consistency with the previous study undertaken on PT supply and need analysis Melbourne's 5839 CCDs by Currie [11]. Although the approaches used in these studies were different, there are clear similarities between the results. There also similarities with another research that calculate PTALs [23, 47].

Overall, accessibility can be considered as a measure of locational disadvantage, particularly from a social planning perspective. Poor accessibility to PT can deter access to different facilities and social advantages. Lucas [48] argued there are interrelationships between transport shortcomings and key areas with social disadvantages such as unemployment, health inequalities and poor education. In this regard, in many transport studies, weighted socio-economic factors have been combined in calculating the level of accessibility to PT [49, 50]. However, in many transport models, socio-economic characteristics have been often considered as independent variables. Therefore, a weighted accessibility index in such models may duplicate the effects of social factors and bias the results. Besides, from a transportation planning perspective, accessibility reflects an indicator of the spatial distribution of PT stops and routes.

6. CONCLUSIONS AND FUTURE DIRECTIONS

This study contained two main parts, including the PTAI and the assessment and comparison of the index using VISTA data. This study employed GIS techniques to accurately measure the level of accessibility to PT in the Melbourne region. The findings indicate the concentration of PT in the inner part of Melbourne, and the CBD is high, and they can be accessed by all three modes. However, the outer suburbs which are characterized by sprawling patterns; PT is generally limited to buses. This can be referred to the policy of increasing bus services based on address needs. Moreover, results revealed the fact that people were more likely to use PT modes when it is more accessible. In terms of numbers of trips generated by PT modes, findings showed that the average numbers of PT trips for all three modes would be higher at the higher levels of PTAI categories.

Overall, the techniques presented are straightforward to apply, while it showed better and more accurate, measurements for PT accessibility based on the VISTA dataset. The quantitative approaches developed can be employed for any number of public modes in other cities around the world. It is designed to be applied with available census and transport modelling tools. Furthermore, the analysis provides reliable and defendable results that enabled the accessibility for about 99% of the SA1s to be calculated. Nonetheless, they can be enhanced by greater details to achieve even more accurate results.

A weakness of this approach is that the index is estimated to be equal to WEFs for SA1s with non-residential uses or no population. These results in the index are having a value of 0 for SA1s with non-residential uses (165 out of 9510 SA1s). Furthermore, the PTAI does not consider the connectivity between public modes that can influence accessibility, particularly in areas of low accessibility. Another weakness of this method is that the index does not take into account the effects of temporal disparity [51–53]. This study has not focused on off-peak periods that tend to have lower PT service frequency and PT users encounter lower level of service and consequently lower mobility. Besides, calculating the AWTs assumed passengers arrived at the stops/stations randomly. Future studies may consider these points when measuring accessibility.

However, this study adopted GIS approaches to calculate the PTAI and illustrated the level of accessibility for the 9510 SA1s in the Melbourne region. The findings, therefore, should provide a measure to identify areas with low levels of accessibility. In addition, this study calculated the PTAI with the knowledge of population distribution within SA1s. In this regard, the index provides a practical means of measuring the levels of accessibility within metropolitan areas, while it can be employed in modelling different aspects of travel behaviour. Besides, considering the applicability new index, it can be concluded that this index not only measures the level of PTALs but also it can be a better predictor when it is applied in a travel behaviour model.

DOI: 10.1002/atr

REFERENCES

1. Lei T, Church R. Mapping transit-based access: integrating GIS, routes and schedules. *International Journal of Geographical Information Science* 2010; **24**(2): 283–304.
2. Mamun S. Public transit accessibility and need indices: approaches for measuring service gap. 2011.
3. Armstrong-Wright A, Thiriez S. Bus services: reducing costs, raising standards. 1987.
4. Taniguchi E, Thompson RG, Yamada T. Concepts and visions for urban transport and logistics relating to human security. Urban Transportation and Logistics: Health, Safety, and Security Concerns, 2013: p. 1.
5. Dodson J, Gleeson B, Sipe NG. Transport disavantage and social status: a review of literature and methods. 2004: Urban Policy Program, Griffith University Brisbane.
6. Dodson J, Gleeson B, Evans R, Sipe N. Transport disadvantage in the Australian metropolis: towards new concepts and methods (n.d).
7. Currie G. Gap analysis of public transport needs: measuring spatial distribution of public transport needs and identifying gaps in the quality of public transport provision. *Transportation Research Record: Journal of the Transportation Research Board* 2004; (1895): 137–146.
8. Dodson J, Sipe N, Gavin N. Shocking the suburbs: urban location, housing debt and oil vulnerability in the Australian city. Urban Research Program, Griffith University, Inc.: Brisbane, 2004.
9. Mavoa S, Witten K, McCreanor T, O'Sullivan D. GIS based destination accessibility via public transit and walking in Auckland, New Zealand. *Journal of Transport Geography* 2012; **20**(1): 15–22.
10. Biba S, Curtin KM Manca G. A new method for determining the population with walking access to transit. *International Journal of Geographical Information Science* 2010; **24**(3): 347–364.
11. Currie G. Quantifying spatial gaps in public transport supply based on social needs. *Journal of Transport Geography* 2010; **18**(1): 31–41.
12. Furth PG, Mekuria MC SanClemente JL. Parcel-level modeling to analyze transit stop location changes. *Journal of Public Transportation* 2007; **10**(2): 5.
13. Lovett A, Haynes R, Sünnenberg G, Gale S. Car travel time and accessibility by bus to general practitioner services: a study using patient registers and GIS. *Social Science & Medicine* 2002; **55**(1): 97–111.
14. Kimpel TJ, Dueker KJ El-Geneidy AM. Using GIS to measure the effect of overlapping service areas on passenger boardings at bus stops. *Urban and Regional Information Systems Association Journal* 2007; **19**(1): 5–11.
15. Zhao F, Chow L-F, Li M-T, Ubaka I, Gan A. Forecasting transit walk accessibility: regression model alternative to buffer method. *Transportation Research : Journal of the Transportation Research Board* 2003; **1835**(1): 34–41.
16. El-Geneidy AM, Tetreault P, Surprenant-Legault J. Pedestrian access to transit: identifying redundancies and gaps using a variable service area analysis. In Transportation Research Board 89th Annual Meeting. 2010.
17. O'Sullivan D, Morrison A Shearer J. Using desktop GIS for the investigation of accessibility by public transport: an isochrone approach. *International Journal of Geographical Information Science* 2000; **14**(1): 85–104.
18. Benenson I, Martens K, Rofé Y, Kwartler A. Public transport versus private car GIS-based estimation of accessibility applied to the Tel Aviv metropolitan area. *The Annals of Regional Science* 2011; **47**(3): 499–515.
19. Cheng C-L, Agrawal AW. TTSAT: a new approach to mapping transit accessibility. *Journal of Public Transportation* 2010; **13**(1): 4.
20. Yigitcanlar T, Sipe N, Evans R, Pitot M. A GIS-based land use and public transport accessibility indexing model. *Australian Planner* 2007; **44**(3): 30–37.
21. Curtis C, Scheurer J. Planning for sustainable accessibility: developing tools to aid discussion and decision-making. *Progress in Planning* 2010; **74**(2): 53–106.
22. Huang R, Wei YD. Analyzing neighborhood accessibility via transit in a GIS environment. *Geographic Information Sciences* 2002; **8**(1): 39–47.
23. Wu BM, Hine JP. A PTAL approach to measuring changes in bus service accessibility. *Transport Policy* 2003; **10** (4): 307–320.
24. Saghapour T, Moridpour S, Thompson RG. Estimating public transport accessibility in metropolitan areas incorporating population density. In Transportation Research Board 95th Annual Meeting. 2016.
25. Saghapour T, Moridpour S, Thompson RG. Public transport accessibility in metropolitan areas: a new approach incorporating population density. *Journal of Transport Geography* 2016; **54**(4): 273–285.
26. Victoria State Government, Victorian government data directory. Vicoria, Australia. 2015.
27. Greater Melbourne area. 2015; New Greater Melbourne Area. Available from: http://www.sro.vic.gov.au/.
28. Department of Transport. Public transport Victoria. PTV (n.d); Available from: http://ptv.vic.gov.au.
29. Department of Transport. Victorian Integrated Survey of Travel and Activity. 2009; Available from: http://www5.transport.vic.gov.au/.
30. TfL. Transport for London. Measuring public transport accessibility levels. 2010.
31. Tyler N. Accessibility and the bus system: from concepts to practice. 2002: Thomas Telford.
32. De Martino A. Geographic accessibility analysis and evaluation of potential changes to the public transportation system. LUMA-GIS Thesis, 2014.
33. Victoria, P.T., Public transport performance. 2012: Public Transport Victoria.
34. Brewer CA, Pickle L. Evaluation of methods for classifying epidemiological data on choropleth maps in series. *Annals of the Association of American Geographers* 2002; **92**(4): 662–681.
35. Andren T, Flood L, Hansen J, Popa D, Tasiran A. Introduction to SAS. Department of Economics, School of Economics and Commercial Law, Gothenburg University, 1999.

DOI: 10.1002/atr

36. Lee J-S, Nam J Lee S-S. Built environment impacts on individual mode choice: an empirical study of the Houston–Galveston metropolitan area. *International journal of sustainable transportation* 2014; **8**(6): 447–470.
37. Winters M, Brauer M, Setton EM, Teschke K. Built environment influences on healthy transportation choices: bicycling versus driving. *Journal of Urban Health* 2010; **87**(6): 969–993.
38. Jun M-J, Kim JI, Kwon JH, Jeong J-E. The effects of high-density suburban development on commuter mode choices in Seoul, Korea. Cities, 2012.
39. Ewing R, Cervero R. Travel and the built environment. *Journal of the American Planning Association* 2010; **76**(3): 265–294.
40. Morse-McNabb E. The Victorian Land Use Information System (VLUIS): a new method for creating land use data for Victoria, Australia. In Surveying and Spatial Sciences Conference. 2011.
41. Boisbunon A, Canu S, Fourdrinier D, Strawderman W, Wells MT. Akaike's information criterion, C_p and estimators of loss for elliptically symmetric distributions. *International Statistical Review* 2014; **82**(3): 422–439.
42. Hu S. Akaike information criterion. Center for Research in Scientific Computation, 2007.
43. Aho K, Derryberry D Peterson T. Model selection for ecologists: the worldviews of AIC and BIC. *Ecology* 2014; **95**(3): 631–636.
44. Fotheringham AS, Wong DW. The modifiable areal unit problem in multivariate statistical analysis. *Environment and planning A* 1991; **23**(7): 1025–1044.
45. Mitra R, Buliung RN. Built environment correlates of active school transportation: neighborhood and the modifiable areal unit problem. *Journal of Transport Geography* 2012; **20**(1): 51–61.
46. Newson R. Confidence intervals for rank statistics: Somers' *D* and extensions. *Stata Journal* 2006; **6**(3): 309.
47. Kerrigan M, Bull D. Measuring accessibility-a public transport accessibility index. Environmental Issues Proceedings of seminar B Held at the PTRC European Transport, Highways and Planning 1992.
48. Lucas K. Transport and social exclusion: Where are we now? *Transport Policy* 2012; **20**: 105–113.
49. Currie G, Stanley J. No way to go: transport and social disadvantage in Australian communities. 2007.
50. Hurni A. Transport and social exclusion in Western Sydney. In Australasian Transport Research Forum (Atrf), 28th, 2005, Sydney, New South Wales, Australia. 2005.
51. Neutens T, Delafontaine M, Scott DM, De Maeyer P. An analysis of day-to-day variations in individual space–time accessibility. *Journal of Transport Geography* 2012; **23**: 81–91.
52. Chen S, Claramunt C Ray C. A spatio-temporal modelling approach for the study of the connectivity and accessibility of the Guangzhou metropolitan network. *Journal of Transport Geography* 2014; **36**: 12–23.
53. Kwan M-P. Beyond space (as we knew it): toward temporally integrated geographies of segregation, health, and accessibility: space–time integration in geography and GIScience. *Annals of the Association of American Geographers* 2013; **103**(5): 1078–1086.

DOI: 10.1002/atr