ACCESSIBLE NEIGHBOURHOODS: TOWARDS ACTIVE TRANSPORTATION

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DECLARATION

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed. I also acknowledge the support I have received for my research through the provision of an Australian Government Research Training Program Scholarship.

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**Awards**


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SUMMARY

A growing number of researchers have recently focused on improving the sustainability of transportation systems by converting routine motorised travel into active modes of transport. The importance of physical activity and its impact on health has not only attracted the attention of practitioners, but it has also turned the attention of planners and policy makers to the achievement of sustainable transportation by enhancing active travel behaviour. To identify effective strategies for increasing pedestrian and bicycle transportation in a specific local area, planners need to identify how the current levels of accessibility in neighbourhoods affect transport mode choice. Although many studies have been conducted on modelling active transportation, the importance of accessibility has been neglected. Therefore, this study proposes new approaches to the measurement of walking, cycling and public transport accessibility while using new measurements in regression models to examine how accessibility can affect active transportation.

Promoting active transportation requires better accessibility to activities and places of interest. Hence, in the first step, recognition of the level of accessibility in neighbourhoods is essential. Several approaches have been developed and used in the research literature which measure accessibility for non-motorised modes of transport. However, existing measurements have some limitations that may affect the accuracy of accessibility levels. Therefore, the first phase of the present study focuses on the development of new accessibility measures for public transport, walking and cycling, which overcome the limitations of past measures.

With respect to the public transport accessibility index, in existing approaches, the distribution of the population is ignored. Therefore, this study proposes a new method of measurement which extends two common approaches incorporating population density. This research also introduces a new index for measuring cycling accessibility, which is a gravity-based measure. Whilst existing cycling accessibility measures are dependent on travel data, this new index measures levels of accessibility independently of travel data. Regarding walking accessibility, existing methods use travel distance or land-use features to measure walkability. However, the method proposed in this study not only considers walking distance thresholds, but also incorporates the diversity and intensity of land use.

The second phase of this study focuses on the application of accessibility measures and the importance of considering accessibility as the explanatory variable in modelling active transportation. For this purpose, new measurements are employed in regression models versus land use factors to examine the performance as well as the importance of including accessibility measures in transport modelling.
CHAPTER 1

INTRODUCTION
Chapter 1: Introduction

1.1 Project Rationale

Over the past decades, the link between the built environment and travel behaviour has received considerable research attention. Sprawling land use patterns in cities and automobile-oriented development have encouraged people to have less physical activity and spend more time travelling in automobiles. The negative consequences of this kind of passive behaviour have been highlighted in metropolitan areas such as Melbourne. Since World War II, Australian cities have been transformed from being compact to sprawling suburban low-density configurations. Transformed land use patterns have been accompanied by increased car ownership and rapid improvements in road systems. On the other hand, during the past two decades, Australia has been rapidly heading towards an obesity epidemic. According to data collected during 1999-2000, approximately 60% of the adult population in Australia was overweight or obese (Thorburn, 2005). According to the Australian Health Survey on Physical Activity (2011-2012), 60% of adults undertake less than 30 minutes, and fewer than 20% do an hour or more of physical activity per day on average. The survey also claimed that if the weight gain trend continues at current rates, by 2025, close to 80% of all Australian adults will be overweight or obese.

Constructing new highways and increasing the capacity of streets, have for a long time been proposed as ways to reduce traffic congestion (Maat et al., 2005). Although these solutions are intended to reduce traffic congestion, increasing roadway capacity may encourage greater use of the private car (Rodier, 2009). Recently, development plans have focused on land use policies to affect travel behaviour. The adjustment of land use patterns and the efficient positioning of activities is known to be one way of reducing travel demand. In recent years, transportation investment has been directed towards the development of physical environments with strong connectivity, in order to improve active travel like walking and cycling (Sallis et al., 1998). Built environment factors, such as the land-use mix, population density, employment density, dissimilarity index, and connectivity, have been found to influence individuals’ transportation mode choice and in turn their level of physical activity (Lee et al., 2014).

Accessibility planning is a crucial area of transport policy and urban planning. Indeed, improved access to public services is a key foundation of integrated transport schemes (Wu and Hine, 2003). Poor accessibility not only affects transport systems, but consequently impacts accessibility to education, jobs, health facilities, etc., especially for vulnerable people in society (Hine and Mitchell, 2003). Accessibility can be directly related to both the quality of the transport system and the land use system, such as the functional density and the land use mix. At the same time, it can be directly related to economic and social goals as well as environmental goals in terms of the resource-
efficiency of activity and mobility patterns. In other words, auto-oriented suburban areas have been found to have a lower degree of accessibility for more sustainable travel options, such as walking and cycling (Bertolini et al., 2005).

Whilst the integration of transport and land use planning has been widely recognized as an essential requirement for sustainable development, the concept of accessibility is believed to provide a central framework for this integration (Bertolini et al., 2005; Wang et al., 2011; Silva et al., 2017). A variety of concepts and tools is available to address the theoretical and methodological aspects around the definition and measurement of accessibility (Iacono et al., 2010; Geurs et al., 2015; Shliselberg, 2015; Silva et al., 2017). However, many of these concepts and tools have not yet been extensively used in professional planning practice. Hence, as Brömmelstroet (2010) argues, there is a significant gap between advances in scientific knowledge regarding accessibility and its application in planning practice.

1.2 Research Aims and Objectives

This research study provides an assessment of the relationship between accessibility and trip patterns. Furthermore, it will assist in developing new environmental variables and active transport models. This study aims to develop new indices for measuring walking, cycling and public transport accessibility. The accessibility measures are then combined into access level measures to be included as explanatory variables in active transport modelling. Hence, the objectives of this study are as follows:

- To develop a new index for measuring public transport accessibility;
- To develop a new index for measuring cycling accessibility;
- To develop a new index for measuring walking accessibility;
- To investigate the importance of including accessibility measures in active transport modelling;
- To apply the access level measures in active transport modelling and compare these with land use measures.

To achieve the abovementioned aims, the following research questions are addressed:

- What are the existing public transport accessibility measures and what are their limitations?
  Do the proposed accessibility measures perform better than the existing ones?
- Is there any relationship between the accessibility measures and active travel?
- How do the proposed accessibility measures affect active transport modelling?
- How does the new accessibility measures perform compared with land use measures in modelling active transport?
1.3 Thesis Outline

Chapter 2 provides a detailed literature review of existing public transport, walking and cycling accessibility measurements. The limitations of existing measures are discussed, and background material on accessibility and active transport is also presented.

Chapter 3 responds to the first aim of the study on the development of a new index for measuring public transport accessibility. The new index is compared with common existing approaches. The results of this chapter were published in the Journal of Transport Geography, Volume 54, June 2016, pages 273-285.

Chapter 4 presents the results of the application of the new public transport accessibility measure in transport modelling. This chapter discusses the priority of the new index compared to common existing approaches. The results of this chapter were published in the Journal of Advanced Transportation Volume 50, Issue 8, December 2016, pages 1785–1801.

Chapter 5 reports on the results of the second aim of the study by introducing the proposed index for measuring cycling accessibility. The applicability of the new index is also investigated using real travel data. The results of this chapter were published in the International Journal of Sustainable Transportation Volume 11, Issue 5, November 2016, pages 381–394.

Chapter 6 covers the third aim of the study by introducing the proposed index for measuring walking accessibility. The new index is compared to the most common walkability measurement. The results of this chapter will be published in the Transportation Research Record: Journal of the Transportation Research Board (TRR Journal). In press.

Chapter 7 compares the applicability of the new walkability index in transport modelling with that of the most common approach. A paper based on the results presented in this chapter has been submitted to the Journal of Sustainable Transportation and it is currently being revised.

Chapter 8 responds to the fourth aim in relation to the importance of including accessibility measures in active transport modelling. A paper based on the results presented in this chapter has been submitted to the Journal of Transport Policy and it is currently being revised.

Chapter 9, in response to the fifth aim of the thesis, investigates the performance of transport models which include access level measures versus land use measures. A paper based on this chapter has been submitted to the Journal of Transportation.

Chapter 10 presents a summary of the study and discussing the outcomes of the research, followed by the conclusions of the study and an outline of future research directions.
1.4 References


Transport Policy, 10, 307-320.
CHAPTER 2

LITERATURE REVIEW
Chapter 2: Literature Review

2.1 Accessibility and Sustainability

Accessibility as a positive spatial descriptor was first introduced by Stewart (1948), who found it a useful independent variable in modelling land values, travel behaviour and economic development (Stewart, 1948; Levine et al., 2017). In the 1970s, researchers argued that accessibility can be an appropriate means for planning and evaluating different aspects of transportation and land use developments (Levine et al., 2017). However, others claim that land use and transportation are best guided by principles of mobility using different measurements such as highway level of service, traffic-impact analysis and cost-benefit analysis (Levine et al., 2017). Nonetheless, since reaching destinations is the reason for undertaking most trips, mobility is gradually being replaced by accessibility in evaluating transportation systems (Grengs et al., 2010; Levine et al., 2012; Levine et al., 2017).

Conceptualisations of accessibility have had a long tradition in academic and planning areas (Bertolini et al., 2005; Geurs and Van Wee, 2004; Handy and Niemeier, 1997). As Silva et al. (2017) argue, accessibility is progressively being recognised as an essential concept to understand cities and urban regions. Accessibility instruments have been found to be valuable tools for land-use and transport planning. However, the translation of such concepts into practical criteria is still very limited. Despite the relatively large number of concepts and criteria available in the literature, they have not been broadly used in planning practice (Silva et al., 2017; Bertolini et al., 2005).

There are numerous interpretations of the concept of accessibility, as well as different methods for evaluating and measuring it (Hallgrimsdottir et al., 2016). The definition of accessibility can vary, depending on the goal and perspective of the study (Igiñiz and Hernández-Minguillón, 2016). The term ‘accessibility’ is commonly defined as the ease with which any land-use activity is reachable from a certain location by a certain transport mode (Dalvi and Martin, 1976; Lee and Goulias, 1997). Accessibility has often been treated as a purely spatial issue. However, several new perspectives have been raised in the information age, such as technology allowing virtual access and access within cyberspace. This may increase the possibility of substituting physical access for virtual access (Couclelis, 2000). Policies and strategies aimed at changing individual travel behaviour patterns can be achieved through concepts such as sustainable transportation planning, sustainable accessibility or sustainable transportation (Miralles-Guasch and Domene, 2010). As Bertolini and Le Clercq (2003) argue, combining the goals of sustainability and accessibility is fundamental to overcoming the major environmental issues, social objectives, and economic concerns.

Meanwhile, walking and cycling can make a considerable contribution to sustainable transport goals,
of which accessibility is the most important factor (Tight et al., 2011). Walking and cycling are also known as ‘active transport’, which refers to human-powered forms of travel (Cole et al., 2010).

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

2.2 Accessibility and Active Transportation

2.2.1 Active transport and built environment

In recent decades, active modes of transport have attracted increased attention in urban mobility studies and policies due to their potential as complementary strategies to achieve urban sustainability (Lamiquiz and López-Domínguez, 2015). In other words, studies of non-motorised means of transportation such as walking, cycling and public transport have increased in recent years, owing to their importance as sustainable transport modes (Vandenbulcke et al., 2009).

The interaction between the built environment and physical activity has also received considerable research attention in recent decades (Handy et al., 2002; Wang et al., 2011). Many studies on the built environment and mobility have found that land-use factors such as density and the mix of land use have a strong influence on non-motorized mobility (Etminani-Ghasrodashti and Ardeshiri, 2016). Frequently, these studies have also considered other influential factors, including connectivity and roadway measures under the category of urban design (Handy et al., 1998; Cervero and Kockelman, 1997; Lee et al., 2014). However, several researchers have found that land-use factors may be more important than urban design features in determining people’s choice of transport mode (Schlossberg et al., 2006; Krizek, 2000).

The arrangement and distribution of different types of land use in the surroundings of living areas is
one of the main factors found to influence urban transport patterns. The provision of 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 (Lee et al., 2014; Boarnet, 2011). Several studies investigating active transport and land use features (Cervero, 1996; Cervero and Kockelman, 1997; Cervero and Gorham, 1995; Ewing and Cervero, 2010a; Ewing and Cervero, 2010b; Friedman et al., 1994; Kitamura et al., 1997) have found that the frequency of walking and cycling trips is different in neighbourhoods depending on the level of being walkable. In these studies, more walkable neighbourhoods were found to have higher population densities, greater mixed land use, and higher connectivity, while less walkable neighbourhoods were found to have low density, mostly residential land use, and low connectivity. In their international review, Légaré et al., (2009) claimed that as a special mode of mobility, walking not only relies on dedicated infrastructure (e.g. pavements and crossings), but is also highly dependent on the built environment. In another study by Lamíquiz and López-Domínguez (2015), the results indicated that street networks and built environment factors are clearly associated with the percentage of walking trips in urban areas. McCormack et al. (2008) argued that the proximity and mix of destinations appear to be strongly associated with walking for transport, and increasing the diversity of destinations may contribute to adults doing more transport-related walking and achieving recommended levels of physical activity.

### 2.2.2 Accessibility measures and non-motorized transportation

Accessibility in terms of proximity is a highly effective tool to promote smart growth planning in cities and has a major influence on physical activity and health. Numerous studies have examined the impacts of different aspects of accessibility on active trips (Coombes et al., 2010; Chin et al., 2008; Djurhuus et al., 2012; Cheng et al., 2013; Paquet et al., 2013).

Whilst the integration of transport and land-use planning is widely recognized as an essential requirement for sustainable development, the concept of accessibility is believed to provide a central framework for this integration (Bertolini et al., 2005; Wang et al., 2011; Silva et al., 2017). A variety of concepts and tools exist for addressing the theoretical and methodological aspects related to the definition and measurement of accessibility (Iacono et al., 2010; Geurs et al., 2015; Shliselberg, 2015; Silva et al., 2017). However, these concepts and tools have not been extensively used in professional planning practice. Hence, as Brömmelstroet (2010) argues, there is a significant gap between the advances in scientific knowledge on accessibility and its application in planning practice. Millward et al. (2013) analysed active-transport behaviour focusing on distance, duration, purposes and destinations of trips, whilst other studies have focused on calculating non-motorized accessibility. For instance, Iacono et al. (2010) developed an accessibility measure for non-motorized modes, namely bicycling and walking. Mavoa et al. (2012) also introduced a combined public transit and walking
accessibility index, highlighting the importance of accessibility for the potential use of non-motorized modes of transport.

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

Although the transportation planning literature contains many examples of measures for calculating accessibility in urban areas, these measures are not employed in practice. Therefore, this thesis aims to contribute to the implementation of accessibility in practice, by innovatively integrating accessibility in active transportation modelling.

2.3 Public Transport Accessibility

Increasing accessibility to public services is a crucial area of transport policy and urban planning, as well as being a key foundation of an integrated transport system (Wu and Hine, 2003). Poor public transport accessibility to education, jobs and health facilities (Hine and Mitchell, 2003) and inequity in transport provision (Langford et al., 2012) can have a large impact on vulnerable people within a society. Accessibility can be measured by the distance between a destination and public transport stops, or by the length of a journey from an origin to a destination via public transportation (Weber, 2003; Cheng and Chen, 2015).

Based on a review by Lei and Church (2010), public transport accessibility measures can be categorized into six main types. The first type of accessibility measure is based on travel time and distance (Murray et al., 1998; Matisziw et al., 2006; Polzin et al., 2002). This class deals with physical access to public transport stops/stations. The second group includes approaches that measure travel times and costs (Wu and Murray, 2005; Liu and Zhu, 2004; O'Sullivan et al., 2000; Mazloumi et al., 2011). In this group, a user’s ability to reach their destination is measured by taking into account the travel time or cost of the transportation network. The third group is integral accessibility, which measures overall access related to a number of possible destinations (van Eck and De Jong, 1999; Wachs and Kumagai, 1973). These approaches measure general access in terms of distance and time for a selected location with respect to an activity type. The fourth category is based on the concept of time geography. This kind of measure is based on users’ movement over space, while their choice of activities is dependent on time (Kwan et al., 2003; Miller and Wu, 2000). The fifth type of measure is based on utility theory. In such approaches, users are considered as customers and public transport
modes as a travel choice set (Rastogi and Rao, 2003; Koenig, 1980). The last category is called relative accessibility and assumes that a user’s choice of travel is a function of cost (Li et al., 2015), time (Salonen and Toivonen, 2013), or convenience and safety (Church and Marston, 2003). In a more general classification, existing accessibility measures can be categorized into three main groups, including access to public transport stops, duration of a journey by public transport and access to a destination via public transport modes (Mavoa et al., 2012; Lin et al., 2014). Most studies of accessibility have considered the physical level of access, focusing on proximity to public transport stops (Biba et al., 2010; Currie, 2010; Furth et al., 2007). Both access to public transport stops and travel time can be considered (Mavoa et al., 2012). In Auckland, New Zealand, potential access between land parcels and destinations via public transport was measured by introducing a public transit and walking accessibility index (PTWAI). This index allows accessibility levels to be categorized based on travel time. Higher travel times indicate a lower level of accessibility.

A substantial body of research has assessed the relative quality of public transport services, especially in terms of accessibility (Orth et al., 2012; Fu and Xin, 2007). Previous studies have measured different aspects of public transport service levels, such as accessibility, mobility, and connectivity. These studies have focused mainly on Geographic Information System (GIS)-based public transit networks (Tribby and Zandbergen, 2012; Mavoa et al., 2012). Among a series of methodological developments within this area, the Public Transport Accessibility Level (PTAL) is an approach developed in the U.K. which measures the level of accessibility. This approach is now a central part of many transport plans in both urban and rural contexts. The PTAL provides a rating scale comprising six levels of public transport accessibility, which include measures such as access walk time, service frequency and waiting time. This approach computes the level of access by public transport for points of interest (Wu and Hine, 2003; Currie, 2010).

A GIS-based land use and public transport accessibility index (LUPTAI) has been developed which is computed by utilizing GIS analysis techniques to measure accessibility based on both public transport travel time and walking distance (Yigitcanlar et al., 2007). This approach uses an origin-based accessibility and destination-based GIS technique, and this index was applied to two pilot studies on the Gold Coast, Australia. Their findings indicated that the LUPTAI could easily be applied to a range of different land-use categories.

‘Needs-gap’ is another approach that has been used to identify spatial gaps between the supply of public transport and the levels of need for groups in Hobart, Australia. (Currie, 2004) The Supply Index (SI) developed for metropolitan Melbourne is a more recent version of that approach (Currie, 2010; Currie, 2004). This research identified significant differences between levels of public transport service supply in outer and inner/middle areas in Melbourne. It also concluded that there are spatial concentrations of very high needs persons in the outer areas of Melbourne. This study used a
combined measure of service frequency and access distance which was calculated for each census collector district (CCD). Graaff et al. (2012) also argued that the distribution of employment and population affects urban form and travel patterns.

Accessibility measures have been generally categorized into three groups: access to public transport stops, duration of journeys by public transport modes, and access to destinations by public transport modes (Mavoa et al., 2012). A large number of studies measuring accessibility have focused on proximity to a public transport stop/station (Biba et al., 2010; Currie, 2010; Furth et al., 2007; Lovett et al., 2002). Some of these studies have measured accessibility levels by considering an administrative division to a public transport stop. Currie (2010) claimed that the use of 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 public transport stops (Biba et al., 2010; Kimpel et al., 2007; Zhao et al., 2003). A key component in modelling access to public transport stops is the walking distance. Typically, the maximum acceptable walking distance is considered to be 400 m and 800 m for public transport stops or stations (Currie, 2010; Currie, 2004; El-Geneidy et al., 2010).

Although physical access to public transport stops is important, the time taken to travel between an origin and destination by public transport modes is another significant factor (Lei and Church, 2010). In addition to studies that focus on access to public transport stops, some studies focus on the duration of a journey undertaken by public transport modes (O'Sullivan et al., 2000; Benenson et al., 2011). Public transport accessibility has been measured by generating maps of accessible areas with the same travel time (O'Sullivan et al., 2000). An accessibility measurement tool which calculates a public transport service area considering travel time has also been developed (Cheng and Agrawal, 2010).

Access to a destination using public transport modes is another technique for measuring accessibility (Curtis and Scheurer, 2010). Access via public transport using business and industrial land parcels has been measured (Huang and Wei, 2002). These researchers computed the distance between census tracks, as the origin points, and the land parcels using a public transport network. Service frequency is a critical aspect of accessibility, which varies with different commuting times (Mavoa et al., 2012). Several studies have been 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., 2012). For the first group, a minimum service frequency standard has been adopted. This approach excludes public transport that does not meet the standard (Curtis and Scheurer, 2010). The second group includes all public transport stops while using service frequency. For instance, using the number of trips per week for each stop or station (Currie, 2010) or category, the service frequency is measured by how often a public transport mode arrives (Yigitcanlar et al., 2007). The needs-gap approach used by Currie (2004) identified spatial gaps in terms of public
transport supply in Hobart, Australia. A more recent version of that approach was developed for metropolitan Melbourne (Currie, 2010). 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 Public Transport Accessibility Level (PTAL) is a UK approach which measures the level of accessibility. The PTAL provides a six-level rating scale of public transport accessibility, which includes measures such as access walk time, service frequency and waiting time. This approach calculates the level of access by public transport to points of interest (Wu and Hine, 2003; Currie, 2010).

Although in previous research, access to public transport has been measured for specific population groups based on socioeconomic characteristics, including age, employment, car ownership, etc. (TfL, 2004), consideration of population density within spatial areas has been ignored. A major weakness of existing approaches is that they assign a level of accessibility to areas without considering the population distribution within those areas (Currie, 2010).

2.4 Cycling Accessibility

Vale et al. (2015) categorize location-based accessibility measures into four main groups: 1) activity-based, which includes gravity-based (also designated attraction-accessibility or potential) and cumulative opportunities measures (also known as isochrones or contour measures) (Iacono et al., 2010); 2) topology infrastructure-based, which include topological measures of the network (Lundberg, 2012; Hull et al., 2012); 3) distance-based, which include analyses of the closest facilities (Apparicio et al., 2008; Sadler et al., 2011); and 4) utility-based measures which are also known as benefits measures (Geurs and Van Wee, 2004).

2.4.1 Distance-based accessibility measures

Distance-based accessibility measures simply define accessibility as a function of the spatial separation between places. In other words, accessibility is a measure of proximity, and therefore, the further away implies lower accessibility. Accessibility measures within this group are categorised into four major types: 1) distance to the closest opportunity; 2) the number of opportunities within a defined distance or time; 3) the mean distance to all opportunities; and 4) the mean distance to a defined number of closest opportunities (Apparicio et al., 2008).

In distance-based accessibility measures, distance is considered as the travel impedance. Euclidean distance, Manhattan distance (Apparicio et al., 2008), shortest network distance (Lundberg, 2012; Hochmair, 2015), and shortest network time (Pearce et al., 2006; Páez et al., 2012) are the four types of distances that are usually used in distance-based accessibility measures. Euclidean distance has been mainly used for walkability measures, particularly in health studies (Carr et al., 2010; Brewster
et al., 2009). Considering the slope and flatness of the routes, travel time and distance are different for both cyclists and pedestrians. However, there have been limited studies that have included slope in such analysis (Pearce et al., 2006).

There are two different ways for measuring distance in analysis procedures. The first calculates the distance to the closest facility of each type, and the second calculates the distance to all facilities close by. The first method calculates the distance from each zone centroid to the closest or the first \( n \) closest facilities (e.g. medical centres). The second approach is based on floating catchment areas that find the closest facility regardless of distance, and measure the distance from each zone centre to the closest or the first \( n \) closest different facilities (e.g. medical centres, shopping centres, etc.).

Aultman-Hall et al. (1997) calculated the shortest distance to schools, open space, and transit stops as neighbourhood destinations. Similarly, a study by Lundberg (2012) measured the shortest distance from home to a university campus, while Apparicio et al. (2008) considered the shortest distance to supermarkets as well as the closest health centres. Those studies which measure the shortest distance to multiple facilities are not restricted to a maximum distance. For instance, accessibility has been computed as the shortest distance to each health centre within the study area or to various community services (Sadler et al., 2011; Silva and Pinho, 2010; Hull et al., 2012).

### 2.4.2 Gravity-based accessibility measures

An important group of access measurement methods, gravity-based accessibility measures, also known as Hansen-type measures (Hansen, 1959), are widely used in transportation planning (Vale et al., 2015). These measures are derived from the denominator of the gravity model (Ingram, 1971) and generally given as:

\[
A_i = \sum a_j f(t_{ij})
\]  

(2.1)

where, \( A_i \) represents the accessibility to zone \( i \), \( a_j \) denotes the activity in zone \( j \), \( t_{ij} \) represents travel impedance between zones \( i \) and \( j \) which can be considered as time, distance or cost, and \( f(t_{ij}) \) is an impedance function that measures the spatial separation between zones \( i \) and \( j \).

These measures assume that travel is a derived demand based on a compromise between a facility and the cost to reach it from a given origin. Hence, closer facilities are more valued than more distant ones. The two-step floating catchment area method (2SFCA), is a special case of a gravity model which was first proposed by Radke and Mu (2000) but later modified by Luo & Wang (2003a) and Luo and Wang, (2003b). The 2SFCA method was developed to measure spatial accessibility to primary care physicians. The method is implemented in the following two steps: 1) it assesses “physician availability” at the physicians’ locations as the ratio of physicians to their surrounding
population; 2) it sums the ratios obtained from the first step around (i.e., within the same threshold travel time from) each residential location (Wang and Luo, 2005).

Most studies measure impedance by travel time. In these studies, accessibility reflects the attractiveness of facilities weighted by the travel time needed to reach those destinations (Sun et al., 2012; Hull et al., 2012; Silva and Pinho, 2010). However, travel distance has also been considered as a travel impedance in some studies (Iacono et al., 2010; Lowry et al., 2012; Vasconcelos and Farias, 2012). Lowry et al. (2012) introduced a bikeability index which focused on bicycle trips. This study assessed the bikeability of the entire road network in terms of access to important destinations.

One practical reason for considering gravity-based measures or other location-based accessibility measures for non-motorized modes of transport is their potential compatibility with regional travel forecasting models. Hence, they can easily extract travel times from one zone to another based on coded networks. In addition, a number of potential opportunities are available at the zone level (Iacono et al., 2010). However, one of the limitations of the use of these measures for non-motorised modes relates to the use of non-motorised modes in travel demand models. With respect to travel time, motorised modes are more sensitive to travel times and levels of network congestion than non-motorised modes of transport. Furthermore, non-motorised route choice tends to include factors that may be more qualitative, experiential or difficult to measure/quantify (Iacono et al., 2010; Tilahun et al., 2007; Hunt and Abraham, 2007).

Another limitation of existing approaches that measure cycling accessibility is that they are highly dependent on travel diary data. In addition, methods that have been applied to measuring cycling accessibility have not focused to date on the cycling availability of destinations in terms of service coverage areas. Some of the measures have focused on determining the level of service, such as the Bicycle Compatibility Index (BCI) or the Bicycle Level of Service (BLOS) for a bicycle network (Harkey et al., 1998a; Harkey et al., 1998b; Landis et al., 1997; Landis et al., 2003). These studies measure the performance of a bicycle network using various geometric measures, such as the width of the bicycle routes, pavement, route types, and connectivity. However, there are other methods that consider bikeability in terms of how accessible different destinations are for bicycles as a transport mode. Such methods measure the potential for cycling using travel behaviour data (Rybarczyk and Gallagher, 2014; Wahlgren and Schantz, 2012; Milakis et al., 2015; Espada and Luk, 2011).

2.5 Walking Accessibility

Walking is currently an intense topic of discussion in urban and transport planning, and researchers have started to focus on walkability as a means to solve a variety of issues, from social ills to health problems relating to global warming and air pollution (Park, 2008). As Manaugh and El-Geneidy
(2011) argue, walkability can be defined as a “match” between residents’ desires and expectations for different types of destinations, their willingness to walk a given distance, and the quality of the required path. Hence, neighbourhoods that have this match between the form of the built environment and residents’ needs will be likely to have higher rates of walking trips.

There has been a notable increase in research investigating walking as a sole active travel mode (Kaplan et al., 2016; Pont et al., 2013; Su et al., 2013; Bejleri et al., 2011; Mitra et al., 2010; Yarlagadda and Srinivasan, 2008; Kerr et al., 2007). The relationship between the physical environment in residential areas and walking activity has also received substantial research attention (Eom and Cho, 2015; Turrell et al., 2013; Yang et al., 2012; Knuiman et al., 2014; Wineman et al., 2014; Christian et al., 2011; Boone-Heinonen et al., 2010). As Eom and Cho (2015) found, a dense, well-connected, and diverse built environment can increase the number of walking trips.

In other words, land-use policies and zoning strategies may influence individuals’ travel mode choice by locating different activities in various urban scales. A mix of destinations and proximities has been found to be strongly associated with walking for transport (Lee et al., 2014; Samimi et al., 2009; Ewing et al., 2014; Handy et al., 2002). McCormack (2014) argue that higher levels of physical activity will be achieved when there is a greater diversity of destinations.

Previous studies have primarily examined whether certain characteristics of the built environment are significantly related to walking. Hence, many measures and indices have been developed and implemented for defining and measuring walkability. These have been widely used to identify positive or negative associations between walking and certain characteristics of the built environment (Manaugh and El-Geneidy, 2011; Pont et al., 2013; Kuzmyak et al., 2006). Increasing accessibility or shortening the distance to destinations by modifying development patterns in denser environments is one of the approaches used for increasing active travel (Vale and Pereira, 2016; Eom and Cho, 2015). There are several methods for calculating walkability, and some of the most common approaches are outlined below.

A substantial body of research has examined factors that affect the demand for walking. Various urban and transport planning studies have shown that urban form is related to active transport (walking/cycling) levels, and affects public transport use, traffic congestion, air quality and open space conservation. It has been found that active transportation is consistently positively associated with urban form variables, including mixed land use, street connectivity and residential density (Frank et al., 2010). Promoting active transportation has recently attracted considerable attention from health practitioners (Frank et al., 2004; Ewing et al., 2003; Saelens et al., 2003). As Owen et al. argued, enhancing participation in moderate-intensity physical activity is a public health priority (Owen et al., 2007b). Walking is known as the most common moderate-intensity activity of adults, and is associated
with significant health benefits (Manson et al., 1999; Hayashi et al., 1999). A comprehensive review of the impacts of the built environment on physical activity health has been conducted by Ding and Gebel (2012).

Several definitions can be found for “walkability” or “walkable” neighbourhoods. It has been argued that walkable neighbourhoods are designed such that residents can walk from home to nearby destinations (Bauman et al., 2012). Manaugh and El-Geneidy (2011) claimed that walkability can be defined as a “match” between residents’ desires and expectations for various types of destinations, their willingness to walk a given distance, and the quality of the required path. Hence, neighbourhoods that have this match between the form of the built environment and residents’ needs will likely have higher rates of walking trips. In another study, walkability has been defined as the proximity from home to non-residential destinations and it concluded that people living in walkable neighbourhoods are less likely to be overweight or obese than people living in more suburban areas that require motorised transportation (Frank et al., 2010).

The link between the built environment and travel behaviour has received considerable research attention in recent decades (Wang et al., 2011). Improving the built environment to make it easier for people to be physically active, in part through more active transportation, is an essential component of increasing physical activity (Dannenberg et al., 2003; Frank et al., 2003; Lavizzo-Mourey and McGinnis, 2003). In other words, the arrangement or distribution of land use and activities in the surroundings of residential 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 travel. There has been a long tradition of investigating the association between the built environment and travel behaviour. However, from the late 1970s, researchers have focused more on travel behaviour and policies (Lee et al., 2014; Boarnet, 2011). Transport and urban planners as well as health practitioners have recently turned to promoting physical activity by physical environment-based solutions.

Pedestrian infrastructures such as sidewalk access, quality and street connectivity have also been identified as important criteria for determining walkability in neighbourhood areas, principally in micro-level studies (Lo, 2009). In some studies, these features have been found to affect the comfort and safety of pedestrians (>AUTHORS MISSING<2004; Cervero and Duncan, 2003; Lo, 2009).

### 2.5.1 Walk Score

Walk Score (2014) is a common approach to measuring walkability. First introduced in 2007, it has been used in macro-level studies and for investigating land use features that affect proximity. The Walk Score algorithm considers points based on the distance to the closest facility in each land use.
category. If the closest facility in a category is within 0.4 km, the maximum number of points is assigned (REDFIN, 2015) and no points are allocated to facilities that are further than 1.6 kms away. Facility categories included are offices, parks, theatres, schools and other common destinations. Using Walk Score, Duncan et al. (2011) and Carr et al. (2010) claimed that walkability in neighbourhoods is based on the distance to different categories of services, including schools, parks and libraries.

2.5.2 Walkability Index (WI)

Another approach is the Walkability Index (WI) introduced by Frank et al. (2007b; Frank et al., 2005; Frank et al., 2006; Frank et al., 2010). The WI is derived from four factors, dwelling density, street connectivity, land use mix and net retail areas, and is calculated from the sum of the z scores of the four mentioned urban form measures. The WI is one of the most common approaches used throughout the literature for measuring walkability (Frank et al., 2005; Frank et al., 2006; Frank et al., 2010; Peiravian et al., 2014; Giles-Corti et al., 2015; Sundquist et al., 2011; Owen et al., 2007a).

The WI has been used for various geographical scales, census divisions, and network buffers around households or commercial centres (Saelens et al., 2003; Cerin et al., 2007). This index integrates three variables: land use mix, connectivity and residential density. A normalized distribution is taken for each variable (z-score) and the three variables are then combined to calculate the WI index. The WI has been used in a wide range of studies measuring walkability or modelling travel behaviour. However, a different range of weights has been considered for components of the index in different studies. For instance, using the WI, Gilderbloom et al. (2015) showed that walkability has an impact on neighbourhood resilience in urban versus suburban areas. In their study, the idea of the value of a walkable environment in Louisville, US was examined to identify how walkability affects neighbourhood stability, economic resilience and livability. In another study, Van Dyck et al. (2010) investigated whether neighbourhood walkability, using the WI, is positively associated with physical activity in Belgian adults and whether this association is moderated by neighbourhood socio-economic status.

2.5.3 Pedestrian Environment Index (PEI)

Taking this notion further, Peiravian et al. (2014) developed an index measuring the pedestrian friendliness of urban neighbourhoods called the Pedestrian Environment Index (PEI). The PEI’s components represent land-use diversity (based on the concept of entropy), population density, commercial density, and intersection density. As a case study, the city of Chicago was analyzed at the sub-traffic analysis zone (sub-TAZ) level.
2.5.4 Walk Opportunities Index (WOI)

Kuzmyak et al. (2006) introduced an index for measuring walking opportunities. The Walk Opportunities Index (WOI) quantifies the various opportunities by measuring the difficulty in reaching them. Its structure is similar to that of the gravity model approach for calculating regional accessibility. The WOI calculates the walking distance to each opportunity in 0.25-mile buffers. With this index, the value of each opportunity is reduced by its travel distance.

2.5.5 Ped-sheds method

Porta and Renne (2005) introduced the Ped-sheds method, where the pedestrian catchment is measured by a network buffer over a straight-line buffer of the same distance. In other words, a Ped-shed is defined as the pedestrian catchment of a land use destination via the pedestrian network. It is usually limited to a specific walking distance of around 1 mile or 2 kms. A higher percentage of coverage means greater accessibility (Babb et al., 2011).

Manaugh and El-Geneidy (2011) examined several existing walkability measures and indices at multiple geographic scales to understand how these measures are related to actual observed travel behaviour. They used four walkability indices, including the online walkscore, the WI, the WOI and the Ped-sheds method. Accordingly, several models were generated for two trip purposes, including shopping trips and education trips, using a different walkability measure for every run, while keeping other variables in the model constant. All the indices and individual measures performed quite well in describing pedestrian behaviour on the island of Montréal in Canada. However, the online walkscore was found to be a better measure of walkability for shopping trips, while the simple Ped-sheds method was found to be the best walkability index for explaining the odds of walking to school. Therefore, their findings indicated that different walkability indices should be used when investigating the level to which the built environment increases the likelihood of persons walking to various destinations.

Some of the existing approaches are very complicated and require prior computation before calculating the index (e.g. WI and PEI). Other approaches, such as the Ped-shed method and Walk Score, which consider the travel distance between the origins and the destinations of trips are simpler. However, no current index considers the thresholds of walking distances for distinct categories of destinations. Furthermore, all the existing approaches consider the diversity of land-uses; while the importance of the intensity of activities has been ignored.
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CHAPTER 3

PUBLIC TRANSPORT ACCESSIBILITY IN METROPOLITAN AREAS: A NEW APPROACH INCORPORATING POPULATION DENSITY
Chapter 3: Public Transport Accessibility in Metropolitan Areas: A New Approach Incorporating Population Density

Abstract

Improving public transport accessibility can be considered an effective way of reducing the external costs and negative side-effects of motorized commuting. Although many studies have measured access levels to public transport stops/stations, there has been limited research on accessibility that integrates population density within geographical areas. This study proposes a new measure that considers public transport service frequency and population density as an important distributional indicator. A Public Transport Accessibility Index (PTAI) is formulated for quantifying accessibility within local areas in metropolitan Melbourne, Australia. A public transport network model is applied to identify the service coverage of public transport modes using a Geographical Information System (GIS). A consistent method is introduced for evaluating public transport accessibility for different levels of analysis, from single elements, including public mode stops, to network analysis. The Victorian Integrated Survey of Travel and Activity (VISTA) is used to evaluate the index and examine the association between commuting trips undertaken by public transport and the level of accessibility within the Melbourne metropolitan region. Furthermore, the new index is compared with two existing approaches using the VISTA dataset. Key findings indicate that the PTAI has a stronger association whilst showing more use of public transport in areas with higher values of the PTAI.

Keywords: PTAI, Public Transport, Accessibility, Network Analysis, Population Density

3.1 Introduction

Shifting from private motorized vehicles to public transportation, walking and cycling can increase the sustainability of transportation and consequently, improve the environment, the economy and public health (Elias and Shiftan, 2012). A well-organized public transportation system is capable of increasing the level of mobility in cities. Hence, a user-friendly public transportation system should consider accessibility to stops/stations, the mobility of the system and the connectivity to other transportation modes (Cheng and Chen, 2015). Providing efficient public transport in terms of accessibility is one of the main objectives of policy makers and planners in metropolitan areas throughout the world. In recent decades, sprawling land-use planning, automobile-oriented developments along with increased car ownership have encouraged people to spend more time travelling by car. High levels of car dependency not only affect the quality of life, but also threaten people’s health. On the other hand, growing use of private motorization has resulted in critical issues such as traffic congestion and environmental impacts. Use of public transport is considered within the definition of active transport as it often involves some walking or cycling to make connections from the origins to the destinations (Taniguchi et al., 2013). For this reason, the provision of high levels of accessibility for public transport systems with good connectivity can promote active transport and sustainability. From a users’ viewpoint, an effective public transport service can be defined as minimum in-vehicle travel time and waiting time (Ceder et al., 2009).

Transportation equity affects residents’ economic as well as social opportunities (Wang and Chen, 2015; Cheng and Bertolini, 2013). In other words, transport problems may result in social exclusion, as reported in several studies (Fransen et al., 2015; Priya and Uteng, 2009; Delmelle and Casas, 2012; Lucas, 2011). It has been shown that some suburban and regional areas in Australia are disadvantaged with respect to public transport, where distance is a major barrier (Currie and Stanley, 2007). Australia has been categorized as a country with high car ownership (Lucas, 2012) with particular groups of people such as youths, seniors, low-income households and Aboriginals encountering difficulties in accessing work, education and social or cultural activities (Lucas, 2012; Altman and Hinkson, 2007; Johnson et al., 2011).

This paper presents a review of previous research in this area. Numerous studies have focused on measuring public transport accessibility. However, there has been limited work on the distribution of the population in measuring accessibility levels. We present a new index to measure public transport accessibility and describe its application to increase understanding of public transport usage in metropolitan Melbourne, Australia. There is a need to incorporate different frequencies of public transport modes, public transport routes and population densities in measuring public transport accessibility. This paper proposes an index that can be used to classify levels of accessibility. The method has been applied to the Melbourne metropolitan area, which is served by a public transport...
system that includes train, tram and bus services. The following section introduces the methodology, and Section 3.3 describes the computation of the index. An analysis and the results of the application of the PTAI in the Melbourne region, along with a comparison of the results between the new index and existing approaches, are presented in Section 3.4. Section 3.5 discusses the results, while Section 3.6 summarizes the findings and outlines avenues for future research.

3.2 Methodology

The aim of this study was to develop an index for the measurement of the level of accessibility to public transport in Melbourne's 9510 Statistical Areas level 1 (SA1s)\(^1\), the second smallest geographic area defined in the Australian Statistical Geography Standard (REFERENCE?). According to the Australian Government Department of Health and Ageing (Neighbourhood Planning and Design, 2009), the physical characteristics of neighbourhoods are accessible based on walkable catchments. This is generally defined as 5 to 10 minutes walking to/from public transport stops/stations. SA1 districts were found to have the closest conformity to walking catchments. In order to define the index, two factors, a weighted equivalent frequency (WEF) and the ratio of population density in SA1s and buffer areas (service areas of different public transport modes) are calculated. This work is consistent with Lei and Church's (2010) classification, as it deals with physical access to public transport stops/stations in terms of walking time and service frequency. Furthermore, the work fits into the first category, access to public transport stops, of the more general three-way classification scheme developed by Mavoa et al. (2012). The methodology has been developed for metropolitan Melbourne, where areas with a denser public transport network and population show greater access to all nearby destinations. The databases and the study area, the conceptual framework, and existing methods and approaches are presented in this section to describe the process for calculating the index.

3.2.1 Datasets and Study Areas

The following approach was developed to calculate the PTAI:

1. Three modes of public transport, including public buses, trams and trains are considered. A database of bus and tram stops, train stations and public transport routes and corridors was obtained from the Victorian Government open data sources (2015). According to this database, the Melbourne region is covered by approximately 17800 bus stops, 1700 tram stops, and 240 train stations. The system includes almost 300 bus routes and a train system comprising 16 lines servicing Greater Melbourne and suburban areas. Figure 3.1 shows the distribution of public transport stops/stations within metropolitan Melbourne. It can be seen that public buses almost cover the inner parts of Melbourne. However, tram stops are

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\(^1\) According to the Australian Bureau of Statistics (ABS), the ABS structure of Melbourne region contains 53074 Mesh Blocks, 9510 Statistical Areas Level 1 (SA1s), 277 Statistical Areas Level 2 (SA2s), 42 Statistical Areas Level 3 (SA3s) and 12 Statistical Areas Level 4 (SA4s).
consistently spread throughout the CBD and contiguous suburbs while train stations radially penetrate the suburbs.

Figure 3.1 Distribution of public transport stops/stations and points of interest in metropolitan Melbourne

1. Service frequency data were calculated from the timetables for each mode during the morning peak hours (7 to 9 am). For example, for a bus route with average 20-minute services during the peak hours, the frequency was calculated to be 3. Timetables are accessible on the Public Transport Victoria (PTV) website (https://www.ptv.vic.gov.au).

2. A database of points of interest (POIs) was obtained from the Australian Urban Research Infrastructure Network (AURIN). This included urban centres, significant buildings, landmarks, public spaces, community facilities and indigenous locations, consisting of 15588 points. Table 3.1 presents the number and percentage of different POI categories. Average distances to public transport stops/station from 25 major POIs are also presented.
Table 3.1 Points of Interest

<table>
<thead>
<tr>
<th>Categories</th>
<th>Number</th>
<th>Percent</th>
<th>Average distance to closest bus stop (m)</th>
<th>Average distance to closest tram stop (m)</th>
<th>Average distance to closest train station (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Administration Facility</td>
<td>332</td>
<td>2.1</td>
<td>372</td>
<td>37</td>
<td>446</td>
</tr>
<tr>
<td>Care Facility</td>
<td>3826</td>
<td>24.5</td>
<td>265</td>
<td>355</td>
<td>605</td>
</tr>
<tr>
<td>Commercial Facility</td>
<td>390</td>
<td>2.5</td>
<td>377</td>
<td>82</td>
<td>366</td>
</tr>
<tr>
<td>Communication Service</td>
<td>143</td>
<td>0.9</td>
<td>387</td>
<td>10</td>
<td>215</td>
</tr>
<tr>
<td>Community Space</td>
<td>27</td>
<td>0.2</td>
<td>656</td>
<td>-</td>
<td>124</td>
</tr>
<tr>
<td>Community Venue</td>
<td>577</td>
<td>3.7</td>
<td>253</td>
<td>31</td>
<td>501</td>
</tr>
<tr>
<td>Control Points</td>
<td>23</td>
<td>0.1</td>
<td>958</td>
<td>-</td>
<td>269</td>
</tr>
<tr>
<td>Cultural Centre</td>
<td>143</td>
<td>0.9</td>
<td>295</td>
<td>50</td>
<td>496</td>
</tr>
<tr>
<td>Dumping Ground</td>
<td>42</td>
<td>0.3</td>
<td>496</td>
<td>13</td>
<td>778</td>
</tr>
<tr>
<td>Education Centre</td>
<td>1869</td>
<td>12.0</td>
<td>267</td>
<td>38</td>
<td>581</td>
</tr>
<tr>
<td>Emergency Facility</td>
<td>545</td>
<td>3.5</td>
<td>306</td>
<td>25</td>
<td>423</td>
</tr>
<tr>
<td>Excavation Site</td>
<td>175</td>
<td>1.1</td>
<td>562</td>
<td>21</td>
<td>389</td>
</tr>
<tr>
<td>Health Facility</td>
<td>1098</td>
<td>7.0</td>
<td>259</td>
<td>39</td>
<td>370</td>
</tr>
<tr>
<td>Hospital</td>
<td>133</td>
<td>0.9</td>
<td>229</td>
<td>60</td>
<td>353</td>
</tr>
<tr>
<td>Industrial Facility</td>
<td>30</td>
<td>0.2</td>
<td>119</td>
<td>12</td>
<td>1218</td>
</tr>
<tr>
<td>Landmark</td>
<td>137</td>
<td>0.9</td>
<td>251</td>
<td>25</td>
<td>326</td>
</tr>
<tr>
<td>Indigenous Locations</td>
<td>1156</td>
<td>7.4</td>
<td>325</td>
<td>30</td>
<td>526</td>
</tr>
<tr>
<td>Worship Places</td>
<td>303</td>
<td>1.9</td>
<td>279</td>
<td>20</td>
<td>326</td>
</tr>
<tr>
<td>Recreational Resources</td>
<td>2460</td>
<td>15.8</td>
<td>255</td>
<td>29</td>
<td>644</td>
</tr>
<tr>
<td>Residential Buildings</td>
<td>405</td>
<td>2.6</td>
<td>201</td>
<td>37</td>
<td>468</td>
</tr>
<tr>
<td>Sign</td>
<td>1360</td>
<td>8.7</td>
<td>577</td>
<td>19</td>
<td>576</td>
</tr>
<tr>
<td>Sport Facility</td>
<td>69</td>
<td>0.4</td>
<td>351</td>
<td>41</td>
<td>832</td>
</tr>
<tr>
<td>Storage Facility</td>
<td>323</td>
<td>2.1</td>
<td>374</td>
<td>5</td>
<td>385</td>
</tr>
<tr>
<td>Pipeline Facility</td>
<td>22</td>
<td>0.1</td>
<td>100</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Total</td>
<td>15588</td>
<td>100.0</td>
<td>315</td>
<td>33</td>
<td>540</td>
</tr>
</tbody>
</table>

Figure 3.2 illustrates the distribution of POIs through the Melbourne region. As the figure shows, Melbourne POIs are mostly concentrated in the inner parts of Melbourne. However, some suburbs such as Sunbury, Melton and Werribee have considerable densities of POIs.
3. A database of mesh blocks from the 2011 Census for the Melbourne Region was accessible from the Australian Bureau of Statistics (ABS) (2011). 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 (the smallest geographical unit released by the ABS) and all other statistical areas, including SA1s. According to the ABS, the Melbourne region contains 53074 mesh blocks and 9510 SA1s.

3.2.2 Conceptual Framework

The PTAI consists of two main procedures. The first step relates to the POIs and public transport supply, and the second step involves calculating the population density in both walking catchments and SA1s. Figure 3.3 shows the conceptual framework of the calculation process for the PTAI. For a given POI, the shortest distance to a public transport stop/station is defined. Thereafter, the equivalent frequency is computed following the steps shown. On the other side, as shown, for public transport modes' service areas, the proportion of population density is calculated for each buffer area and SA1.

![Diagram of Conceptual Framework](image)

Figure 3.3 Conceptual framework of the calculation process

3.2.3 Approach

PTAL and SI

The approach introduced here extends the more recent and common approaches, including the UK
approach (TfL, 2010) measuring public transport accessibility levels (PTAL) and the supply index (SI) introduced by Currie (2010). PTAL measures accessibility using local indicators and accessibility modelling. It uses a six-level scale to rate public transport service access, and includes measurements such as walk time, waiting time and service frequency. The index developed in this paper calculates the sum of equivalent doorstep frequency (EDF) of all different public transport modes.

SI is a supply index calculated for Melbourne’s 5839 census collector districts (CCDs). The index is a combined measure of service frequency (number of public transport vehicle arrivals per week) and access distance, as shown in Equation 3.1.

\[ SI_{\text{CCD}} = \sum N \left( \frac{\text{Area}_{B_n}}{\text{Area}_{CCD}} \times SL_{B_n} \right) \]  

where SI_{CCD} is the supply index for CCDs and N is the number of walking buffers to public transport stops/stations in each CCD. B_n is the buffer n for each stop/station, Area is the square kilometre area of the CCD and SL is the service level of the public transport modes (Currie, 2010).

Both indexes, PTAL and SI, were calculated for SA1s and the results are presented in Table 3.2. According to the table, based on the PTAL, about 50% or about 2 million residents have zero to moderate access to public transport modes, while for SI, these figures rise to 67% or 2.6 million residents.

<table>
<thead>
<tr>
<th>PTAL/SI Categories</th>
<th>PTAL</th>
<th>SI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of SA1s</td>
<td>Population (%)</td>
</tr>
<tr>
<td>Zero Access/Supply</td>
<td>52</td>
<td>16243 (0.4)</td>
</tr>
<tr>
<td>Very Poor/Very Low</td>
<td>1370</td>
<td>560271 (14.2)</td>
</tr>
<tr>
<td>Poor/Low</td>
<td>1398</td>
<td>604059 (15.3)</td>
</tr>
<tr>
<td>Moderate/Below Average</td>
<td>1857</td>
<td>773731 (19.6)</td>
</tr>
<tr>
<td>Good/Above Average</td>
<td>1415</td>
<td>582554 (14.8)</td>
</tr>
<tr>
<td>Very Good/High</td>
<td>1624</td>
<td>670184 (17.0)</td>
</tr>
<tr>
<td>Excellent/Very High</td>
<td>1794</td>
<td>734169 (18.6)</td>
</tr>
<tr>
<td>Total</td>
<td>9510</td>
<td>3941211 (100.0)</td>
</tr>
</tbody>
</table>

### 3.3 PTAI Calculation

The present study aims to measure the level of accessibility for each SA1. The index measures the accessibility of a selected POI from the public transport network considering walk time and service frequency, which reflect the estimated doorstep frequency. The Public Transport Accessibility Index (PTAI) also incorporates the share of population density in public transport mode service areas and SA1s.
As mentioned previously, there are approximately 20,000 public transport stops in the Melbourne metropolitan region. This area has about 16,000 POIs including community services and facilities, landmarks, non-residential and public buildings. In some SA1s with two or more stops/stations, service areas were merged using the same break value. Network analysis was conducted separately for each public transport mode. For instance, considering a shopping centre as a selected POI, the distance of the nearest public bus stop was measured. Thereafter, the same process was applied for the closest tram stop and train station. In other words, these steps were followed for all three modes. In order to determine the service frequency for a POI, network analysis of the closest facility was applied. The process of computing the accessibility index can be broken into several stages, from measuring the walking distances and times to estimating population densities in service areas of public transport modes. The following sections describe the formulation of the index. The calculation of the WEF extends the approach used in measuring public transport accessibility levels in London (TfL, 2010).

**Walk Time (WT)**

The walking time was the first component calculated from a specified POI to the closest public transport stops. Distances from the POI were converted to a measure of time, assuming an average walk speed of 4.8 kilometres/hour or 80 metres/minute (TfL, 2010). Walk distances, using network analysis by ArcGIS 10.2, were calculated from a particular POI to the closest public transport stop/station, including bus stops, tram stops, and train stations. The maximum walk time for buses and trams was defined as 10 minutes or a distance of 800 meters, and the maximum walking time for trains was considered to be 15 minutes or a distance of 1200 meters.

**Average Waiting Time (AWT)**

The Average Waiting Time is the average time between arriving at a stop/station and the arrival time of desired services. For each selected route, the AWT was considered as the interval between services. For instance, for a public transport mode running services every 5 minutes or 12 frequencies per hour, the AWT is 2.5 minutes. In other words, a passenger may have to wait about 6 minutes for a desired service to arrive. The AWT is estimated as half the headway (i.e. the time interval between services), as shown in Equation (3.2).

\[
AWT_{ij} = 0.5 \times \left(\frac{60}{F_{ij}}\right) \quad i = 1,2,3, \ldots, n \quad j = 1,2,3 \tag{3.2}
\]

where, \(AWT_{ij}\) is the average waiting time (in minutes) at the closest stop/station to the POI \(i\) for public transport 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 the POI \(i\).
Total Access Time (TAT)

After calculating the WT and AWT, the Total Access Time (TAT) of a selected POI to the nearest public transport stop/station is calculated. This includes walking times from the POI to the stop/station and average waiting times. TAT, as shown in Equation (3.3), is comprised of both WT and AWT. Since the boundaries of SA1s coincide with roads, the TAT for each SA1 is considered as the TAT of the closest POI to the SA1 boundaries.

\[ TAT_{ij} = WT_{ij} + AWT_{ij} \quad i = 1,2,3, ..., n \quad j = 1,2,3 \]  

(3.3)

where, \( TAT_{ij} \) is the total access time (minutes) of public transport mode \( j \) at the closest stop/station to the POI \( I \), and \( WT_{ij} \), as explained above, is the walk time (in minutes) from the POI \( i \) to the closest stop/station of public transport mode \( j \).

Equivalent Frequency (EF)

\( TATs \) were converted to an equivalent frequency using Equation (3.4). This measures the doorstep availability of a route at the specified POI. The Equivalent Frequency (EF) as presented in Equation (3.5) is calculated as 30 minutes divided by the TAT.

\[ EF_{ij} = \frac{30}{TAT_{ij}} \quad i = 1,2,3, ..., n \quad j = 1,2,3 \]  

(3.4)

where, \( EF_{ij} \) is the equivalent frequency for public transport mode \( j \) at the closet stop/station to the POI \( i \).

Weighted Equivalent Frequency (WEF)

The Weighted Equivalent Frequency (WEF) is calculated as a summation of the EFs of public transport modes with a weighting in favour of the most dominant mode (Equation 3.5).

\[ WEF_{ij} = \alpha EF_{id} + \beta \sum_{j \neq d} \sum_{i} EF_{ij} \quad i = 1,2, ..., n \quad j = 1,2,3 \]  

(3.5)

\( WEF_{ij} \) is the weighted equivalent frequency for public transport mode \( j \) at the closest stop/station to the POI \( i \), \( EF_{id} \) is the equivalent frequency of the most dominant public transport mode at the closest stop/station to the POI \( i \), \( \alpha \) and \( \beta \) are the coefficients considered for the equivalent frequency of the most dominant public transport mode and all other public transport modes.

In the present study considering factors of popularity, time and number of passengers transferred by public transport modes (see Table 3.4), \( \alpha \) and \( \beta \) were defined as 1 for the train (the dominant mode) and 0.5 for the two other modes (TfL, 2010).
WEFs for SA1s

The WEFs calculated for POIs were transferred to the SA1s. For this purpose, spatial joining (using ArcGIS 10.2) was used based on the criterion of closeness to the boundaries of SA1s. Hence, considering any POI, the WEF was transferred from the one which had the minimum distance to the boundary of its surrounding SA1s. The reason for this was that since SA1 boundaries are compatible with roads, the closest POI to a SA1 boundary also has the shortest distance to the road. This may make particular POIs more accessible than their counterparts.

Population Density

Population density was used as an indicator of the spatial distribution of the population when calculating the index. Population densities were calculated for both buffer areas and SA1s. Based on typical walk catchments for public transport modes, 400 metres was considered for accessing bus and tram stops and 800 metres was assumed for accessing train stations. Thereafter, service areas of public transport modes were overlapped with SA1s, using a Geographic Information System (GIS) to calculate the share of population density for each 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 the 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. Figure 3.4 presents a map of public transport stop/station service areas. This was produced using network analysis and shows the areas of metropolitan Melbourne which are covered by public transport services. Typically, the inner suburbs have three overlapping public transport modes, while in outer suburbs, the public bus is the dominant mode.
Figure 3.4 Service areas of public transport modes in Melbourne region

Figure 3.5 illustrates the overlapping areas of a selected SA1 with walking catchments from the tram stops. Populations within buffer areas were calculated based on the proportion of buffer areas overlapping the mesh blocks (assuming a homogenous distribution of populations within mesh blocks). It should be noted that the population for each SA1 was also calculated from the mesh blocks from which the corresponding SA1s are built. Mesh blocks nest completely within SA1 areas; this means that the area or population for a given SA1 is the sum of the areas and the population of the mesh blocks contained within it. In this example, the population of the selected SA1 is equal to 393, which is the total population of all the mesh blocks within this SA1. As shown in Figure 3.5, the selected SA1 contains 6 mesh blocks and 9 buffer areas. When calculating the population of the buffer areas, the proportions of buffer areas overlapping mesh blocks were matched to the corresponding mesh block populations. Table 3.3 shows information on the population of mesh blocks and buffer areas in the SA1 coded 20701114819. Thereafter, the population density was calculated using buffer areas as well as SA1s. Subsequently, the population density for buffer areas was estimated as 1277 people per km$^2$ (244 divided by 0.19 km$^2$) and the population density of this SA1 was 1369 people per km$^2$ (393 divided by 0.29 km$^2$). Hence, the ratio of population density for the buffer areas and the SA1 was 0.93. The total proportion of the buffer areas to the SA1 area (or total area of mesh blocks) is 0.66. If we calculated the buffer area as a proportion of the SA1 area and assumed the population was uniformly distributed across the SA1 we would assume a buffer population of $(0.191/0.287) \times 393 = 262$. However, the use of mesh blocks provides a more appropriate estimate. Furthermore, disaggregation by mesh blocks assisted in not falling foul of the ecological fallacy and the modifiable
areal unit problem (MAUP) (Ian, 2010; Wong, 2009). As presented in Table 3.3, the real population of the buffer areas is 244. The reason is that some mesh blocks may contain no persons.

Table 3.3 An example of the calculation procedure of the estimated population for buffer areas

<table>
<thead>
<tr>
<th>Buffers Numbers</th>
<th>SA1 Codes</th>
<th>Mesh Block Codes</th>
<th>Mesh Block Area (m²)</th>
<th>Mesh Block Population</th>
<th>Mesh Block Land Uses</th>
<th>Buffer Area (m²)</th>
<th>Area Proportion</th>
<th>Estimated Buffer Population</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1</td>
<td>20701114819</td>
<td>200569800000</td>
<td>27279.949</td>
<td>101</td>
<td>Residential</td>
<td>27279.949</td>
<td>1.000</td>
<td>101</td>
</tr>
<tr>
<td>B2</td>
<td>20701114819</td>
<td>200560900000</td>
<td>26478.229</td>
<td>96</td>
<td>Residential</td>
<td>914.046</td>
<td>0.035</td>
<td>3</td>
</tr>
<tr>
<td>B3</td>
<td>20701114819</td>
<td>200560900000</td>
<td>59421.310</td>
<td>0</td>
<td>Parkland</td>
<td>27430.634</td>
<td>0.462</td>
<td>0</td>
</tr>
<tr>
<td>B4</td>
<td>20701114819</td>
<td>206984900000</td>
<td>23744.889</td>
<td>85</td>
<td>Residential</td>
<td>12631.484</td>
<td>0.532</td>
<td>45</td>
</tr>
<tr>
<td>B5</td>
<td>20701114819</td>
<td>200596900000</td>
<td>49246.309</td>
<td>111</td>
<td>Residential</td>
<td>772.107</td>
<td>0.021</td>
<td>2</td>
</tr>
<tr>
<td>B6</td>
<td>20701114819</td>
<td>200606200000</td>
<td>36024.267</td>
<td>0</td>
<td>Parkland</td>
<td>28434.661</td>
<td>0.249</td>
<td>0</td>
</tr>
<tr>
<td>B7</td>
<td>20701114819</td>
<td>200606200000</td>
<td>114082.487</td>
<td>0</td>
<td>Parkland</td>
<td>49246.309</td>
<td>0.432</td>
<td>0</td>
</tr>
<tr>
<td>B8</td>
<td>20701114819</td>
<td>200597000000</td>
<td>25538.881</td>
<td>96</td>
<td>Residential</td>
<td>27430.634</td>
<td>0.965</td>
<td>93</td>
</tr>
<tr>
<td>B9</td>
<td>20701114819</td>
<td>200597000000</td>
<td>27279.949</td>
<td>101</td>
<td>Residential</td>
<td>914.046</td>
<td>0.035</td>
<td>3</td>
</tr>
<tr>
<td>Total</td>
<td>20701114819</td>
<td>-</td>
<td>287031.132</td>
<td>393</td>
<td>-</td>
<td>191332.605</td>
<td>0.667</td>
<td>244</td>
</tr>
</tbody>
</table>

Figure 3.5 Illustration of calculation of population density for buffer areas and SA1s

PTAI Index

For each SA1 the PTAI is calculated using the formula given in Equation (3.6). The index is a combined measure of $WEF$ and population density ratio given as:

$$if \ D_{Bij} = 0;$$  \hspace{1cm} (3.6)
\[ PTAI_{SA1} = \sum_{j=1}^{3} \sum_{i=1}^{l} \left( 1 + \frac{D_{Bij}}{D_{SA1i}} \right) \cdot WEF_{SA1i} \]

if \( D_{Bij} \neq 0 \);

\[ PTAI_{SA1} = \sum_{j=1}^{3} \sum_{i=1}^{l} \left( \frac{D_{Bij}}{D_{SA1i}} \right) \cdot WEF_{SA1i} \]

where, \( PTAI_{SA1} \) denotes the public transport accessibility index for a given \( SA1 \) and \( D_{Bij} \) is the population density of buffer \( i \) for public transport mode \( j \), \( D_{SA1} \) is the population density of the \( SA1 \), and \( WEF_{SA1} \) is the weighted equivalent frequency calculated for the corresponding \( SA1 \).

In this approach, accessibility is calculated for the spatial coverage of each \( SA1 \) which is covered by walking buffers to public transport 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 both bus and tram stops, the 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 groups accessibility levels into 6 categories, where category 1 represents a very poor level and level 6 represents an excellent level of accessibility (Table 3.1). A value of 0 indicates that there is either no accessibility or no population in a given \( SA1 \). In areas with no population or non-residential uses, the PTAI is equal to \( WEF_{SA1} \).

### 3.4 Results

Table 3.4 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 is based on quantiles, since they are one of the best methods for simplifying comparisons as well as aiding general map-reading (Brewer and Pickle, 2002). Zero accessibility is provided for 16243 residents or 0.55% of the total population. Very poor areas are mostly located in outer Melbourne. Overall, around 50% of the total population have zero to moderate accessibility to public transport. Figures in different PTAI categories show a high degree of consistency with the PTAL and SI presented in Table 3.1.
Table 3.4 PTAI Ranges and Categories

<table>
<thead>
<tr>
<th>Ranges</th>
<th>PTAI Categories</th>
<th>SA1s</th>
<th>Population</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No.</td>
<td>Percent</td>
</tr>
<tr>
<td>0</td>
<td>N/A</td>
<td>52</td>
<td>0.55</td>
</tr>
<tr>
<td>&lt; 2</td>
<td>Very Poor</td>
<td>1331</td>
<td>14.00</td>
</tr>
<tr>
<td>2 – 3.5</td>
<td>Poor</td>
<td>1607</td>
<td>16.90</td>
</tr>
<tr>
<td>3.5 – 6</td>
<td>Moderate</td>
<td>1791</td>
<td>18.83</td>
</tr>
<tr>
<td>6 - 12</td>
<td>Good</td>
<td>1969</td>
<td>20.70</td>
</tr>
<tr>
<td>12 - 20</td>
<td>Very Good</td>
<td>1480</td>
<td>15.56</td>
</tr>
<tr>
<td>&gt; 20</td>
<td>Excellent</td>
<td>1280</td>
<td>13.46</td>
</tr>
<tr>
<td>Total</td>
<td>N/A</td>
<td>9510</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Figure 3.6 illustrates the distribution of PTAI categories in the Melbourne region. As explained above, the PTAI is categorized into 6 bands. The first category represents very poor accessibility, while the last category corresponds to an excellent level of accessibility to public transport. The first category has 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 the figure shows, outer Melbourne, where public transport is mainly provided by public buses has low levels of accessibility in comparison to inner parts and the CBD.

Table 3.5 presents a summary of the descriptive statistics of the index components. This shows that there are on average 414 residents in each SA1 with an average area of 0.93 km$^2$. The average number
of stops/stations per SA1 is 2.1, which receive a total of 9.6 services during peak times. The average WEF per SA1 is 5.5 and the average value of the PTAI per SA1 is 8.8. On average, 28% of the Melbourne area is covered by the walking catchments of bus stops. This proportion is 4% and 3% for train stations and tram stop walking buffers, respectively.

Table 3.5 Descriptive statistics of indicators in each SA1

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Mean</th>
<th>S.D.</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area (km²)</td>
<td>0.93</td>
<td>10.2</td>
<td>0.002</td>
<td>854.3</td>
</tr>
<tr>
<td>Population</td>
<td>414</td>
<td>209.5</td>
<td>0</td>
<td>6224</td>
</tr>
<tr>
<td>Frequency of Bus services</td>
<td>2.2</td>
<td>1.5</td>
<td>0</td>
<td>20</td>
</tr>
<tr>
<td>Frequency of Tram services</td>
<td>2.9</td>
<td>4.1</td>
<td>0</td>
<td>12</td>
</tr>
<tr>
<td>Frequency of Train services</td>
<td>4.5</td>
<td>2.6</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>Number of public transport stops/stations per SA1</td>
<td>2.1</td>
<td>2.5</td>
<td>0</td>
<td>60</td>
</tr>
<tr>
<td>WEF</td>
<td>5.5</td>
<td>5.3</td>
<td>0</td>
<td>659.7</td>
</tr>
<tr>
<td>PTAI</td>
<td>8.8</td>
<td>10.7</td>
<td>0</td>
<td>98.6</td>
</tr>
<tr>
<td>Proportion of SAs covered by walk buffers of bus stops (%)</td>
<td>28%</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Proportion of SAs covered by walk buffers of tram stops (%)</td>
<td>4%</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Proportion of SAs covered by walk buffers of train stations (%)</td>
<td>3%</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

3.4.1 PTAI Assessment

The Victorian Integrated Survey of Travel and Activity (VISTA) data set was adopted to assess and evaluate the index. The VISTA dataset was published by the Department of Economic Development, Jobs, Transport and Resources (EDJTR) in 2009. 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), and the regional cities of Geelong, Ballarat, Bendigo and Shepparton, and the 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 16411 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 details of 93,902 trips stages made by 22,184 individuals in the MSD. Whilst the VISTA dataset contained the SA1 codes, the statistical analysis was applied using the same spatial scale. This prevented the occurrence of the MAUP and geographical errors (Mitra and Buliung, 2012).

There were 93,902 commuting trips in the VISTA data (see Table 3.6). Approximately one-fifth of the total trips (19.5% of total trips) were by public transport. Of this number, 2.8% were made by public bus, 11.8% by train and 4.3% by tram, making trains the most popular public transport mode. For this reason, a weighting of 1 was used for trains when producing the accessibility index.
Table 3.6 Number and Percentage of trips made by different modes in the Melbourne region

<table>
<thead>
<tr>
<th>Transport Modes</th>
<th>Frequency</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle Driver</td>
<td>42989</td>
<td>45.8</td>
<td>45.8</td>
</tr>
<tr>
<td>Vehicle Passenger</td>
<td>21073</td>
<td>22.4</td>
<td>68.2</td>
</tr>
<tr>
<td>Motorcycle</td>
<td>174</td>
<td>.2</td>
<td>68.4</td>
</tr>
<tr>
<td>Private Motorized</td>
<td>64236</td>
<td>68.4</td>
<td>-</td>
</tr>
<tr>
<td>Walking</td>
<td>9625</td>
<td>10.3</td>
<td>78.7</td>
</tr>
<tr>
<td>Bicycle</td>
<td>1340</td>
<td>1.4</td>
<td>80.1</td>
</tr>
<tr>
<td>Non-Motorized</td>
<td>10965</td>
<td>11.7</td>
<td>-</td>
</tr>
<tr>
<td>Public Bus</td>
<td>3230</td>
<td>3.4</td>
<td>83.5</td>
</tr>
<tr>
<td>Train</td>
<td>11095</td>
<td>11.8</td>
<td>95.3</td>
</tr>
<tr>
<td>Tram</td>
<td>3999</td>
<td>4.3</td>
<td>99.6</td>
</tr>
<tr>
<td>Public Transport</td>
<td>18324</td>
<td>19.5</td>
<td>-</td>
</tr>
<tr>
<td>Other</td>
<td>377</td>
<td>.4</td>
<td>100</td>
</tr>
<tr>
<td>Total</td>
<td>93902</td>
<td>100.0</td>
<td></td>
</tr>
</tbody>
</table>

Using SPSS V.22, cross-tabulation analysis along with the Chi-square and Cramer’s V tests were applied to investigate whether there is any association between the accessibility index produced and commuting by public transport modes. Table 3.7 presents the results of cross-tabulation analysis between PTAI categories and public transport modes. Public transport modes are grouped as train, tram, and public bus, while the PTAI is categorized from very poor to excellent. The rows present counts and percentages for the three different public transport modes, while the columns are divided based on the PTAI categories, which represent the level of accessibility. The results show that travelling by train increases from 7.8% to 20.6% as the accessibility level increases through statistical areas. There is also a similar trend for trams. However, considering the change from moderate to good levels of accessibility, commuting by tram shows a sharp increase (more than 35%). In contrast, in areas with good to excellent levels of accessibility, travelling by public bus declines. This is possibly because highly accessible areas are provided with three public transport modes, and according to Table 3.6 trains and trams offer more attractive travel alternatives than public buses.

Table 3.7 Cross tabulation results for public transport modes and PTAI categories

<table>
<thead>
<tr>
<th>Public Transport Modes</th>
<th>PTAI categories</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Very poor</td>
<td>poor</td>
</tr>
<tr>
<td>Train</td>
<td>Observed (%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>868 (7.8)</td>
<td>1182 (10.7)</td>
</tr>
<tr>
<td></td>
<td>Expected</td>
<td></td>
</tr>
<tr>
<td></td>
<td>954.9</td>
<td>992.4</td>
</tr>
<tr>
<td>Tram</td>
<td>Observed (%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>80 (2.0)</td>
<td>57 (1.4)</td>
</tr>
<tr>
<td></td>
<td>Expected</td>
<td></td>
</tr>
<tr>
<td></td>
<td>344.2</td>
<td>357.7</td>
</tr>
<tr>
<td>Public Bus</td>
<td>Observed (%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>629 (19.5)</td>
<td>400 (12.4)</td>
</tr>
<tr>
<td></td>
<td>Expected</td>
<td></td>
</tr>
<tr>
<td></td>
<td>278.0</td>
<td>288.9</td>
</tr>
<tr>
<td>Total</td>
<td>Observed (%)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1577 (8.6)</td>
<td>1639 (8.9)</td>
</tr>
<tr>
<td></td>
<td>Expected</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1577.0</td>
<td>1639.0</td>
</tr>
</tbody>
</table>
The number of persons commuting by public transport modes and the type of transport based on different PTAI categories are shown in Figure 3.7. It can be seen that there is a sharp increase in commuting by train when the levels of accessibility are higher. Of the three modes, public buses do not show the same trend compared to trains and trams. Surprisingly, in areas with high levels of accessibility, use of public buses declines slightly. On the other hand, travelling by train and tram rises sharply.

Figure 3.7 PTAI categories and mode use in the Melbourne region

The Chi-square test was used to test for a statistically significant association between travelling by public transport modes and PTAI categories. The results, as shown in Table 3.8, were found to be statistically significant ($\chi^2 = 3245.382, p < .001$).

Table 3.8 Chi-square test of association for public transport modes and PTAI categories

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>df</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pearson Chi-Square</td>
<td>3245.382a</td>
<td>10</td>
<td>.000b</td>
</tr>
<tr>
<td>Likelihood Ratio</td>
<td>3371.838</td>
<td>10</td>
<td>.000</td>
</tr>
<tr>
<td>Linear-by-Linear Association</td>
<td>50.457</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
<td>N of Valid Cases</td>
<td>18324</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 277.98.

Cramer’s V test, the most preferred test between Chi-square based measurements, was used to investigate the strength of association between public transport use and the PTAI categories (Goodman and Kruskal, 1954; Hanneman et al., 2012). The value of the test statistic ranges between 0 and 1, representing no relationship to a strong relationship between two variables, respectively. As can be seen in Table 3.9, the results of Cramer’s V test show that there is an acceptable relationship between commuting by public transport modes and the level of accessibility.
Table 3.9 Chi-square based measures of association for public modes

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phi</td>
<td>.421</td>
<td>.000</td>
</tr>
<tr>
<td>Cramer's V</td>
<td>.298</td>
<td>.000</td>
</tr>
<tr>
<td>Contingency Coefficient</td>
<td>.388</td>
<td>.000</td>
</tr>
<tr>
<td>N of Valid Cases</td>
<td>18324</td>
<td>-</td>
</tr>
</tbody>
</table>

a. Significant at 95% confidence level

3.4.2 Comparison between the PTAI, PTAL and SI

To compare the new index with PTAL and SI, Chi-square based tests of association were applied. The test results show a stronger association between the PTAI ($\chi^2 = 3245.382$, $p<.001$) and public transport modes than the PTAL ($\chi^2 = 2314.599$, $p<.001$) and SI ($\chi^2 = 2671.708$, $p<.001$). Hence, based on the VISTA data set, the PTAI can be considered as a more accurate index for measuring public transport accessibility in the Melbourne metropolitan area. Appendix 3A presents the cross-tabulation results for both the PTAL and SI indexes.

Table 3.9 Chi-square based measures of association for PTAL, SI and PTAI and Public Transport Modes

<table>
<thead>
<tr>
<th></th>
<th>PTAL</th>
<th>SI</th>
<th>PTAI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Value p-value</td>
<td>Value p-value</td>
<td>Value p-value</td>
</tr>
<tr>
<td>Pearson Chi-Square</td>
<td>2314.599</td>
<td>.000</td>
<td>2671.708</td>
</tr>
<tr>
<td>Likelihood Ratio</td>
<td>2512.231</td>
<td>.000</td>
<td>2877.431</td>
</tr>
<tr>
<td>Phi</td>
<td>.355</td>
<td>.000</td>
<td>.382</td>
</tr>
<tr>
<td>Cramer's V</td>
<td>.251</td>
<td>.000</td>
<td>.270</td>
</tr>
<tr>
<td>Contingency Coefficient</td>
<td>.335</td>
<td>.000</td>
<td>.357</td>
</tr>
<tr>
<td>N of Valid Cases</td>
<td>18324</td>
<td>-</td>
<td>18324</td>
</tr>
</tbody>
</table>

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 327.34.
b. Significant at 95% confidence level
c. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 450.90.
d. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 277.98.

3.5 Discussions

This paper has presented an approach developed to measure the level of accessibility in metropolitan Melbourne. This approach included the production of a public transport accessibility index associated with SA1s in the Melbourne region. The PTAI was assessed to see whether there is any significant difference between the level of accessibility and the use of public transport. Overall, the results show a statistically significant association between both variables. In other words, the PTAI is a valid means of measuring public transport mode use in the Melbourne region based on the VISTA.

The results indicate that 0.55% of SA1s have zero accessibility to public transport, with 1.74% of SA1s having no population representing 0.4% of Melbourne residents having no access to public
transport. 13.03% and 16.82% of residents also have very poor or poor access to public transport. These PTAI categories mainly relate to the outer parts of the Melbourne region (Figure 3.1). However, these levels of accessibility are not exclusively in outer areas. In the Melbourne region, (Figure 3.8) about 30% of residents have zero to poor levels of accessibility, while in outer Melbourne only 17% of residents have above-average levels of accessibility. As discussed above, approximately 30% of the Melbourne region is covered by public transport walking catchments. This includes approximately 17,800 bus stops, 1,700 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 peak hours, they are used less than trains (by 8.3%) and trams (by about 1%).

This study used the VISTA to evaluate the proposed PTAI. The PTAI was assessed using the Chi-square test of association. The results indicate that there is a statistically significant relationship between the PTAI categories and the use of public transport. Nevertheless, the use of public buses in SA1s with high levels of accessibility was not as high as the other two modes. Although public buses have the highest numbers of stops with a reasonable service area, the productivity of the service is poor. In other words, although bus routes are fairly well dispersed throughout the suburbs even in areas with low density may imply effective bus service delivery, the figures represent the opposite. As Currie states, “It is a sad fact that while needs are high in the urban fringe, the limited bus services provided carry relatively few people and have many empty seats.” (Currie, 2010, p. 39; Mazloumi et al., 2011). To undertake a comparison with previous approaches, the PTAL and SI were calculated for SA1s, and the results show consistency with these indices. Although the approaches used in these studies are different, there are clear similarities between the results. There are also similarities with the results of other research which calculate public transport accessibility levels (Kerrigan and Bull, 1992; Wu and Hine, 2003).

Overall, accessibility can be considered as a measure of locational disadvantage, particularly from a social planning perspective. Poor accessibility to public transport can deter access to different facilities and social activities. It has been argued that there are inter-relationships between transport shortcomings and key areas of social disadvantage such as unemployment, health inequality and poor education (Lucas, 2012). For this reason, in many transport studies, weighted socioeconomic factors are combined to calculate levels of accessibility to public transport (Currie and Stanley, 2007; Hurni, 2005). Hence, in many transport models, socioeconomic characteristics have been considered as independent variables. Therefore, a weighted accessibility index in such models may duplicate the effects of social factors and bias the results. Furthermore, from a transportation planning perspective, accessibility reflects an indicator of the spatial distribution of public transport stops and routes. However, Kwan (1998; 2013; 2015; 1999) has highlighted the importance of temporal disparity in people’s accessibility. While mobility is an essential element of an individual’s spatiotemporal experiences, accessibility cannot be fully understood by focusing on only residential spaces.
3.6 Conclusions and Future Research Directions

This study utilized GIS techniques to objectively measure the level of accessibility to public transport in the Melbourne metropolitan area. The PTAI provides a practical means of measuring levels of accessibility within metropolitan areas. It has been compared with previous approaches. The findings indicate that the concentration of public transport in the inner parts of Melbourne and the CBD is high, and it can be accessed by all three modes. However, in the outer suburbs, which are characterized by dispersed patterns, public transport is generally limited to buses. This can be referred to as a policy of increasing bus services based on needs.

Overall, the techniques presented are straightforward to apply. The quantitative approaches developed can be employed for any number of public transport modes in other cities around the world. The new method is designed to be applied with available census data and transport modelling tools. Furthermore, the analysis provides reliable and defendable results, and accessibility could be measured for 99.4% of statistical areas. In the present study, the results were improved by using mesh blocks for calculating the population of buffer areas. This means that if SA1s were used for estimating buffer populations, the results could be miscalculated by the variation of -187 to 360 persons. In other words, buffer populations would be under-estimated or over-valued by 12 persons per SA1. Nonetheless, the accuracy can be enhanced by greater detail (e.g. using parcel-based data) to achieve even more accurate results.
A weakness of this approach is that the index does not take into account the effects of temporal disparity (Neutens et al., 2012; Chen et al., 2014; Kwan, 2013) in public transport accessibility (e.g., bus/tram/train schedules vary between day and evening hours, and between weekdays and weekends, etc.). Future studies may consider this point when measuring accessibility. Furthermore, the PTAI does not consider connectivity between public modes, which can influence accessibility, particularly in areas of low accessibility.

3.7 References


WONG, D. 2009. The modifiable areal unit problem (MAUP). The SAGE handbook of spatial analysis, 105-123.

## Appendix A

### Table 3.10 Cross tabulation results for public transport modes and SI categories

<table>
<thead>
<tr>
<th>Public Transport Modes</th>
<th>SI categories</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Very Low</td>
<td>Low</td>
<td>Below Average</td>
<td>Above Average</td>
<td>High</td>
<td>Very High</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Train</td>
<td>Observed (N)</td>
<td>1978</td>
<td>1803</td>
<td>2316</td>
<td>1698</td>
<td>1583</td>
<td>1717</td>
<td>11095</td>
</tr>
<tr>
<td></td>
<td>Observed (%)</td>
<td>17.8</td>
<td>16.3</td>
<td>20.9</td>
<td>15.3</td>
<td>14.3</td>
<td>15.5</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>Expected</td>
<td>1835.2</td>
<td>1548.8</td>
<td>2142.2</td>
<td>1750.5</td>
<td>1786.8</td>
<td>2031.4</td>
<td>11095.0</td>
</tr>
<tr>
<td>Tram</td>
<td>Observed (N)</td>
<td>870</td>
<td>649</td>
<td>756</td>
<td>484</td>
<td>248</td>
<td>223</td>
<td>3230</td>
</tr>
<tr>
<td></td>
<td>Observed (%)</td>
<td>26.9</td>
<td>20.1</td>
<td>23.4</td>
<td>15.0</td>
<td>7.7</td>
<td>6.9</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>Expected</td>
<td>534.3</td>
<td>450.9</td>
<td>623.6</td>
<td>509.6</td>
<td>520.2</td>
<td>591.4</td>
<td>3230.0</td>
</tr>
<tr>
<td>Public Bus</td>
<td>Observed (N)</td>
<td>3031</td>
<td>2558</td>
<td>3538</td>
<td>2891</td>
<td>2951</td>
<td>3355</td>
<td>18324</td>
</tr>
<tr>
<td></td>
<td>Observed (%)</td>
<td>16.5</td>
<td>14.0</td>
<td>19.3</td>
<td>15.8</td>
<td>16.1</td>
<td>18.3</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>Expected</td>
<td>3031.0</td>
<td>2558.0</td>
<td>3538.0</td>
<td>2891.0</td>
<td>2951.0</td>
<td>3355.0</td>
<td>18324.0</td>
</tr>
</tbody>
</table>

### Table 3.11 Cross tabulation results for public transport modes and PTAL categories

<table>
<thead>
<tr>
<th>Public Transport Modes</th>
<th>PTAL categories</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Very poor</td>
<td>poor</td>
<td>moderate</td>
<td>good</td>
<td>very good</td>
<td>excellent</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Train</td>
<td>Observed (N)</td>
<td>1069</td>
<td>1736</td>
<td>1950</td>
<td>1942</td>
<td>2297</td>
<td>2101</td>
<td>11095</td>
</tr>
<tr>
<td></td>
<td>Observed (%)</td>
<td>9.6</td>
<td>15.6</td>
<td>17.6</td>
<td>17.5</td>
<td>20.7</td>
<td>18.9</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>Expected</td>
<td>1124.4</td>
<td>1387.8</td>
<td>1627.6</td>
<td>1987.8</td>
<td>2452.2</td>
<td>2515.2</td>
<td>11095.0</td>
</tr>
<tr>
<td>Tram</td>
<td>Observed (N)</td>
<td>83</td>
<td>65</td>
<td>258</td>
<td>758</td>
<td>1266</td>
<td>1569</td>
<td>3999</td>
</tr>
<tr>
<td></td>
<td>Observed (%)</td>
<td>2.1</td>
<td>1.6</td>
<td>6.5</td>
<td>19.0</td>
<td>31.7</td>
<td>39.2</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>Expected</td>
<td>405.3</td>
<td>500.2</td>
<td>586.6</td>
<td>716.5</td>
<td>883.9</td>
<td>906.6</td>
<td>3999.0</td>
</tr>
<tr>
<td>Public Bus</td>
<td>Observed (N)</td>
<td>705</td>
<td>491</td>
<td>480</td>
<td>583</td>
<td>487</td>
<td>484</td>
<td>3230</td>
</tr>
<tr>
<td></td>
<td>Observed (%)</td>
<td>21.8</td>
<td>15.2</td>
<td>14.9</td>
<td>18.0</td>
<td>15.1</td>
<td>15.0</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>Expected</td>
<td>327.3</td>
<td>404.0</td>
<td>473.8</td>
<td>578.7</td>
<td>713.9</td>
<td>732.2</td>
<td>3230.0</td>
</tr>
<tr>
<td>Total</td>
<td>Observed (N)</td>
<td>1857</td>
<td>2292</td>
<td>2688</td>
<td>3283</td>
<td>4050</td>
<td>4154</td>
<td>18324</td>
</tr>
<tr>
<td></td>
<td>Observed (%)</td>
<td>10.1</td>
<td>12.5</td>
<td>14.7</td>
<td>17.9</td>
<td>22.1</td>
<td>22.7</td>
<td>100.0</td>
</tr>
<tr>
<td></td>
<td>Expected</td>
<td>1857.0</td>
<td>2292.0</td>
<td>2688.0</td>
<td>3283.0</td>
<td>4050.0</td>
<td>4154.0</td>
<td>18324.0</td>
</tr>
</tbody>
</table>
CHAPTER 4

MODELLING ACCESS TO PUBLIC TRANSPORT IN URBAN AREAS
Chapter 4: Modelling Access to Public Transport in Urban Areas

Abstract

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 to the measurement of public transport accessibility, few methods have been developed for the measurement of accessibility levels that incorporate spatial aspects. Population density is an important distributional indicator which has also been ignored in previous methods of quantifying accessibility. This paper outlines the research context for the measurement of public transport accessibility, and then describes a proposed methodology and the application of the public transport accessibility index (PTAI) in the Melbourne metropolitan area, Australia. Using the Victorian Integrated Survey of Travel and Activity (VISTA) data set, separate ordered logit regression models are applied to examine how the new index performs with a series of predictor variables compared to 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 than previous approaches.

Keywords: PTAI, Accessibility, Ordered Logit Model, Population Density

4.1 Introduction

Public transport improves sustainability as well as being a more social means of transportation (Lei and Church, 2010), which may lead to the increased liveability and sustainability of cities (Mamun, 2011). Public transportation provides long-term sustainability by reducing highway congestion and moving large numbers of people over considerable distances (Armstrong-Wright and Thiriez, 1987). This enhances systemic mobility, while decreasing the economic and environmental burdens of increasing private motorized travel. Furthermore, an improved public transport system provides mobility to those who do not have access to automobiles (Mamun, 2011). In other words, the use of public transport is considered within the definition of active transport, as it often involves some walking or cycling to connect to trip origins and destinations (Taniguchi et al., 2013).

A number of research studies have identified that persons living in many suburban areas in Australian metropolitan areas are significantly disadvantaged by current transport services (Dodson et al., 2004; Currie, 2004). More recently, research has indicated that increasing fuel prices and home loan interest rates have intensified the transport difficulties experienced by persons living in the fringe areas of Australian cities (Dodson et al., 2006). However, improving public transport accessibility in terms of service coverage and availability may result in a more reliable transport system as a whole (Mamun, 2011).

A substantial body of research has been conducted relating to the measurement of public transport accessibility. Nevertheless, there is limited research quantifying public transport accessibility incorporating spatial factors. Moreover, the importance of population density in geographical areas and its influence on the level of accessibility has largely been ignored. Hence, this study presents a new approach to the measurement of public transport accessibility in geographical areas which includes population density.

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

4.2 Methodology

This study presents a method for measuring public transport accessibility and modelling the number of trips undertaken by public transport modes. In the first step, the Public Transport Accessibility Index (PTAI) is introduced, which is an index for measuring the level of accessibility to public
transport in Melbourne’s 9510 Statistical Areas level 1 (SA1s), the second smallest geographic area defined in the Australian Statistical Geography Standard (Saghapour et al., 2016; Saghapour et al., In press). 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 public transport stops/stations) are calculated. To calculate the PTAI a number of datasets were adopted.

4.2.1 Datasets

4.2.1.1 Public Transport Stops/Stations

Three modes of public transport, including public buses, trams and trains, were considered. A database of bus and tram stops, train stations and public transport routes and corridors were obtained from the Victorian Government’s open data sources (2015). According to the database, the Melbourne region is covered by approximately 17800 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 4.1) and suburban regions.

![Greater Melbourne Area (2015)](image)

4.2.1.2 Public Transport Service Frequency

Service frequency data were calculated from the timetable of each mode during the morning peak hours (7 to 9 am). Timetables are accessible on the Public Transport Victoria (PTV) website (https://www.ptv.vic.gov.au). Based on the data set, average walk times from POIs to the closest tram
stops, bus stops and train stations were 1 min., 5 mins. and 7 mins., respectively, and, the average waiting times for desired services from selected POIs were 8 mins., 2 mins. and 5 mins, respectively to the closest tram stops, bus stops and train stations.

4.2.1.3 Points of Interest (POIs)

A database of POIs was obtained from Australian Urban Research Infrastructure Network (AURIN). This included urban centres, significant buildings, landmarks, public spaces, community facilities and indigenous locations, consisting of 15,588 points. Figure 4.2 shows the distribution of POIs and public transport stops/stations.

![Distribution of POIs and Public transport stops/stations in Melbourne region](image)

**Figure 4.2 Distribution of POIs and Public transport stops/stations in Melbourne region**

4.2.1.4 Geographical Areas

A database of mesh blocks from the 2011 Census for the Melbourne Region was accessed from the Australian Bureau of Statistics (ABS). This data set contains the total usual resident population and total number of dwellings from the 2011 Census of Population and Housing for mesh blocks and all other statistical areas, including SA1s. According to the ABS, the Melbourne region contains 53074 mesh blocks, 9510 SA1s, 277 statistical areas level 2 (SA2s) and 31 local government areas (LGAs). Figure 4.3 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.
4.2.1.5 VISTA Dataset

The VISTA dataset (2009) was obtained from the Victorian Integrated Survey of Travel and Activity (VISTA). This was a cross-sectional survey conducted from 2009 to July 2010. It covers the Melbourne Statistical Division (MSD) as defined by the ABS, and the regional cities of Geelong, Ballarat, Bendigo and Shepparton, and the Latrobe Valley. Data were collected regarding demographics, 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) were considered. This study used trip stages undertaken by public transport to assess the index. According to the 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.

4.2.2 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 public transport network considering walk time and service frequency, which reflects the estimated doorstep frequency. The Public Transport Accessibility Index (PTAI) also incorporates the share of population density in public transport mode service areas and SA1s.
As mentioned previously, there are approximately 20,000 public transport stops in the Melbourne region. This area is covered by about 16,000 POIs, including community services and facilities, landmarks, non-residential and public buildings. In some SA1s with two or more stops/stations, service areas were merged using the same break value. Network analysis was conducted separately for each public transport mode. For instance, for a shopping centre as a selected POI, the distance of the nearest public bus stop was 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 order to determine the service frequency for a POI, network analysis of the closest facility was applied. The process of computing the accessibility index can be broken into several stages, from measuring the walking distances and times to estimating population densities in service areas of public transport modes. The following sections describe the formulation of the index. The calculation of the WEF extends the approach used in measuring public transport accessibility levels in London (TfL, 2010).

**Walk Time (WT)**

The walk time (estimated not actual time) was the first component calculated from a specified POI to the closest public transport stops. Distances from the POI were converted to a measure of time, assuming an average walking speed of 4.8 kilometres/hour or 80 metres/minute (TfL, 2010). Walk distance, using network analysis by ArcGIS 10.2, was calculated from a particular POI to the closest public transport stop/station, including bus stops, tram stops, and train stations.

**Average Waiting Time (AWT)**

The AWT is the average time between arriving at a stop/station and the arrival time of the desired service. For each selected route, the AWT was considered as the interval between services. For instance, for a public transport mode running services every 5 minutes or 12 frequencies per hour, the AWT is 2.5 minutes. The AWT is estimated as half the headway (i.e. the time interval between services) as shown in Equation (4.1).

\[
\text{AWT}_{ij} = 0.5 \times \left( \frac{60}{F_{ij}} \right) \quad i = 1,2,3, \ldots, n \quad j = 1,2,3 \quad (4.1)
\]

Where \( \text{AWT}_{ij} \) is the average waiting time (minutes) at the closest stop/station to POI \( i \) for public transport 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 \( i \).

**Total Access Time (TAT)**

After calculating the WT and AWT, the Total Access Time (TAT) of a selected POI to the nearest public transport stop/station is calculated. This includes walking time from the POI to the stop/station
and average waiting time. TAT, as shown in Equation (4.2), comprises WT and AWT.

\[ TAT_{ij} = WT_{ij} + AWT_{ij} \quad i = 1,2,3, \ldots, n \quad j = 1,2,3 \]  

(4.2)

where, TAT\(_{ij}\) is the total access time (in minutes) of public transport mode \( j \) at the closet stop/station to POI \( I \), and WT\(_{ij}\), as explained above, is the walk time (in minutes) from POI \( i \) to the closest stop/station of public transport mode \( j \).

**Equivalent Frequency (EF)**

TATs were converted to equivalent frequencies using Equation (4.3). This measures the doorstep availability of a route at the specified POI. The Equivalent Frequency (EF) as presented in Equation (4.5) is calculated as 30 minutes divided by the TAT. This treats access time as a notional average waiting time as though the route was available at the "doorstep" of the selected POI (Tyler, 2002; Wu and Hine, 2003; TfL, 2010; De Martino, 2014).

\[ EF_{ij} = \frac{30}{TAT_{ij}} \quad i = 1,2,3, \ldots, n \quad j = 1,2,3 \]  

(4.3)

where, \( EF_{ij} \) is the equivalent frequency for public transport mode \( j \) at the closest stop/station to the POI \( i \).

**Weighted Equivalent Frequency (WEF)**

The Weighted Equivalent Frequency (WEF) is calculated as the summation of the EFs of public transport modes with a weighting in favour of the most dominant mode (Equation 4.4).

\[ WEF_{ij} = \alpha EF_{id} + \beta \sum \sum EF_{ij} \quad i = 1,2, \ldots, n \quad j = 1,2,3 \]  

(4.4)

where, \( WEF_{ij} \) is the weighted equivalent frequency for public transport mode \( j \) at the closest stop/station to the POI \( i \), \( EF_{id} \) is the equivalent frequency of the most dominant public transport mode at the closest stop/station to POI \( i \), and \( \alpha \) and \( \beta \) are the coefficients considered for the equivalent frequency of the most dominant public transport mode and all other public transport modes. In the current study, according to the average weekly service level of the public transport modes reported by Public Transport Victoria (PTV) (2012), \( \alpha \) and \( \beta \) were assigned the value of \( 1 \) for the train (the dominant mode) and \( 0.5 \) for the two other modes.
**WEFs for SA1s**

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

**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 public transport modes, 400 metres was considered for access to bus and tram stops and 800 metres was assumed for access to train stations. Thereafter, service areas of public transport modes were overlapped with SA1s, using a Geographic Information System (GIS) to calculate the share of population density for each SA1, based on the assumption of a homogeneous distribution of population within a SA1. To avoid duplication, the residential population was transferred to buffer catchments according to 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 4.1 presents information about the population and areas of SA1s and walking catchments of public transport modes. As the table indicates, SA1s have a mean population of 414 persons with an average area of 0.93 square kilometres.

<table>
<thead>
<tr>
<th>Categories</th>
<th>Population</th>
<th>Area (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Deviation</td>
</tr>
<tr>
<td>SA1s</td>
<td>414</td>
<td>209.5</td>
</tr>
<tr>
<td>Walking Buffers for Tram Stops</td>
<td>31</td>
<td>41.3</td>
</tr>
<tr>
<td>Walking Buffers for Train Stations</td>
<td>66</td>
<td>55.6</td>
</tr>
<tr>
<td>Walking Buffers for Bus Stops</td>
<td>26</td>
<td>35.1</td>
</tr>
</tbody>
</table>

**4.2.2.1 PTAI Index**

For each SA1, the PTAI was calculated using the formula given in Equation (4.5). The index is a combined measure of $WEF$ and population density ratio given as:
If $D_{Bij} = 0$;

$$PTAI_{SA1} = \sum_{j=1}^{3} \sum_{i=1}^{l} \left( 1 + \frac{D_{Bij}}{D_{SA1i}} \right) \times WEF_{SA1i}$$

If $D_{Bij} \neq 0$;

$$PTAI_{SA1} = \sum_{j=1}^{3} \sum_{i=1}^{l} \left( \frac{D_{Bij}}{D_{SA1i}} \right) \times WEF_{SA1i}$$

where, $PTAI_{SA1}$ denotes the public transport accessibility index for a given $SA1$, $D_{Bij}$ is the population density of buffer $i$ for public transport mode $j$, $D_{SA1i}$ is the population density of the $SA1$, and $WEF_{SA1i}$ is the weighted equivalent frequency calculated for the corresponding $SA1$.

In this approach, accessibility is calculated for the spatial coverage of each $SA1$ which is indicated by the walking buffers to public transport 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 both a bus stop and a tram stop, the measurements are double-counted, which indicates that these areas have a higher level of accessibility to public transport. A higher value of the PTAI indicates a higher level of accessibility. The index is allocated to 6 categories of accessibility levels, where category 1 represents a very poor level and level 6 represents an excellent level of accessibility (Table 4.2). 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 4.2 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 is based on quantiles, since they are one of the best methods for simplifying comparisons as well as aiding general map-reading (Brewer and Pickle, 2002). 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 the total population has zero to moderate accessibility to public transport.
Table 4.2 PTAI Ranges and Categories

<table>
<thead>
<tr>
<th>PTAI Categories</th>
<th>Number of SAIs</th>
<th>Population</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No.</td>
<td>Percent</td>
</tr>
<tr>
<td>0</td>
<td>N/A</td>
<td>52</td>
</tr>
<tr>
<td>&lt; 2</td>
<td>Very Poor</td>
<td>1331</td>
</tr>
<tr>
<td>2 – 3.5</td>
<td>Poor</td>
<td>1607</td>
</tr>
<tr>
<td>3.5 – 6</td>
<td>Moderate</td>
<td>1791</td>
</tr>
<tr>
<td>6 – 12</td>
<td>Good</td>
<td>1969</td>
</tr>
<tr>
<td>12 – 20</td>
<td>Very Good</td>
<td>1480</td>
</tr>
<tr>
<td>&gt; 20</td>
<td>Excellent</td>
<td>1280</td>
</tr>
<tr>
<td>Total</td>
<td>N/A</td>
<td>9510</td>
</tr>
</tbody>
</table>

Figure 4.4 illustrates the distribution of PTAI categories in the Melbourne region. As explained above, the PTAI is categorized into 6 bands. The first category represents very poor accessibility, while the last category corresponds to excellent accessibility to public transport. The first and last categories were 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 the table shows, outer Melbourne, where public transport is mainly provided by public buses, has lower levels of accessibility in comparison to the inner parts and the CBD.

Table 4.3 presents a summary of the descriptive statistics of the index components. This shows that...
there are on average 414 residents in each SA1 with an average area of 0.93 km\(^2\). The average number of stops/stations per SA1 is 2.1, which receive a total of 9.6 services during peak times. The average WEF per SA1 is 5.5 and the average value of the PTAI per SA1 is 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.

Table 4.3 Descriptive statistics of indicators in each SA1

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

4.2.2.2 Existing Measures

PTAI extends the more recent and common approaches, including the UK approach (TfL, 2010) by measuring public transport accessibility levels (PTALs) and the supply index (SI) introduced by Currie (2010). PTAL measures accessibility using local indicators and accessibility modelling. It uses a six-level scale to rate public transport service access, which includes measurements such as walk time, waiting time and service frequency. The index developed in the present study calculates the sum of equivalent doorstep frequency (EDF) of all different public transport modes. SI is a supply index calculated for Melbourne’s 5839 census collector districts (CCDs). The index is a combined measure of service frequency (number of public transport vehicle arrivals per week) and access distance.

Both indexes, PTAL and SI, were calculated for SA1s and the results are presented in Table 4.4. Based on the PTAL, approximately 50% or 2 million residents have zero to moderate access to public transport modes, while for SI, these figures rise to 67% or 2.6 million residents.
Table 4.4 Public Transport Accessibility Levels (PTAL) and Supply Index (SI) for SA1s

<table>
<thead>
<tr>
<th>PTAL/SI Categories</th>
<th>PTAL</th>
<th>SI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of SA1s</td>
<td>Population (%)</td>
</tr>
<tr>
<td>Zero Access/Supply</td>
<td>52</td>
<td>16,243 (0.4)</td>
</tr>
<tr>
<td>Very Poor/Very Low</td>
<td>1,370</td>
<td>560,271 (14.2)</td>
</tr>
<tr>
<td>Poor/Low</td>
<td>1,398</td>
<td>604,059 (15.3)</td>
</tr>
<tr>
<td>Moderate/Below Average</td>
<td>1,857</td>
<td>773,731 (19.6)</td>
</tr>
<tr>
<td>Good/Above Average</td>
<td>1,415</td>
<td>582,554 (14.8)</td>
</tr>
<tr>
<td>Very Good/High</td>
<td>1,624</td>
<td>670,184 (17.0)</td>
</tr>
<tr>
<td>Excellent/Very High</td>
<td>1,794</td>
<td>734,169 (18.6)</td>
</tr>
<tr>
<td>Total</td>
<td>9,510</td>
<td>3,941,211 (100.0)</td>
</tr>
</tbody>
</table>

4.3 Data Analysis

Built environment factors, as well as public transport 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 1,822 SA1s. The following sections present the results of the models applied to the data while comparing the new index with the previous measurements.

4.3.1 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. $e^{\text{Coeff}}$). The interpretation of 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 (Andren et al., 1999). A typical model for the cumulative logits is shown in Equation (4.6):

$$\text{logit}[P(Y \leq j)] = \alpha_j + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n = \alpha_j + \hat{\beta} X$$

(4.6)

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 socioeconomic and built environment factors. M1 presents the results of ordered logit models considering all the predictor
variables and the PTAI as the public transport accessibility measure. M2 and M3 contain all variables used in the M1; however, SI and PTAL are used for public transport accessibility measures, respectively. Public transport (PT) trips are defined as an ordered dependent variable. Age, gender, car licence, employment type, household size, household structure, and number of cars in the household were employed as socioeconomic variables (Lee et al., 2014; Winters et al., 2010; Jun et al., 2012; Ewing and Cervero, 2010a). Built environment factors include roadway measure (RDW), land-use mix entropy index (LUMIX) and public transport accessibility measurements (PTAI/SI/PTAL). The RDW examines how far the network spreads over an area. It is quantified by the total roadway length divided by the total area and the distance is normalised by 100m². The LUMIX was calculated using Equation (4.7) (Lee et al., 2014). The values vary from 0 to 1, while 1 indicates a perfect balance among different types of land uses and 0 represents homogeneity.

\[
LUMIX = - \left( \sum_{j=1}^{J} \frac{P_j \ln P_j}{\ln J} \right)
\]  

(4.7)

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-use categories, including residential, commercial, industrial, transport and infrastructure, community services and sport and recreation centres, were chosen to calculate LUMIX. These categories were defined based on the ten main use categories defined by the Australian Valuation Property Classification Codes (AVPCC) (Morse-McNabb, 2011). Table 4.5 shows the list of independent variables and their description, as well as the hypothesised relationship with the dependent variable.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>Hypothesised relationship</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Age of respondent</td>
<td>+/-</td>
</tr>
<tr>
<td>Sex</td>
<td>Gender</td>
<td>+/-</td>
</tr>
<tr>
<td>Licence</td>
<td>Driver licence</td>
<td>-</td>
</tr>
<tr>
<td>Employment Type</td>
<td>Type of work</td>
<td>+/-</td>
</tr>
<tr>
<td>HH Size</td>
<td>Usual number of residents in household</td>
<td>+</td>
</tr>
<tr>
<td>HH Structure</td>
<td>Demographic structure of household</td>
<td>+/-</td>
</tr>
<tr>
<td>Car No.</td>
<td>Number of vehicles in household</td>
<td>-</td>
</tr>
<tr>
<td>PTAI</td>
<td>Public Transport Accessibility Index</td>
<td>+</td>
</tr>
<tr>
<td>SI</td>
<td>Supply Index</td>
<td>+</td>
</tr>
<tr>
<td>PTAL</td>
<td>Public Transport Accessibility Level</td>
<td>+</td>
</tr>
<tr>
<td>RDW</td>
<td>Roadway Measure</td>
<td>-</td>
</tr>
<tr>
<td>LUMIX</td>
<td>Land Use mix entropy index</td>
<td>+</td>
</tr>
</tbody>
</table>

Note: HH structure was converted to five dummy variables: sole person, couple no children, couple with children, one parent and other; Employment type was converted into three dummy variables: full time, part time and other; sex and driver licence were defined as binary variables.
As stated above, in the VISTA dataset travel 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 trip stages made by 22,184 individuals in the MSD. Table 4.6 shows the frequency of PT trips categorised into 5 groups from very low to very high ranges of PT trips generated in SA1s.

**Table 4.6 Frequency of PT trips**

<table>
<thead>
<tr>
<th>PT Trip Categories</th>
<th>PT Trips</th>
<th>Frequency</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Low</td>
<td>1-9</td>
<td>15169</td>
<td>19.7</td>
<td>19.7</td>
</tr>
<tr>
<td>Low</td>
<td>9-14</td>
<td>13965</td>
<td>18.1</td>
<td>37.8</td>
</tr>
<tr>
<td>Average</td>
<td>15-23</td>
<td>15585</td>
<td>20.2</td>
<td>58.1</td>
</tr>
<tr>
<td>High</td>
<td>24-39</td>
<td>15974</td>
<td>20.7</td>
<td>78.8</td>
</tr>
<tr>
<td>Very High</td>
<td>40+</td>
<td>16327</td>
<td>21.2</td>
<td>100.0</td>
</tr>
<tr>
<td>N/A</td>
<td>Total</td>
<td>77020</td>
<td>100.0</td>
<td></td>
</tr>
</tbody>
</table>

*Note: Analysis was run on records related to SA1s with none zero PT trips.*

Table 4.7 suggests the descriptive statistics for the variables used in the ordered logit models. These statistics were calculated for 77,020 trip stage records. In terms of socio-demographic characteristics, the respondents were 38 years old on average and equally distributed in terms of gender. The average HH size shows that respondents were almost all from households with the usual number of approximately three residents.

**Table 4.7 Descriptive Statistics**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>PT Trips</td>
<td>25.04</td>
<td>19.57</td>
<td>1.00</td>
<td>106.00</td>
</tr>
<tr>
<td>Age</td>
<td>37.55</td>
<td>19.76</td>
<td>0.00</td>
<td>96.00</td>
</tr>
<tr>
<td>Sex</td>
<td>1.53</td>
<td>0.50</td>
<td>1.00</td>
<td>2.00</td>
</tr>
<tr>
<td>Licence</td>
<td>1.24</td>
<td>0.42</td>
<td>1.00</td>
<td>2.00</td>
</tr>
<tr>
<td>HH Size</td>
<td>3.25</td>
<td>1.35</td>
<td>1.00</td>
<td>6.00</td>
</tr>
<tr>
<td>Employment Type</td>
<td>2.05</td>
<td>0.93</td>
<td>1.00</td>
<td>3.00</td>
</tr>
<tr>
<td>HH Structure</td>
<td>2.86</td>
<td>0.99</td>
<td>1.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Car No.</td>
<td>1.90</td>
<td>0.95</td>
<td>0.00</td>
<td>4.00</td>
</tr>
<tr>
<td>PTAI</td>
<td>33.26</td>
<td>360.30</td>
<td>0.00</td>
<td>7,235.57</td>
</tr>
<tr>
<td>SI</td>
<td>17,191.58</td>
<td>17,132.71</td>
<td>0.00</td>
<td>222,037.92</td>
</tr>
<tr>
<td>PTAL</td>
<td>16.40</td>
<td>174.80</td>
<td>0.00</td>
<td>3,482.64</td>
</tr>
<tr>
<td>RDW (m)</td>
<td>1.36</td>
<td>0.79</td>
<td>0.00</td>
<td>5.57</td>
</tr>
<tr>
<td>LUMIX</td>
<td>0.42</td>
<td>0.15</td>
<td>0.00</td>
<td>0.87</td>
</tr>
</tbody>
</table>

n=77,020 trip stages

In order to examine the applicability of the new index compared to existing approaches, three ordered logistic regression models were estimated. All the variables were considered constant in the models with the exception of the public transport accessibility measures. The PTAI and other variables were employed to run model M1, and SI was used in M2 and the PTAL in M3 (see Table 4.8). The coefficient values for public transport measurements are different in the models, and the PTAL in M1 has the highest value. This can be interpreted as follows: when the PTAL increases by one unit, the
odds of being in the higher levels of PT trips increase, given that all other variables in the model are held constant. Furthermore, M1 has the lowest Akaike information criterion (AIC), which 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 that of each of the other models. Hence, the AIC provides a means for model selection (Boisbunon et al., 2014; Hu, 2007; Aho et al., 2014). In terms of association, as shown in Table 4.8, age, number of cars in the household and being male are negatively associated with public transport trips. Built environment features also have a significant impact on the number of public transport trips. LUMIX and public transport 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 there being a higher level of PT trips for a unit increase of LUMIX. In contrast, while the RDW decreases by about 0.1 in M1, the log odds of being in a higher level of PT trips decreases. This figure is 0.05 in M3. With regard to public transport access measurements, a larger increase in the log odds of being at a higher level of PT trips is expected with the PTAI in the model.
### Table 4.8 Outputs of the ordered logit model for public transport trips.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( M1 )</th>
<th>( M2 )</th>
<th>( M3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coef.</td>
<td>S.E.</td>
<td>OR</td>
</tr>
<tr>
<td>Age***</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.999</td>
</tr>
<tr>
<td>Sex (Male)**</td>
<td>-0.038</td>
<td>0.014</td>
<td>0.963</td>
</tr>
<tr>
<td>Licence (Yes)</td>
<td>0.000</td>
<td>0.021</td>
<td>1</td>
</tr>
<tr>
<td>HH Size***</td>
<td>0.044</td>
<td>0.008</td>
<td>1.045</td>
</tr>
<tr>
<td>Employment Type</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full Time***</td>
<td>0.077</td>
<td>0.016</td>
<td>1.08</td>
</tr>
<tr>
<td>Part Time</td>
<td>-0.002</td>
<td>0.022</td>
<td>0.998</td>
</tr>
<tr>
<td>HH Structure</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sole Person***</td>
<td>-0.159</td>
<td>0.037</td>
<td>0.853</td>
</tr>
<tr>
<td>Couple No Children***</td>
<td>-0.099</td>
<td>0.029</td>
<td>0.906</td>
</tr>
<tr>
<td>Couple with Children***</td>
<td>-0.087</td>
<td>0.024</td>
<td>0.917</td>
</tr>
<tr>
<td>Single Parent***</td>
<td>-0.277</td>
<td>0.033</td>
<td>0.758</td>
</tr>
<tr>
<td>Car No.***</td>
<td>-0.180</td>
<td>0.008</td>
<td>0.836</td>
</tr>
<tr>
<td>LUMIX***</td>
<td>0.164</td>
<td>0.012</td>
<td>1.178</td>
</tr>
<tr>
<td>RDW***</td>
<td>-0.091</td>
<td>0.012</td>
<td>0.913</td>
</tr>
<tr>
<td>PTAI***</td>
<td>0.307</td>
<td>0.004</td>
<td>1.36</td>
</tr>
<tr>
<td>SI***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PTAL***</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: (1) Public transport trips were 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.

(2) 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) Significance codes: \( * \) \( * \) \( * \) \( p < 0.001 \), \( ** \) \( p < 0.01 \), \( *** \) \( p < 0.001 \).

(4) Overall goodness-of-fit:
- M1: Log Likelihood = 7451.69; AIC = 240282.51;
- M2: Log Likelihood = 6536.15; AIC = 241198.06;
- M3: Log Likelihood = 4732.28; AIC = 243001.92.

After estimating and comparing the three ordered logit models, the standard difference-of-means test (Equation 4.8) was also used to test the statistical differences in the estimated coefficients obtained from the ordered logistic regression models. The reason for this was to investigate whether there were any significant differences between the coefficients estimated by the three models.

\[
t = \frac{\hat{\beta}_i - \hat{\beta}_j}{SE[\hat{\beta}_i - \hat{\beta}_j]} \quad (4.8)
\]

where, \( \hat{\beta}_i \) is the estimated coefficient of a built environment variable, \( i \), and \( SE \) denotes the standard error (Fotheringham and Wong, 1991; Mitra and Buliung, 2012). The estimated coefficients from the models were compared, and the results are presented in Table 4.9. The t-statistics results indicate that there is a significant difference between the coefficients of public transport accessibility.
measurements estimated by the three models.

Table 4.9 Outputs of the ordered logit model for public transport trips.

<table>
<thead>
<tr>
<th>Measurements</th>
<th>Coef. (S.E.)</th>
<th>t.diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>PTAI</td>
<td>0.3072 (0.00445)</td>
<td>-</td>
</tr>
<tr>
<td>SI</td>
<td>0.2598 (0.00419)</td>
<td>-</td>
</tr>
<tr>
<td>PTAL</td>
<td>0.1787 (0.00397)</td>
<td>-</td>
</tr>
<tr>
<td>M1/M2</td>
<td>-</td>
<td>182.3077***</td>
</tr>
<tr>
<td>M1/M3</td>
<td>-</td>
<td>267.7083***</td>
</tr>
<tr>
<td>M2/M3</td>
<td>-</td>
<td>368.6364***</td>
</tr>
</tbody>
</table>

*** Significance codes: p<0.001

4.3.2 Tests of Association

Ordinal and interval tests of association were applied to compare the relationship between the public transport accessibility measures and the number of PT trips. The Somers’ D, Gamma and Spearman tests are asymmetric measures of association between two variables, which plays a central role as a parameter in rank or non-parametric statistical methods (Newson, 2006). Moreover, in terms of linear association, PTAI had a higher value ($r=0.350$, $p<0.001$). Table 4.10 presents the results of the test. As the table shows, the PTAI has a better association than the existing approaches.

Table 4.10 Tests of association between public transport trips and public transport measurements

<table>
<thead>
<tr>
<th>Tests of Association</th>
<th>PTAI</th>
<th>SI</th>
<th>PTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ordinal by Ordinal</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Somers’D</td>
<td>0.255</td>
<td>0.000</td>
<td>0.219</td>
</tr>
<tr>
<td>Gamma</td>
<td>0.257</td>
<td>0.000</td>
<td>0.244</td>
</tr>
<tr>
<td>Spearman</td>
<td>0.309</td>
<td>0.000</td>
<td>0.296</td>
</tr>
<tr>
<td>Interval by Interval</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pearson's R</td>
<td>0.350***</td>
<td>0.000</td>
<td>0.287***</td>
</tr>
<tr>
<td>N of Valid Cases</td>
<td>77020</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*** Significance codes: p<0.001

Figure 4.5 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.
This study introduces a new approach to the measurement of public transport accessibility. The PTAI defines and extends existing public transport accessibility indexes by including public transport mode service frequency and population density. It is a useful measurement for examining the level of accessibility of public transport, and it provides the ability to investigate accessibility at a variety of geographical scales. Hence, the index may be useful in neighbourhood to regional studies. The transit frequency component provides a useful complement to the PTAI and makes it more representative of real access than either component alone. This index allows the level of accessibility in the Melbourne region to be explored. The results indicate that 0.5% of SA1s have zero accessibility to public transport. Of this percentage, 1.74% of SA1s have no population and 52 SA1s, representing 0.4% of Melbourne residents, have no access to public transport. About 30% of residents have very poor or poor access to public transport. These PTAI categories mainly belong to the outer parts of the Melbourne region (Figure 4.4). However, these levels of accessibility are not exclusive to outer areas. In the Greater Melbourne area, about 50% of residents have zero to moderate levels of accessibility, while outer Melbourne has only 17% of residents who have above-average levels of accessibility. Approximately 30% of the Melbourne region is covered by public transport walking catchments. This includes about 17,800 bus stops, 1,700 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 peak hours, they are used less than trains (by 8.3%) and trams (by about 1%).

Two recent common approaches, SI and PTAL, have been explained and developed for SA1s in the Melbourne region. The new index shows great consistency with the existing approaches. All three indices, along with a series of socioeconomic characteristics and built environment factors, were applied in three separate ordered logit models. The M1 model included the PTAI along with other
predictor variables, whilst the M2 and M3 models used SI and PTAL as the measures of public transport accessibility, respectively. A comparison of the results showed that M1 had the lowest AIC ($AIC_{M1} = 240282 < AIC_{M2} = 241198 < AIC_{M3} = 243001$) and was 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 a higher level of PT trips being expected when there is a one-unit increase in PTAI compared to its counterparts.

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

The results of the study show consistency with the previous study of public transport supply and needs analysis Melbourne’s 5,839 census collector districts (CCDs) by Currie (2010). Although the approaches used in these studies differ, there are clear similarities between the results. There also similarities with other studies which calculate public transport accessibility levels (Kerrigan and Bull, 1992; Wu and Hine, 2003).

Overall, accessibility can be considered as a measure of locational disadvantage, particularly from a social planning perspective. Poor accessibility to public transport can deter access to different facilities and social advantages. Lucas (2012) argues there are inter-relationships between transport shortcomings and key areas of social disadvantage, such as unemployment, health inequality, and poor education. In this regard, in some transport studies, weighted socioeconomic factors have been combined in calculating the level of accessibility to public transport (Currie and Stanley, 2007; Hurni, 2005). However, in many transport models, socioeconomic characteristics have often been considered as independent variables. Therefore, a weighted accessibility index in such models may duplicate the effects of social factors and bias the results. Furthermore, from a transportation planning perspective, accessibility reflects an indicator of the spatial distribution of public transport stops and routes.

**4.5 Conclusions and future directions**

This study contained two main parts, 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 public transport in the Melbourne region. The findings indicate that the concentration of public transport in the inner parts of Melbourne and the CBD is high, and they can be accessed by all three modes. However, in the outer suburbs, which are characterised by sprawling patterns of housing,
public transport is generally limited to buses. This can be referred to the policy of increasing bus services based on address needs. Moreover, the results reveal that people are more likely to use public transport when it is more accessible. In terms of numbers of trips generated by public transport modes, the findings show that the average numbers of PT trips for all three modes is higher for higher levels of PTAI categories.

Overall, the techniques presented are straightforward to apply, and the approach produces better and more accurate measurements of public transport accessibility based on the VISTA dataset. The quantitative approach proposed 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 enable the accessibility for about 99% of SA1s to be calculated. Nonetheless, the accuracy 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. This results in the index having a value of 0 for SA1s with non-residential uses (165 out of 9,510 SA1s). Furthermore, the PTAI does not consider the connectivity between public modes which 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 (Neutens et al., 2012; Chen et al., 2014; Kwan, 2013). This study does not focus on off-peak periods, which tend to have lower public transport service frequency and public transport users encounter lower levels of service and consequently lower mobility. In addition, in calculating the average waiting times it was assumed that passengers arrive at the stops/stations randomly. Future studies may consider these points when measuring accessibility.

However, this study has adopted GIS approaches to calculate the PTAI and illustrate the level of accessibility for the 9,510 SA1s in the Melbourne region. Therefore, the findings provide a measure to identify areas with low levels of accessibility. In addition, this study calculates the PTAI with the knowledge of population distributions within SA1s. In this regard, the index provides a practical means of measuring the levels of accessibility within metropolitan areas, and it can be employed in modelling different aspects of travel behaviour. In addition, the proposed new index not only measures the level of public transport accessibility levels, but is also a better predictor when applied in a travel behaviour model.

4.6 References


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CHAPTER 5

MEASURING CYCLING ACCESSIBILITY IN METROPOLITAN AREAS
Chapter 5: Measuring Cycling Accessibility in Metropolitan Areas

Abstract

Different measures of cycling accessibility have been proposed in transportation planning. However, these measurements are mainly restricted by the availability of travel behaviour data. In addition, there has been limited comprehensive research on the importance of cycling accessibility of destinations based on the travel time or distance. In this chapter, a new index for measuring cyclability in metropolitan areas is proposed. The Cycling Accessibility Index (CAI) has been developed for quantifying cycling accessibility within local areas in metropolitan Melbourne, Australia. The CAI is defined according to gravity-based measures of accessibility. This index measures cycling accessibility levels in terms of the diversity of land uses, the number of activities in statistical areas and travel impedances between origins and destinations. The Victorian Integrated Survey of Travel and Activity (VISTA, 2009) dataset was used to evaluate the index and investigate the association between cycling accessibility levels and number of bicycle trips in local areas. The index was assessed by investigating the association between levels of cycling accessibility and number of bicycle trips in statistical areas. Key findings indicate that there is a significant positive association between bicycle trips and the CAI.

Keywords: cycling; accessibility; travel impedance; bicycle network.

5.1 Introduction

The term “accessibility” can be defined as the ease of access to a desirable destination. Hansen (1959) presented the first attempt to link land use and activities to the transportation network. Although transportation planning mainly concentrates on automobile-oriented developments, improving accessibility has recently become an important objective for urban planners (Iacono, Krizek, & El-Geneidy, 2010; Vale, 2013). There are numerous measures of accessibility in urban and transportation planning, which are often automobile-based (Handy & Clifton, 2001). Previous research on bicycle accessibility to destinations indicates that people commonly exclude potential destinations because of distance and travel time. A question that arises is how people define an acceptable distance for bicycle use and how this threshold affects the level of bicycle accessibility to destinations (Milakis, Cervero, Van Wee, & Maat, 2015; Rahul & Verma, 2014). Several factors, such as gender (Akar, Fischer, & Namgung, 2013; Bonham & Wilson, 2012), exogenous restrictions (such as danger, vandalism and facilities) (Fernández-Heredia, Monzón, & Jara-Díaz, 2014), safety (Mesbah, Thompson, & Moridpour, 2012), stress in terms of traffic volume and speed (Lowry, Furth, & Hadden-Loh, 2016; Mekuria, Furth, & Nixon, 2012; Sorton & Walsh, 1994), the relationship between commuting time and work duration (Schwanen & Dijkstra, 2002) and the time needed to spend on other activities (Hupkes, 1982), have been identified as the main factors influencing acceptable cycling travel time (Milakis et al., 2015). Existing studies on cycling accessibility mainly focus on access to employment as an important factor in forming urban structures. However, access to other destinations, such as retail, recreation and education, can also influence travel behaviour (Daly, 1997; Iacono et al., 2010).

Although non-motorised accessibility to various destinations has recently emerged as an important issue in transport and urban planning (Iacono et al., 2010; Krizek, 2005), most measures introduced are not comprehensive (Iacono et al., 2010). The main limitation of these studies is that measuring walking or cycling accessibility is highly dependent on travel data by non-motorized modes. In contrast, travel data for non-motorized transportation are limited, and in most cases they are questionnaire-based and may not be reliable. The provision of detailed, consistent and robust metrics for accessibility offers a defensible foundation for sustainability policy regarding travel and the built environment. In this regard, introducing accurate accessibility measures for walking or cycling should assist transport planners in making more rational decisions in infrastructure provision for non-motorized transportation (Devkota, Dudycha, & Andrey, 2012; Iacono et al., 2010; Levine, 2010). McNeil (2011) also argues that by taking into account route infrastructure and destination accessibility, neighbourhood bikeability may be affected. This paper introduces an index that measures the level of cycling accessibility within geographical areas. It demonstrates how cycling access to different
destinations can be reliably measured. The cycling accessibility index has been developed using a dataset from metropolitan Melbourne, Australia.

Section 5.2 describes the methodology developed. Analysis and results of application of the CAI in the Melbourne metropolitan region are presented in Section 5.3. Section 5.4 discusses the results and summarizes the findings and outlines avenues for future research.

5.2 Methods

This chapter proposes an index for measuring cycling accessibility levels in Melbourne’s 9510 Statistical Areas level 1 (SA1s). SA1s are the second smallest geographic areas defined in the Australian Statistical Geography Standard (2011). In measuring cycling accessibility, two factors, distance or travel time between origins and destinations and the cycling catchments of destinations are considered. Cycling catchments are calculated based on the service area of destinations and the travel distance, which is considered as the distance between origins and destinations. Network models are applied to identify acceptable cycling catchments as well as an origin-destination (O-D) cost matrix of origins and destinations using a geographical information system (GIS). The calculation procedure is fully explained in the section on the approach. The databases, study area and conceptual framework are presented in the following sections which describe the procedure for calculating the index.

5.2.1 Datasets

As explained in previous sections, the aim of this part of the study was to measure cycling accessibility within Melbourne’s 9510 Statistical Areas Level 1 (SA1s). For this purpose, several datasets were adopted, which are described as follows.

Geographical Areas

A database of mesh blocks from the 2011 Census for the Melbourne Region is available from the Australian Bureau of Statistics (ABS, 2011). 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, the Melbourne region contains 53074 mesh blocks, 9510 SA1s, 277 statistical areas level 2 (SA2s) and 31 local government areas (LGAs). Figure 5.1 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.
Point of Interests (POIs)

A database of points of interest (POIs) was obtained from PSMA Australia (PSMA, 2011). POIs include urban centres, significant buildings, landmarks, public spaces, community facilities and indigenous locations, and those for Melbourne include 15,588 points. These POIs are considered as destinations and categorized into four groups of activities as described in Table 5.1.

Table 5.1 Description of Destination Categories

<table>
<thead>
<tr>
<th>Destination Categories</th>
<th>No.</th>
<th>Percentage</th>
<th>Average No. in each SA 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education Centres</td>
<td>1869</td>
<td>12.0</td>
<td>1.5</td>
</tr>
<tr>
<td>Health and Care Facilities</td>
<td>5602</td>
<td>35.9</td>
<td>1.7</td>
</tr>
<tr>
<td>Retail and Recreation Centres</td>
<td>4559</td>
<td>29.2</td>
<td>1.6</td>
</tr>
<tr>
<td>Community Services</td>
<td>3558</td>
<td>22.8</td>
<td>1.6</td>
</tr>
<tr>
<td>Total</td>
<td>15588</td>
<td>100.0</td>
<td>2.8</td>
</tr>
</tbody>
</table>

Figure 5.2 illustrates the distribution of POIs throughout the Melbourne region. As the table shows, POIs are mostly concentrated in the inner parts of Melbourne. However, some suburbs in the outer northern and western areas, such as Sunbury, Melton and Werribee have considerable densities of POIs.
Figure 5.2 Distribution of points of interest

Principal Bicycle Network

The Bicycle Network dataset was obtained from the Victorian Government open data sources (2015). This dataset was produced by the Roads Corporation of Victoria (VicRoads) in 2015, however, the last verification date was in 2011. The dataset contains information on the 4,139 bicycle path segments with an average length of 1 km. Figure 5.3 presents the bicycle network in the Melbourne metropolitan area.
VISTA Dataset

The VISTA dataset (2009) was provided by the Victorian Integrated Survey of Travel and Activity (VISTA, 2009). This was a cross-sectional survey conducted from 2009 to July 2010. It covers the Melbourne Statistical Division (MSD) as defined by the ABS, and regional cities in the State of Victoria, including Geelong, Ballarat, Bendigo and Shepparton, and the Latrobe Valley. Demographic data, trip information and car ownership details were collected from randomly selected residential properties. A total of 16,411 households (42,002 individuals) responded to this survey, a response rate of 47%. In this research, only residents within the MSD (22,201 individuals) were considered and reported bicycle trips were used to assess the index.

5.2.2 Study Area

Melbourne, with a total population of approximately 4.5 million, is the largest metropolitan area in the Australian State of Victoria, and the second most populous city in Australia and Oceania. It has an average net population density of about 22 people per km².

Victorian government policy generally supports bicycle-friendly projects. The Bicycle Plan is the City of Melbourne's action plan for a connected bicycle network, improving links to existing routes and making cycling more accessible. Recently, a significant effort has been made to make Melbourne a more bicycle-friendly city. The City of Melbourne’s Bicycle Plan 2016-20 was endorsed by The Melbourne City Council on 15 March 2016 and endorsed Melbourne becoming a cycling city (2016).
There has been significant growth in cycling in the Central Business District (CBD) of Melbourne (population about 70K), and figures present cycles at 8% of all peak-hour (7am-10am) commuter traffic. Planning for improvements to CBD bicycle routes and other major arterial routes is proceeding. Several projects, including a bicycle hiring system, similar to Vélib’ in Paris, started in June 2010 (Melbourne City Council, 2008).

Figure 5.4 shows the number of bicycle trips in Melbourne’s major suburbs. Although a higher number of bicycle trips was expected in the city centre, the figure shows a different pattern. As the figure shows, the number of bicycle trips in the central city is not as high as in some other suburbs, such as Brunswick, Yarra and Maribyrnong.

![Figure 5.4 Number of bicycle trips in Melbourne’s major suburbs](image)

### 5.2.3 Conceptual Framework

The CAI calculation procedure has two main steps. The first step relates to the SA1s’ weighted centroids as origins, and the second step involves calculations relating to the destinations (POIs).

Figure 5.5 illustrates the conceptual framework of the calculation procedure. A network analysis including service area and O-D cost matrix analysis, using the ArcGIS 10.2 software, are applied to calculate both the cycling catchments of the destinations and travel distances between origins and destinations ($D_{ij}$). Thereafter, the ratio of cycling catchment areas to SA1 areas on one side and the ratio of $D_{ij}$ to bicycle path lengths within SA1s on the other side are used to compute the Cycling Accessibility Index.
Figure 5.5 Conceptual framework of the calculation process

SA1s Weighted Centroids\(^2\)

A database of mesh blocks from the 2011 Census for the Melbourne Region was accessed from the ABS (2011). This dataset contains the total usual resident population and the total number of dwellings from the 2011 Census of Population and Housing for mesh blocks (the smallest geographical unit released by the ABS) and all other statistical areas, including SA1s. According to the ABS, the Melbourne region contains 53,074 mesh blocks and 9,510 SA1s. SA1s with an average population of 414 people and average area of 1 square km are built up from or, are approximated by, the mesh blocks and each SA1 contains five mesh blocks on average. The mesh block with the highest population within the corresponding SA1 is defined as a weighted centroid of the SA1 and it is considered as an origin. Figure 5.6 illustrates mesh blocks, SA1s and weighted centroids. As the figure indicates, the centroid for the selected SA1 is placed on the mesh block with the highest population of 87 people.

\(^2\) Population weighted centroid is a geographical term that is different from ‘weighted average’. Population weighted centroid is an algorithm used in ArcGIS to obtain a summary reference point for the centre of the population.
Destinations

Service area and OD-cost matrix analysis was undertaken for each set of destinations separately. For example, 4 km buffers were calculated for education centres, and 4km buffer areas were also computed for health and care facilities. Similarly, for travel distances between origins and destinations, an OD-cost matrix was applied separately for each group of destinations. Austroads, the Association of Australian and New Zealand Road Transport and Traffic Authorities (Austroads, 2011), examined how travel time impacts accessibility. They mainly adopted the figures from the UK Department for Transport (DfT, 2010). Their findings showed that there are limits to the length of time people are willing to travel to access an opportunity. A median desirable travel time is one that satisfies half of the road users. They also defined the maximum desirable travel time/distance, as one which a significant percentage of people would find it unfeasible to regularly travel and may be forced to relocate their residence closer to the destination or find a less suitable destination but one that is closer. This study uses the median desirable travel time/distance, as it assumes there is a greater probability of choosing a bicycle as a mode of transport to access different destinations. Moreover, the median travel times/distances were found to be more consistent with the findings reported by McDonald (2007) in the United States, Rahul & Verma (2014) in Bangalore, Milakis et al. (2015) in Berkeley, Iacono et al. in the United States (2010) and McNeil (2011) in the United States. Table 5.2 shows the acceptable travel times and distances as well as the median desirable bicycle travel times, with an average cycling speed of 16 km per hour (Espada & Luk, 2011). The average speed of 15 to 16 km/h has been considered in previous research for cyclists (Espada, Bennett, Green, & Hatch, 2015; Espada & Luk, 2011; Paris, 2010; Prud'homme & Bocarejo, 2005). This study uses the speed of 16 km/h, adopted from the Austroads network operation planning framework (Espada & Luk, 2011).
### Table 5.2 Median desirable bicycle travel times and distances for different groups of activities

<table>
<thead>
<tr>
<th>Destinations Categories</th>
<th>Median Desirable Travel Time (minutes)</th>
<th>Median Desirable Travel Distance (Km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education Centres</td>
<td>15</td>
<td>4</td>
</tr>
<tr>
<td>Health and Care Facilities</td>
<td>15</td>
<td>4</td>
</tr>
<tr>
<td>Retails and Recreation Centres</td>
<td>10</td>
<td>2.5</td>
</tr>
<tr>
<td>Community Services</td>
<td>20</td>
<td>5.3</td>
</tr>
</tbody>
</table>

#### 5.3 Approach

As explained in the previous section, cycling catchments and travel distances between origins and destinations were calculated considering the acceptance of the median desirable travel distance (see Table 5.2). Travel distances between origins and destinations are required to identify how far destinations are located from the origins (weighted centroid of SA1s).

##### 5.3.1 Area Ratio ($AR_i$)

Cycling catchments were calculated for each destination based on the acceptable distance or travel time. For this purpose, the service area of network analyst tools in ArcGIS 10.2 was used. Cycling catchments were calculated for each category of destinations. Thereafter, the ratio of cycling catchments in each group to the area of the corresponding SA1 were calculated. Computed ratios were then summed to represent $AR_i$ as formulated in Equation 5.1.

$$AR_i = \sum_{j=1}^{4} N \times \left( \frac{Area_{CCj}}{Area_i} \right)$$  \hspace{1cm} (5.1)

where, $AR_i$ is the ratio of cycling buffers’ areas to the area of the corresponding SA1, $N$ is the number of buffers in the SA1, $Area_{CC}$ denotes the area of the cycling catchments of destinations, and $Area_i$ indicates the area of the SA1.
Figure 5.7 Illustration of buffer areas for activities

Figure 5.7 illustrates the buffer areas generated for activities within each type of destination. In this example, the selected SA1 is covered by the service areas which are separately generated for each activity within each category of destinations. The total number of buffers (generated for activities within acceptable distance) was 12. Table 5.3 presents the process for calculating $AR_i$ for the selected SA1 (shown in Figure 5.7). The proportions of buffer areas to the area of the SA1 were multiplied by the number of buffers in each category, and then summed to calculate the $AR_i$. The SA1s’ weighted centroid as well as POIs (separately in each category) are also presented in the example. It should be noted that, in some cases, the SA1s’ weighted centroid was located outside a SA1 boundary.

The Area Ratio (AR) defined in Equation 5.2 measures both the diversity and intensity of land uses. Given that $N$ in Equation 5.2 denotes the number of activities available for cyclists within acceptable travel distance, $AR$ reflects the intensity of different land uses. Hence, the more activities available, the higher the value of $AR$ calculated. On the other hand, the total value of the $AR$ reflects the diversity of land uses, because it is computed by summing the $AR$ values of all destination categories. In other words, for a given SA1, if the number of destinations available within an acceptable distance is doubled, the total value of $AR$ is also doubled for a constant value of $Area_{cd}/Area_i$. 
Table 5.3 Example of area ratio calculation

<table>
<thead>
<tr>
<th>Destinations Categories/SA1</th>
<th>Area (sq. m)</th>
<th>Area_{ccj}/Area_{SA1}</th>
<th>No. of buffers</th>
<th>AR_i</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education Centres</td>
<td>14949.82</td>
<td>0.999</td>
<td>3</td>
<td>2.997</td>
</tr>
<tr>
<td>Health and Care Facilities</td>
<td>13929.27</td>
<td>0.932</td>
<td>3</td>
<td>2.796</td>
</tr>
<tr>
<td>Retails and Recreation Centres</td>
<td>5638.79</td>
<td>0.377</td>
<td>4</td>
<td>1.508</td>
</tr>
<tr>
<td>Community Services</td>
<td>10517.78</td>
<td>0.703</td>
<td>3</td>
<td>2.109</td>
</tr>
<tr>
<td>SA1_i</td>
<td>14952.40</td>
<td>1</td>
<td>12</td>
<td>9.410</td>
</tr>
</tbody>
</table>

Table 5.4 shows the total area of cycling buffers within the Melbourne area for all types of destinations (education centres, health and care facilities, retail and recreational centres and community services). The proportion of SA1s covered by cycling buffers (%) is also presented. The table shows that the highest coverage belongs to community services (9.53%), which have the coverage area of 840.35 square kms. In contrast, retail and recreation centres have the least coverage with 5.45%. The reason for this is that the median desirable travel time was defined as 20 minutes for community services, while the desirable time for retail and recreation was a minimum of 10 minutes (Table 5.2).

Table 5.4 Median desirable bicycle travel times and distances for different groups of activities

<table>
<thead>
<tr>
<th>Destinations Categories</th>
<th>Total Area of Cycling Buffers (sq. km)</th>
<th>Proportion of SA1s covered by cycling buffers (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education Centres</td>
<td>791.82</td>
<td>8.98</td>
</tr>
<tr>
<td>Health and Care Facilities</td>
<td>774.66</td>
<td>8.79</td>
</tr>
<tr>
<td>Retails and Recreation Centres</td>
<td>480.89</td>
<td>5.45</td>
</tr>
<tr>
<td>Community Services</td>
<td>840.35</td>
<td>9.53</td>
</tr>
</tbody>
</table>

5.3.2 Travel Impedance (X_{ij})

Travel distance was calculated for origins and destinations using O-D cost matrix analysis. The cut-off values were defined according to the median desirable travel times for each type of destination (Table 5.2). The average distances between origins and the set of destination choices within each category were calculated as $\bar{D}_{ij}$. $X_{ij}$ is the summed value of average distances divided by the total length of bicycle routes (length of bicycle infrastructure) in each SA1.

$$X_{ij} = \sum_{i=1}^{n} \sum_{j=1}^{4} \left( \frac{\bar{D}_{ij}}{B_{li}} \right)$$  \hspace{1cm} (5.2)

where, $X_{ij}$ is the travel distance between origin $i$ and destination $j$ divided by the total length of bicycle paths within the corresponding SA1, $\bar{D}_{ij}$ is the average travel distance between origin $i$ and destination $j$, and $B_{li}$ denotes the total (summed) length of bicycle paths in the $SA1$. 
Table 5.5 presents an example of the calculation of $X_{ij}$ for a given SA1. The table shows that 18 education centres were available within the acceptable travel distance (based on the cut-off value of 15min/4km) with an average distance of 2,860 metres. This was equal to 3,159 for community services with 66 available destinations within an acceptable distance (20min/5.3km). In this example, the value for $\hat{D}_{ij}$ calculated by the summed values of average travel distances is equal to 11,302.57 m. This is then divided by the total bicycle length within the corresponding SA1 to compute the $X_{ij}$.

### 5.3.3 Cycling Accessibility Index (CAI)

For each SA1, the CAI was calculated using the formula shown in Equation 5.3. The index is a combined measure of $AR_i$ and exponential function of $X_{ij}$ given as:

$$\text{CAI}_i = AR_i + \sum_{j=1}^{4} e^{-X_{ij}} \quad (X_{ij} \neq 0)$$

5.3

where, $\text{CAI}_i$ is the Cycling Accessibility Index for each SA1, $AR_i$ represents the ratio of cycling catchment areas to the area of the corresponding SA1, and $X_{ij}$ is the distance or travel time between origin $i$ and destination $j$ divided by the total length of bicycle paths within the corresponding SA1 $i$. For areas with no bicycle network, the CAI is equal to $AR_i$. The reason for this is that cyclists may share the road with other modes within those areas. In addition, for areas with no destinations (or no POIs) within an acceptable distance or travel time, the value is zero.

Figure 5.8 illustrates the logic associated with Equation 5.3. As shown in Figure 5.8(a), when considering constant numbers for $AR_i$, increasing $X_{ij}$ causes the level of cycling accessibility to decline. Figure 5.8(a) shows that for constant values of $X_{ij}$, the cycling accessibility index (CAI) and $AR_i$ are positively correlated. Assuming $X_{ij}$ is equal to 1, Figure 5.5(b) also shows that $\text{CAI}$ increases when the $AR_i$ increases. This means that for a specified distance, the greater the coverage of cycling catchments, the more cycling accessibility there is. However, it should be noted that higher values of $AR_i$ may indicate that more accessible destinations are from a specified origin. In contrast, assuming a constant value for $AR_i$ in Figure 5.8(b), the CAI decreases as $X_{ij}$ increases. This implies that the further
the locations are away, the lower the CAI is.

Figure 5.8 Relationships between CAI, \( X_{ij} \) and \( AR_i \)

### 5.4 Results

Table 5.6 presents the ranges and categories of the CAI. The index is grouped into four main categories: poor, moderate, good, and excellent, and a zero group. The classification method used for the CAI categories is based on quintiles (Espada & Luk, 2011; TfL, 2010) since they are one of the best methods for simplifying comparisons as well as aiding general map-reading (Brewer & Pickle, 2002). Zero accessibility is estimated for 86,929 residents or 2.6% of the total population. Poor accessible areas are mostly located in outer Melbourne. Overall, around 50% of the total population has zero to moderate cycling accessibility.

#### Table 5.6 CAI Ranges and Categories

<table>
<thead>
<tr>
<th>CAI Categories</th>
<th>CAI Ranges</th>
<th>SA1s</th>
<th>Population</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No</td>
<td>%</td>
</tr>
<tr>
<td>NA/Zero</td>
<td>0</td>
<td>246</td>
<td>2.6</td>
</tr>
<tr>
<td>Poor</td>
<td>&lt; 0.5</td>
<td>2,013</td>
<td>21.2</td>
</tr>
<tr>
<td>Moderate</td>
<td>0.5 - 2</td>
<td>2,560</td>
<td>26.9</td>
</tr>
<tr>
<td>Good</td>
<td>2 – 4.5</td>
<td>2,452</td>
<td>25.8</td>
</tr>
<tr>
<td>Excellent</td>
<td>&gt; 4.5</td>
<td>2,239</td>
<td>23.5</td>
</tr>
<tr>
<td>Total</td>
<td>NA</td>
<td>9,510</td>
<td>100.0</td>
</tr>
</tbody>
</table>

A map showing the distribution of CAI is presented in Figure 5.9. As explained above, the CAI is categorized into four bands. The first category represents poor accessibility while the last category corresponds to an excellent level of cycling accessibility. The first and last categories are 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. However, the inner suburbs are not exempt from lower levels of accessibility.

Figure 5.9 CAI categories in the Melbourne Region

5.4.1 CAI Evaluation

As mentioned in the previous section, VISTA records 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 details of 93,902 trips stages made by 22,184 individuals in the MSD. As shown in Table 5.7, 1,340 or 1.4% of total trips were undertaken by bicycle. These numbers of bicycle trips are reported from 320 SA1s. Considering the total number of bicycle trips (1,340), the average number of bicycle trips in each SA1 is about 4. Using the SAS software, the CAI was assessed using Chi-Square tests of association.
Table 5.7 Number and percentage of trips made by different modes in the Melbourne region

<table>
<thead>
<tr>
<th>Transport Modes</th>
<th>Frequency</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle Driver</td>
<td>42,989</td>
<td>45.8</td>
<td>45.8</td>
</tr>
<tr>
<td>Vehicle Passenger</td>
<td>21,073</td>
<td>22.4</td>
<td>68.2</td>
</tr>
<tr>
<td>Motorcycle</td>
<td>174</td>
<td>0.2</td>
<td>68.4</td>
</tr>
<tr>
<td>Walking</td>
<td>9,625</td>
<td>10.3</td>
<td>78.7</td>
</tr>
<tr>
<td>Bicycle</td>
<td>1,340</td>
<td>1.4</td>
<td>80.1</td>
</tr>
<tr>
<td>Public Bus</td>
<td>3,230</td>
<td>3.4</td>
<td>83.5</td>
</tr>
<tr>
<td>Train</td>
<td>11,095</td>
<td>11.8</td>
<td>95.3</td>
</tr>
<tr>
<td>Tram</td>
<td>3,999</td>
<td>4.3</td>
<td>99.6</td>
</tr>
<tr>
<td>Other</td>
<td>377</td>
<td>0.4</td>
<td>100</td>
</tr>
<tr>
<td>Total</td>
<td>93,902</td>
<td>100.0</td>
<td></td>
</tr>
</tbody>
</table>

Outlier Detection for CAI values

Prior to evaluating the CAI, the calculated values of the index were examined for outliers. Median and mean absolute values were selected to identify outliers. Figure 5.10 presents the box and whisker plots for the CAI values.

![Box and Whisker Plots for CAI values](image)

Table 5.8 shows the results of the outlier detection, in which 71 or 5% of values were designated as outliers. Hence, after eliminating the outliers, the number of observations used for analysis was 1269.

101
Table 5.8 Basic statistics and outlier analysis for CAI

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>4.44</td>
</tr>
<tr>
<td>Median</td>
<td>2.97</td>
</tr>
<tr>
<td>Std. Deviation</td>
<td>4.43</td>
</tr>
<tr>
<td>Mean Absolute Deviation</td>
<td>3.29</td>
</tr>
<tr>
<td>Multiplier</td>
<td>3</td>
</tr>
<tr>
<td>Lower</td>
<td>-7.19</td>
</tr>
<tr>
<td>Upper</td>
<td>13.14</td>
</tr>
<tr>
<td>Number of Observations Read</td>
<td>1340</td>
</tr>
<tr>
<td>Number of Observations Used</td>
<td>1340</td>
</tr>
<tr>
<td>Number of Outliers</td>
<td>71</td>
</tr>
<tr>
<td>Proportion of Outliers</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Bicycle Trips and CAI categories

Chi-Square tests were applied to investigate whether there was any association between the estimated accessibility index and the number of bicycle trips in each SA1. Table 5.9 presents the results of correlation analysis between CAI categories and bicycle trips. The results show that the CAI and number of bicycle trips in SA1s have a significant degree of association ($\chi^2 = 601.349, p < .001$).

Table 5.9 Chi-Square Test for bicycle trips and CAI categories

<table>
<thead>
<tr>
<th>Statistic</th>
<th>DF</th>
<th>Value</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-Square</td>
<td>51</td>
<td>601.349</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Likelihood Ratio Chi-Square</td>
<td>51</td>
<td>609.548</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Mantel-Haenszel Chi-Square</td>
<td>1</td>
<td>36.585</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Phi Coefficient</td>
<td></td>
<td>0.688</td>
<td></td>
</tr>
<tr>
<td>Contingency Coefficient</td>
<td></td>
<td>0.567</td>
<td></td>
</tr>
<tr>
<td>Cramer’s V</td>
<td></td>
<td>0.397</td>
<td></td>
</tr>
</tbody>
</table>

Sample Size: 1269

5.5 Discussions and Conclusions

This part of the study adopted a GIS approach to calculate a Cycling Accessibility Index to illustrate the level of accessibility for the 9,510 SA1s in the Melbourne metropolitan region. The CAI utilizes GIS techniques, including an OD cost matrix and service area analysis, to objectively measure cycleability. The findings provide a measure to identify areas with low levels of accessibility. An approach to the measurement of the level of accessibility for cycling in metropolitan Melbourne is also presented. The index developed consists of two parts, the ratio of the cycling catchment area and the SA1 area, and an impedance function of travel distance between the defined origins and destinations. The analysis was applied to four types of destinations, including education centres, health and care facilities, community services and retail and recreation centres. Service areas were calculated by originating POIs in each of the four named categories, separately. Service areas were
then converted to ratios by dividing by the corresponding SA1’s area. The coverage ratios of destinations were estimated to be 8.95, 8.79, 9.53 and 5.45, respectively. To measure the travel impedance, the weighted centroids of SA1s were considered as origins and four categories of POI were represented as destinations. Using the VISTA dataset, the CAI was assessed to see whether there was any significant difference between the level of cycling accessibility and the use of bicycles in statistical areas. For this purpose, Chi-Square tests were run using CAI categories and bicycle trips. The results indicated that the level of cycling accessibility within statistical areas was significantly associated with the number of bicycle trips made in these areas. In other words, the CAI was evaluated as a valid means of measuring cycling accessibility in the Melbourne region based on the VISTA dataset.

Key findings indicate that 2.6% of SA1s or 2.2% of residents have no cycling accessibility and about 50% have poor to moderate accessibility. Although areas with zero to moderate levels of cycling accessibility mainly belong to the outer areas of Melbourne, the inner suburbs were not excluded. Furthermore, the results indicate that the inner part of Melbourne and the CBD is more accessible by bicycle as a transport mode. However, the outer suburbs, which are characterized by dispersed patterns, have no to little coverage of bicycle networks and therefore less cycling accessibility.

In brief, accessibility can be considered as a measure of locational status, particularly from a social planning perspective. In addition, from a sustainable transportation planning perspective and for the promotion of active transportation, poor cycling access can deter travel to different facilities and social opportunities. This study has several strengths and limitations. Combining a geometric measure of bicycle networks and travel impedance has enabled us to define a practical means of measuring levels of accessibility within metropolitan areas, independent of travel behaviour data. In addition, this approach considers both the diversity of land uses and the number of activities, while existing approaches have mostly focused on either the diversity or intensity of land uses (Devkota et al., 2012; Iacono et al., 2010). Based on existing knowledge, the diversity of land use is significantly associated with non-motorized trips (Cervero, Sarmiento, Jacoby, Gomez, & Neiman, 2009; Handy & Xing, 2011; Lee, Nam, & Lee, 2014). Hence, different categories of destinations were taken into account in the derivation of the CAI to allow the impacts of land use diversity to be incorporated. Furthermore, the number of cycling buffers reflects the number of activities in local areas, which is a significant factor in determining accessibility (Iacono et al., 2010).

5.6 Future research directions

The techniques presented are straightforward to apply. The quantitative approaches developed can be employed for different types and categories of destinations in other cities around the world. The new method is designed to be applied with available census data and transport modelling tools.
Furthermore, the methods presented provide reliable and defendable results, and accessibility could be measured for about 95% of statistical areas. In contrast to previous research, this study calculates cycling accessibility within a large geographical extent (Iacono et al., 2010). Nonetheless, the CAI can be enhanced by greater detail to achieve even more accurate results. According to El-Geneidy, Krizek, & Iacono (2007) and Parkin & Rotheram (2010), the speed of cyclists may depend on several factors, including the type of facility, segment length, trip length, number of signalised intersections, average daily traffic, time of day and personal characteristics. In the present study, due to the availability of data, travel distances were calculated based on segment length only, but considering the other factors could enhance the accuracy of the results. In developing the cycling measure of accessibility, a balance between practical considerations and theoretical rigour has been achieved. The index is based on gravity-based measures and as Geurs and Van Wee (2004) state, these kinds of measures are operational, and relatively easy to interpret and communicate.

However, temporal and individual or household-level constraints may have a significant influence on the level of accessibility which a person actually experiences at a given location (Weber, 2006). The concept of space and time geography has resulted in enhancing person-based accessibility measures (Kwan, 1998, 2013; Kwan, Murray, O'Kelly, & Tiefelsdorf, 2003). The ability to account for individual-level characteristics or constraints, such as the availability of motorised/non-motorised modes, gender, household size, household structure, etc. (Damant-Sirois & El-Geneidy, 2015; Fernández-Heredia et al., 2014) would affect the relationship between accessibility and travel behaviour by non-motorized modes. However, the importance of the natural environment and ecological factors, such as the weather (Motoaki & Daziano, 2015; Ortúzar, Iacobelli, & Valeze, 2000), vegetation (Van Holle et al., 2014) and slope (Galanis, Papanikolaou, & Eliou, 2014), should not be ignored. Hence, the analysis could be extended to determine interaction spaces for groups of individuals (Neutens, Witlox, Van De Weghe, & De Maeyer, 2007). Another weakness of this approach is that the index did not weight bicycle routes based on their different characteristics, such as widths, pavements and types of route. Future studies may consider these factors when measuring accessibility. In addition, this study focused on computing the relative accessibility levels for SA1s for groups of destinations, and the differences between acceptable travel time/distance for activities within each category were ignored. For example, education centres, universities and secondary schools may have different travel patterns. Therefore, running separate analyses for major activities within the categories may improve the accuracy of the results.

5.7 References


Parkin, J., & Rotheram, J. (2010). Design speeds and acceleration characteristics of bicycle traffic for use in planning, design and appraisal. *Transport Policy, 17*(5), 335-341. doi: [http://dx.doi.org/10.1016/j.tranpol.2010.03.001](http://dx.doi.org/10.1016/j.tranpol.2010.03.001)


CHAPTER 6

MEASURING WALKING ACCESSIBILITY IN METROPOLITAN AREAS
Chapter 6: Measuring Walking Accessibility in Metropolitan Areas

Abstract

Promoting walking trips is considered as a key element in achieving more sustainable transportation. This paper proposes a new index for measuring walkability in metropolitan areas. This index measures walkability levels in terms of the diversity and intensity of different uses in spatial areas while considering the travel distance/time as travel impedance between origins and destinations. A Walking Access Index (WAI), which is a location-based measure for accessibility, is formulated for quantifying accessibility within local areas in metropolitan Melbourne, Australia. GIS software was employed to compute distances between origins and destinations. The Victorian Integrated Survey of Travel and Activity (VISTA) was used to evaluate the new index and examine the association between walking trips and levels of accessibility within the metropolitan region of Melbourne. Furthermore, the new index is compared with one of the most common approaches using the VISTA dataset. Key findings indicate that the WAI has a stronger association with recorded walking trips, with more walking trips recorded in areas with higher values of the WAI.

Keywords: Walking Access Index, Accessibility, Destination, Travel Distance

6.1 Introduction

Providing efficient walkable neighbourhoods is one of the main objectives of policy makers and planners throughout the world. In recent decades, sprawling cities and automobile-oriented developments along with increased car ownership have encouraged people to spend more time traveling by car. High levels of car dependency not only affect quality of life, but also threaten people’s health. In addition, the growing use of private motorized vehicles has resulted in critical issues, such as increasing traffic congestion and air pollution.

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, and there will be a considerable distance from residential areas to workplaces. These phenomena mean that auto-oriented transport is needed for regular trips, such as travelling to work, school and shopping. The way in which cities and transport corridors are designed and developed is an important contributor to physical inactivity (Saelens et al., 2003; Ewing and Cervero, 2010; Pratt et al., 2004). A well-designed neighbourhood assists in improving the health and wellbeing of a community, by encouraging people to be more physically active and engaged in the community (Ewing and Cervero, 2010). Australia has been categorized among countries with the highest car ownership ratios and particular groups of people such as youths, seniors, low-income households and Aboriginals encounter difficulties in accessing work, education and social or cultural activities (Lucas, 2012).

This chapter presents a review of previous research in this area. Numerous studies have focused on measuring walkability. However, there has been limited research which has considered walking distances to different destinations as one of the main barriers to active transport. Therefore, this study describes a new concept to measure walking accessibility, followed by an implementation of the new index in metropolitan Melbourne, Australia. Moreover, the chapter presents a comparison of the new index with one of the most common approaches for measuring walking accessibility.

The following section provides background information. The methodology section describes the approach used to compute the index, analysis and results of the application of the WAI in the Melbourne region. A comparison of the results between the new index and existing approaches is also presented. The discussion and conclusions summarize the key findings of this research and present the limitations of this study and future research directions.

6.2 Methodology

This study introduces a measure for determining the level of walkability in Melbourne’s 9510 Statistical Areas level 1 (SA1s), the second smallest geographic area defined in the Australian Statistical Geography Standard (ASGS, 2011).
6.2.1 Datasets
To calculate the WAI, the following datasets were utilized:

1. A database of points of interest (POIs) was obtained from the Australian Urban Research Infrastructure Network (AURIN). This database includes 15,588 points, including urban centres, significant buildings, landmarks and public spaces, community facilities and indigenous locations. These POIs are considered as destinations and categorized into six groups of destinations, as described in Table 6.1.

<table>
<thead>
<tr>
<th>Destinations Categories</th>
<th>No.</th>
<th>Percentage</th>
<th>Average No. in each SA1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary and Secondary Schools</td>
<td>1,608</td>
<td>11.6</td>
<td>4.2</td>
</tr>
<tr>
<td>Tertiary Institutions</td>
<td>83</td>
<td>0.6</td>
<td>2.6</td>
</tr>
<tr>
<td>Child Care Centres</td>
<td>3,471</td>
<td>25.1</td>
<td>8.1</td>
</tr>
<tr>
<td>Medical Centres</td>
<td>1,019</td>
<td>7.4</td>
<td>6.9</td>
</tr>
<tr>
<td>Retail and Recreation Centres</td>
<td>3,091</td>
<td>22.4</td>
<td>9.1</td>
</tr>
<tr>
<td>Community Services and Libraries</td>
<td>4,559</td>
<td>33.0</td>
<td>14.3</td>
</tr>
<tr>
<td>Total</td>
<td>13,831</td>
<td>100.0</td>
<td>1.5</td>
</tr>
</tbody>
</table>

1. A dataset containing road networks which was published by the Department of Environment, Land, Water & Planning in 2012. It contains line features delineating the state-wide road network and includes bridges, connectors, footbridges, foot tracks, roads, etc.

2. A database of mesh blocks from the 2011 Census for the Melbourne Region is available from the Australian Bureau of Statistics (ABS). This data set contains the total usual resident population and total number of dwellings from the 2011 Census of Population and Housing for mesh blocks (the smallest geographical unit released by the ABS) and all other statistical areas, including SA1s. According to the ABS, the Melbourne region contains 53,074 mesh blocks and 9,510 SA1s.

3. The VISTA dataset (2009) provided by the Victorian Integrated Survey of Travel and Activity (VISTA, 2009). This was a cross-sectional survey conducted from 2009 to July 2010. It covers the Melbourne Statistical Division (MSD) as defined by the ABS and regional cities in the State of Victoria. A total of 16,411 households (42,002 individuals) responded to this survey, a response rate of 47%. In the present research, only the residents within the MSD (22,201 individuals) were considered and reported walking trips were used to assess the index.

6.2.2 Approach
The aim of the present study was to measure the level of accessibility for Melbourne’s SA1s. For this purpose, the weighted centroids of SA1s selected based on the mesh block population are considered as origins and POIs are defined as destinations. The index is an accurate measurement of the accessibility of POIs to the weighted SA1s’ centroid. Then, using OD-cost network analysis, the
average distances from each of the SA1 weighed centroids to all available destinations within acceptable walking distances were calculated. As presented in Table 6.1, POIs are categorised into six groups of destinations. Travel impedance is based on the desirable and maximum travel time/distance. Origins and destinations and the approach are described in detail in the following sections.

**Origins (SA1s’ Weighted Centroid)**

A database of mesh blocks from the 2011 Census for the Melbourne Region was accessed from the ABS (2011). This dataset contains the total usual resident population and total number of dwellings from the 2011 Census of Population and Housing for mesh blocks (the smallest geographical unit released by the ABS) and all other statistical areas, including SA1s. According to the ABS, the Melbourne region contains 53,074 mesh blocks and 9,510 SA1s. SA1s have an average population of 414 people and an average area of one square km and each SA1 contains five mesh blocks on average. The mesh block with the highest population within the corresponding SA1 is defined as a weighted centroid of the SA1 and it is considered as an origin. Figure 6.1 illustrates mesh blocks, SA1s and weighted centroids. As the figure shows, the centroid for the selected SA1 is placed on the mesh block with the highest population of 87 people. It should be noted that SA1s are built up, or approximated by, the mesh blocks. In other words, mesh blocks are completely nested within SA1s. For this reason, the populations of SA1s were calculated from the sum of the mesh blocks’ population. Hence, the weighted centroids of SA1s are equal to the population-weighed centroids.

![Figure 6.1 Illustration of definition of weighted centroid for SA1s](image-url)
**Destinations (POI categories)**

As described previously, POIs are categorised into six major destination groups, including primary and secondary schools, tertiary institutions, child care centres, medical centres, community services and libraries and retail and recreation centres. OD-cost matrix analysis was applied for each set of destinations separately. For each category, two thresholds including the desirable and maximum travel times/distances were defined. These values were adopted from Austroads, the Association of Australian and New Zealand Road Transport and Traffic Authorities, (Austroads, 2011), and were derived from studies of how travel time/distance impacts accessibility. Austroads also adopted values derived by the UK Department for Transport (DfT, 2010). The figures adopted are also consistent with research conducted by Millward et al. in the United States (Millward et al., 2013), Rattan et al. in Canada (Rattan et al., 2012), and Rendall et al. in New Zealand (Rendall et al., 2011). A (median) desirable travel time is one that satisfies half of the road users, while the maximum desirable travel time/distance is one which a significant percentage of people would find it unfeasible to regularly travel and may be forced to relocate their residence closer to the destination or find a less suitable destination but one that is closer. In the present study, both median and maximum desirable travel time/distances are used to calculate the index. Table 6.2 shows the acceptable travel times and distances as well as the median desirable walking travel times. These values were adopted from the Austroads network operation planning framework (Espada et al., 2015; Espada and Luk, 2011).

**Table 6.2 Median desirable bicycle travel times and distances for different groups of activities**

<table>
<thead>
<tr>
<th>Destination Categories</th>
<th>Travel Time (min)</th>
<th>Travel Distance (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Desirable</td>
<td>Maximum</td>
</tr>
<tr>
<td>Primary and Secondary Schools</td>
<td>&lt; 10</td>
<td>&lt; 20</td>
</tr>
<tr>
<td>Tertiary Institutions</td>
<td>&lt; 15</td>
<td>&lt; 30</td>
</tr>
<tr>
<td>Child Care Centres</td>
<td>&lt; 10</td>
<td>&lt; 20</td>
</tr>
<tr>
<td>Medical Centres</td>
<td>&lt; 10</td>
<td>&lt; 20</td>
</tr>
<tr>
<td>Retail and Recreation centres</td>
<td>&lt; 10</td>
<td>&lt; 20</td>
</tr>
<tr>
<td>Community Services and Libraries</td>
<td>&lt; 15</td>
<td>&lt; 30</td>
</tr>
</tbody>
</table>

* Desirable travel distance is defined as the median desirable travel distance which is one which satisfies half of the road users.

Walking times are converted to a measure of distance, assuming an average walking speed of 4.8 kilometres/hour or 80 meters/minute (Espada and Luk, 2011;> London,<?? 2010). Walking distances are calculated for each SA1’s weighted centroid to all available POIs with the acceptable travel distances using network analysis undertaken using ArcGIS 10.2. It should be noted that maximum travel distances are defined as cut-off values (maximum travel distances) for each category. Thereafter, average walking distances are computed for each centroid/origin. As shown in Table 6.2, for primary and secondary schools, child care centres, medical centres and retail and recreation centres, the desirable and maximum travel distances are 800m and 1,600m, respectively.
6.2.3 WAI Index

Equation 6.1 presents the formula used to calculate the walking access index (WAI) for each SA1. For SA1 $i$, the index is computed as:

$$WAI_{SA1_i} = \sum_{j=1}^{m} N_i \times \left( \frac{D_j^M - D_j^A}{D_j^P} \right)$$  \hspace{1cm} (6.1)

where, $WAI_{SA1_i}$ is the Walking Access Index, $N$ is the number of POI available within the acceptable walking distance, $D_j^M$ is the maximum walking distance to destination type $j$, $D_j^P$ denotes the desirable walking distance to destination type $j$, and $D_{ij}^A$ represents the average walking distance from a SA1 weighted centroid $i$ to destination type $j$. The new index reflects both the diversity and intensity of land use, while considering the availability of a number of destinations as well as the number of activities. A higher value of the WAI indicates a higher level of accessibility. The index can be allocated to 6 categories of accessibility level, where category 1 represents a very poor level and level 6 represents an excellent level of accessibility (Table 6.1). A value of 0 indicates no accessibility in terms of the availability of destinations within the acceptable distance (cut-off values). Figure 6.2 provides an example of calculating the WAI.

![Figure 6.2 Illustration of WAI calculations](image)
Figures 6.2(a) and 6.2(b) illustrate how the WAI implies the intensity of land uses. In Figure 6.2(a), only one destination from category \( j \) is available within the acceptable distance. In contrast, in Figure 6.2(b), one more destination from the same category has been added. Assuming a desirable distance of 800 m and a maximum distance of 1600 m, the \( WAI \) is calculated to be 1 \( (WAI_{ij} = 1 \times ((1600 - 800)/800) = 1) \) for Figure 6.2(a) and 1.5 \( (WAI_{ij} = 2 \times ((1600 - 1000)/800) = 1.5) \) for Figure 6.2(b). Note that in Figure 6.2(b), because of the availability of two destinations, the average distance of 1000 m is deducted from the maximum distance (see Equation 6.1). Hence, this example shows that by considering one destination category, as the number of available destinations increases, the WAI value also increases. In other words, this indicates that in areas with a higher intensity of land use, walking accessibility is higher. Figure 6.2(c) illustrates the same situation as Figure 6.2(b) with the exception of \( d_{ij}' \), which has an additional POI from another destination category \( (j') \). In this case, assuming a walking distance of 600 m for this POI, the total value of the WAI for the origin \( (O_i) \) increases to 2.75 \( (WAI_{ij} = 1 \times ((1600 - 600)/800) = 1.25; WAI_i = 1.5 + 1.25 = 2.75) \). Therefore, the availability of different destination categories or diversity of land use contribute a higher value for WAI.

### 6.3 Results

Table 6.3 presents different categories of the WAI. This index was grouped into six main categories including very low, low, moderate, good, very good and excellent, and a zero group. The classification method used for WAI categories is quantiles, which are an appropriate method for simplifying comparison as well as aiding general map-reading (Brewer and Pickle, 2002). Zero accessibility is provided for 43,082 residents or 1.46% of SA1s. This category represents situations where there is neither a destination group nor activities (POIs) within acceptable walking distance. Outer Melbourne is mainly covered by very low WAI category areas. Overall, 51.1% of SA1s or 51.3% of the total population has zero to moderate walking accessibility.

<table>
<thead>
<tr>
<th>WAI Categories</th>
<th>Ranges</th>
<th>Number of SA1s</th>
<th>Population</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No.</td>
<td>Percent</td>
</tr>
<tr>
<td>Zero/NA</td>
<td>0</td>
<td>139</td>
<td>1.46</td>
</tr>
<tr>
<td>Very Low</td>
<td>&lt; 8</td>
<td>1391</td>
<td>14.63</td>
</tr>
<tr>
<td>Low</td>
<td>8 – 14</td>
<td>1563</td>
<td>16.44</td>
</tr>
<tr>
<td>Moderate</td>
<td>14 – 20</td>
<td>1765</td>
<td>18.56</td>
</tr>
<tr>
<td>Good</td>
<td>20 – 25</td>
<td>1122</td>
<td>11.80</td>
</tr>
<tr>
<td>Very good</td>
<td>25 – 37</td>
<td>1891</td>
<td>19.88</td>
</tr>
<tr>
<td>Excellent</td>
<td>&gt;37</td>
<td>1639</td>
<td>17.23</td>
</tr>
<tr>
<td>Total</td>
<td>–</td>
<td>9510</td>
<td>100.00</td>
</tr>
</tbody>
</table>
Figure 6.3 illustrates the distribution of WAI categories in the Melbourne region. As explained above, the WAI is categorized into six bands. The first category represents very low walking accessibility while the last category signifies an excellent level of walking accessibility. The first and last categories have been further sub-divided into sub-levels to provide better clarity. Higher levels of accessibility are mostly concentrated in the inner parts of the Melbourne region.

![Figure 6.3 Distribution of WAI categories in Melbourne region](image)

Table 6.4 shows a summary of descriptive statistics of the index components. As shown, the average population and area of each SA1 are 414 residents and 0.93 km², respectively. An average number of POI per SA1 is 2.8. Average distances are also presented for each group of destinations. The WAI has an average of 24.1 with maximum value of 221.4.

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA1’s Area (km²)</td>
<td>0.93</td>
<td>10.2</td>
<td>0.002</td>
<td>854.3</td>
</tr>
<tr>
<td>SA1’s Population</td>
<td>414</td>
<td>209.5</td>
<td>0</td>
<td>6,224</td>
</tr>
<tr>
<td>Number of POI per SA1</td>
<td>2.8</td>
<td>4.2</td>
<td>1</td>
<td>205</td>
</tr>
<tr>
<td>Distance of Primary and Secondary Schools</td>
<td>1,063.0</td>
<td>259.5</td>
<td>0</td>
<td>1,599.4</td>
</tr>
<tr>
<td>Distance of Tertiary Institutions</td>
<td>1,649.7</td>
<td>519.4</td>
<td>0</td>
<td>2,398.9</td>
</tr>
<tr>
<td>Distance of Child Care Centres</td>
<td>1,068.7</td>
<td>195.8</td>
<td>5.1</td>
<td>1,598.6</td>
</tr>
<tr>
<td>Distance of Medical Centres</td>
<td>1,111.7</td>
<td>272.4</td>
<td>17.2</td>
<td>1,599.6</td>
</tr>
<tr>
<td>Distance of Retail and Recreation Centres</td>
<td>1,090.5</td>
<td>191.5</td>
<td>43.7</td>
<td>1,599.7</td>
</tr>
<tr>
<td>Distance of Community Services and Libraries</td>
<td>1,615.3</td>
<td>276.8</td>
<td>78.2</td>
<td>2,398.8</td>
</tr>
<tr>
<td>WAI</td>
<td>24.1</td>
<td>20.5</td>
<td>0</td>
<td>221.4</td>
</tr>
</tbody>
</table>
6.3.1 WAI Assessment

The VISTA data set (2009) was adopted to assess and evaluate the new index. The present research considered only residents sampled within the MSD (22,201 individuals). In VISTA, travel is recorded in the form of trip stages, where a “trip stage” is a segment of travel with a single purpose and without a change of mode. The dataset contains detailed information on 93,902 trip stages made by 22,184 individuals in the Melbourne region. The dataset includes 17,089 trip stages recorded as walking, or approximately 18% of the total trip stages.

Cross-tabulation analysis and tests of association were used to identify whether there is any association between the accessibility index and walking trips from the VISTA dataset. Table 6.5 describes the descriptive statistics of walking trips, which are categorized into five groups. As the table shows, the minimum and maximum numbers of total walking trips in SA1s are 1 and 108, respectively.

Table 6.5 Descriptive statistics of walking trips in SA1s

<table>
<thead>
<tr>
<th>Walking Trips</th>
<th>N</th>
<th>%</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than 9 trips</td>
<td>3,103</td>
<td>18.2</td>
<td>5.44</td>
<td>2.040</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>9 to 16 trips</td>
<td>3,502</td>
<td>20.5</td>
<td>12.25</td>
<td>2.273</td>
<td>9</td>
<td>16</td>
</tr>
<tr>
<td>17 to 26 trips</td>
<td>3,479</td>
<td>20.4</td>
<td>21.55</td>
<td>3.141</td>
<td>17</td>
<td>26</td>
</tr>
<tr>
<td>27 to 41 trips</td>
<td>3,481</td>
<td>20.4</td>
<td>33.04</td>
<td>4.100</td>
<td>27</td>
<td>41</td>
</tr>
<tr>
<td>More than 42</td>
<td>3,524</td>
<td>20.6</td>
<td>58.76</td>
<td>14.172</td>
<td>42</td>
<td>108</td>
</tr>
<tr>
<td>Total</td>
<td>17,089</td>
<td>100.0</td>
<td>26.73</td>
<td>20.01</td>
<td>1</td>
<td>108</td>
</tr>
</tbody>
</table>

A Chi-square test of association was used to test the statistical association between walking trips and WAI categories. The results show a statistically significant association, $X^2 = 3,129.976$, $p < 0.001$ (see Table 6.6).

Table 6.6 Chi Square test for WAI categories and walking trips

<table>
<thead>
<tr>
<th></th>
<th>Stat.</th>
<th>df</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pearson Chi-Square</td>
<td>3,129.976a</td>
<td>20</td>
<td>.000</td>
</tr>
<tr>
<td>Likelihood Ratio</td>
<td>3,421.601</td>
<td>20</td>
<td>.000</td>
</tr>
<tr>
<td>Linear-by-Linear Association</td>
<td>2,166.293</td>
<td>1</td>
<td>.000</td>
</tr>
<tr>
<td>N of Valid Cases</td>
<td>17,089</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 513.14.

6.3.2 Comparison with the existing approach(s)

As explained above, the WI is one of the most common approaches used in calculating walkability (Frank et al., 2005; Frank et al., 2006; Frank et al., 2010; Peiravian et al., 2014; Giles-Corti et al., 2015; Sundquist et al., 2011; Owen et al., 2007). The typical form of the WI is as follows:
\[ WI = (Z_{\text{score}_{\text{LUMIX}}} + Z_{\text{score}_{\text{Residential\_Density}}} + (\alpha Z_{\text{score}_{\text{connectivity}}}) \]  

(6.2)

The Walkability Index (WI) for each SA1 was calculated as the sum of the z-scores for the three components included in the index, i.e. residential density (the ratio of residential units to the residential area), street connectivity (intersection density), and land use mix. The land use mix, or entropy score (LUMIX), indicates the degree to which a diversity of land use types is present in a spatial extent. Six different land use categories, including residential, commercial, industrial, transport and infrastructure, community services and sport and recreation centres, were selected to calculate the entropy index, using Equation 6.3.

\[ LUMIX_i = -\left(\sum_{j=1}^{J} (P_j \cdot \ln P_j)\right)/\ln J \]  

(6.3)

where, \( LUMIX \) indicates the entropy index within a buffer \( I \), \( P_j \) represents the proportion of a type of land use \( j \), 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 land uses. The WI was computed for SA1s, using Equation (6.2). Finally, the z-score of the connectivity shows the intersection density within SA1s. AURIN (Sinnott et al., 2011) developed the WI for the Melbourne region using the above equation. AURIN provides a web-based environment for calculating the WI for different statistical subdivisions in the Melbourne area. In the present study, the same method was used for calculating the WI for SA1s. It should be noted that different values for \( \alpha \) were used as the coefficients for normalized values of connectivity. However, in AURIN \( \alpha \) is set to 1. However, the WI’s calculated values for SA1s vary from -1.8 to +50.8. The new index was then compared with the WI using statistical tests of association. According to the results presented in Table 6.7, the WAI has a stronger association with higher values of symmetric measures. Hence, based on the VISTA data set, it can be concluded that the WAI is a more accurate index for measuring walkability in the Melbourne metropolitan area.

**Table 6.7 Tests of association between WAI/WI and walking trip stages**

<table>
<thead>
<tr>
<th>Symmetric Measures</th>
<th>WAI</th>
<th>WI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Stat.</td>
<td>p-value</td>
</tr>
<tr>
<td>Nominal by Nominal</td>
<td>Phi</td>
<td>0.428</td>
</tr>
<tr>
<td></td>
<td>Cramer's V</td>
<td>0.214</td>
</tr>
<tr>
<td></td>
<td>Contingency Coefficient</td>
<td>0.393</td>
</tr>
<tr>
<td>Ordinal by Ordinal</td>
<td>Gamma</td>
<td>0.345</td>
</tr>
<tr>
<td></td>
<td>Spearman Correlation</td>
<td>0.357</td>
</tr>
<tr>
<td>Interval by Interval</td>
<td>Pearson's R</td>
<td>0.356</td>
</tr>
<tr>
<td>N of Valid Cases</td>
<td></td>
<td>17089</td>
</tr>
</tbody>
</table>

* Significant at 0.99 confidence level.
6.4 Discussions and Conclusions

This chapter calculated and mapped the level of walking accessibility in metropolitan Melbourne. A walking accessibility measure which is associated with 9,510 Melbourne’s SA1s was presented. SA1s’ weighted centroids were considered as origins and POI were grouped into four categories as destinations.

The method developed can be used to compare neighbourhoods which are within the same study area in terms of their walkability. Using this method, planners and policy makers can compare and rank areas already built, and identify new areas where investment might improve the pedestrian environment (Peiravian et al., 2014). As Peiravian et al. (2014) argue, 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 and López-Domínguez (2015) claim that how urban areas are configured influences pedestrian needs because it makes the built environment more attractive, safer and closer, by influencing and bringing together the location of shops and services. The method introduced in the present study not only considers the proximity of different uses, but also the intensity of uses in terms of the number of activities within different destination categories.

The results indicate that 1.5% of SA1s representing 1.1% of Melbourne residents have no walking access to different destinations, while 15.2% and 16.6% of residents have very low or low walking access. These WAI categories mainly belong to the outer parts of the Melbourne region (see Figure 6.3). However, these kinds of accessibility are not exclusive to the outer areas. The inner Melbourne region has an area of approximately 3,504 km², of which an area of 1,457 km² (42% of the inner area) is covered by zero to moderate walking accessibility. This figure implies that a considerable number of SA1s have below average walking accessibility. As the findings indicate that the concentration of POIs in the inner region of Melbourne and CBD is high, the inner parts of Melbourne have better walking access than outer areas. In addition, outer suburbs which are characterized by dispersed patterns show increases in distances and decreases in the odds of walking. The study used the VISTA data set to evaluate the index for accessibility, and the WAI was assessed using tests of association. The results indicate that there is a statistically significant relationship between the WAI categories and walking trips. One of the most common approaches used to measure walkability, the WI, was also computed for SA1s and compared with the new index using statistical analyses. The findings indicate that WAI can be considered as a more accurate measure, using the VISTA dataset.

Walkable communities and active living are closely related to the issue of sustainable living. A change of physical environment affects urban mobility, particularly in metropolitan areas. People tend to use motorized vehicles more in developed countries (Cubukcu, 2013). The promise of planning and
policy actions to improve walkability is that walking can be encouraged by enhancing the quality of the built environment, which can in turn affect travel walking distance, walking time and transport mode choice (Kim et al., 2014). As Randall and Baetz (2001) argued, neighbourhoods should be constructed with sustainability concepts in mind. Those providing good pedestrian and cycling environments and more green space can enhance the level of physical activities.

The techniques used throughout this research are quite easy to develop and apply. The quantitative approaches can simply be employed for different types of destinations in other cities in Australia or all around the world. The calculation method is easy to apply with available census and network modelling tools. Furthermore, the analysis provides reliable and defendable results, which can be computed for 98.5% of SA1s. However, they can be improved by greater detail to achieve more accurate results.

One of the limitations of the study is that several of the categories are likely to be single buildings, such as child care centres and libraries, which may be less powerful attractants than retail centres, which are collections of multiple shops. An additional limitation is that since many authorities are not likely to have a similar POI database, widespread use may be limited. However, as long as land-use maps are available, a POI database can be created by turning features to points. Hence, future work may consider these factors.

In summary, the WAI presented in this study has been evaluated and compared with one of the most common approaches to the measurement of walkability. Using a different association test on the same real travel behaviour data, the findings indicate that the WAI is a more accurate approach with higher validity for measuring walkability in neighbourhoods or other geographical scales.

6.5 References


CHAPTER 7

ESTIMATING WALKING ACCESS LEVELS INCORPORATING DISTANCE THRESHOLDS OF BUILT ENVIRONMENT FEATURES
Chapter 7: Estimating Walking Access Levels Incorporating Distance Thresholds of Built Environment Features

Abstract

Physical inactivity has become a major public health challenge in recent decades, and active travel can contribute to more sustainable and healthy travel habits. Walking as a mode of transportation can provide health benefits, and the impact of the built environment on physical activity has been highlighted in numerous studies. This paper introduces a new approach to the quantification of walkability incorporating distance thresholds. The paper presents the research context for the Walking Access Index (WAI), a description of the methodology developed, and an application of the proposed index in the Melbourne metropolitan area, Australia. An integrated approach combining transport and land-use planning concepts was employed to construct the WAI. Using the Victorian Integrated Survey of Travel and Activity (VISTA) data set, separate negative binomial (NB) regression models were applied to examine how the new index performs compared to an existing approach. Key findings indicate that a greater number of residents are likely to have walking trips when living in a more walkable environment. Furthermore, it was found using statistical modelling that the WAI produces better results than one of the common approaches.

Keywords: Walking Accessibility Index, Accessibility, NB regression model, Land use diversity

7.1 Introduction

During recent decades, sprawling segregated land-use planning, automobile-oriented developments and increasing car ownership levels have encouraged people to use less active means of travel and spend more time traveling by automobile. This not only affects the quality of life, but also threatens people’s health. Numerous health studies have recognized the increasing likelihood of different diseases, such as obesity, cardio-metabolic disease, and diabetes, as a result of sedentary travel behaviour (Thorp et al., 2011; Van der Ploeg et al., 2012; Ainsworth and Ainsworth, 2012; Samimi et al., 2009).

According to the World Health Organization (WHO), physical inactivity is one of the key risk factors causing major non-contagious diseases such as cardiovascular disease, cancer and diabetes. Each year, 3.2 million deaths occur due to lack of sufficient physical activity (WHO, 2009). In Australia, the burden of physical inactivity has been estimated to be around $400 million each year (Coombes et al., 2013; Zheng et al., 2010; Bauman et al., 2002). As Dora (1999) argues, the burden of transport on health is much more than would be expected.

In recent years, transport investment has been directed towards forming physical environments with strong connectivity, to improve active travel modes such as walking and cycling (Kaplan et al., 2016; Knuiman et al., 2014). Built environment factors, such as the land-use mix, population density, employment density, and dissimilarity indices, have been found to have an influence on individuals’ choice of transport mode and their level of physical activity (Marquet et al., 2016; Hendrigan and Newman, 2015; Lee et al., 2014). 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). However, transport infrastructure has a fundamental role in individuals’ transport choices, while sedentary behaviour as well as insufficient infrastructure may lead to physical inactivity. According to Dannenberg et al. (2003), the form and design of the built environment, through the proximity of different facilities and services, affect the amount of physical activity undertaken. Frank et al. (2004) claimed that the odds of obesity increase by 6% for each additional hour spent in a car and conversely decline by 4.8% for each additional kilometre walked per day. Swanson and McCormack (2012) took this further, arguing that being overweight and obese was more prevalent among those who drive more than 1680 min/week compared with those who drive less than 209 min/week.

Pedestrian infrastructure such as sidewalk access, street scale and enclosure, quality and street connectivity have also been identified as important criteria for determining walkability in neighbourhood areas, principally in micro-level studies (Park et al., 2016; Park et al., 2015; Lo, 2009). Numerous studies have focused on measuring walkability. However, there has been limited research
which has considered walking of distance thresholds to different destinations as one of the main barriers to active transport. Hence, this study describes a new concept to measure walking accessibility, the Walking Accessibility Index (WAI), a macro-level measurement, followed by an implementation of the new index in metropolitan Melbourne, Australia. This chapter compares the results of the WAI with those of one of the most common approaches to the measurement of walking accessibility. The following section provides background information. The methodology section describes the approach used to compute the index, and the analysis and results of the application of the WAI in the Melbourne region, together with the results of the application of common existing approaches in Melbourne. The results of the comparison are then discussed, while in the closing section, conclusions and future directions of this study are outlined.

7.2 Methodology

This study introduces an index for assessing the level of walkability in Melbourne’s 9,510 Statistical Areas level 1 (SA1s), the second smallest geographic area defined in the Australian Statistical Geography Standard (Pink, 2011).

7.2.1 Datasets

To calculate the WAI, the following datasets were utilised:

Points of Interest (POIs)

A database of POIs was obtained from PSMA Australia (2011), including urban centres, significant buildings, landmarks, public spaces, community facilities and indigenous locations, and included 15,588 points. These POIs are considered as destinations and categorized into six groups of destinations as described in Table 7.1.

Table 7.1 Description of Destination Categories

<table>
<thead>
<tr>
<th>Destination Categories</th>
<th>No.</th>
<th>Percentage</th>
<th>Average No. in each SA1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary and Secondary Schools</td>
<td>1,608</td>
<td>11.6</td>
<td>4.2</td>
</tr>
<tr>
<td>Tertiary Institutions</td>
<td>83</td>
<td>0.6</td>
<td>2.6</td>
</tr>
<tr>
<td>Child Care Centres</td>
<td>3,471</td>
<td>25.1</td>
<td>8.1</td>
</tr>
<tr>
<td>Medical Centres</td>
<td>1,019</td>
<td>7.4</td>
<td>6.9</td>
</tr>
<tr>
<td>Retail and Recreation Centres</td>
<td>3,091</td>
<td>22.4</td>
<td>9.1</td>
</tr>
<tr>
<td>Community Services and Libraries</td>
<td>4,559</td>
<td>33.0</td>
<td>14.3</td>
</tr>
<tr>
<td>Total</td>
<td>13,831</td>
<td>100.0</td>
<td>1.5</td>
</tr>
</tbody>
</table>

Figure 7.1 illustrates the distribution of POIs throughout the Melbourne region. As the figure shows, POIs are concentrated mostly in the inner parts of Melbourne. However, some suburbs in the outer northern and western areas such as Sunbury, Melton and Werribee have considerable densities of
A database of mesh blocks from the 2011 Census for the Melbourne Region was accessed from the Australian Bureau of Statistics (ABS, 2011). 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, the Melbourne region contains 53,074 mesh blocks, 9,510 SA1s, 277 statistical area level 2 zones (SA2s) and 31 local government areas (LGAs). Figure 7.2 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 are approximated by whole mesh blocks.
Road Network Data

A dataset containing road networks (Swanson and McCormack, 2012) published by the Department of Environment, Land, Water & Planning was accessed. It contains line features delineating the state-wide road network, including bridges, connectors, footbridges, foot tracks and roads.

VISTA Dataset

The VISTA dataset (2009) was provided from the Victorian Integrated Survey of Travel and Activity (VISTA). This is a cross-sectional survey conducted from 2009 to July 2010. It covers the Melbourne Statistical Division (MSD) as defined by the ABS, and the regional Victorian cities of Geelong, Ballarat, Bendigo and Shepparton, and the Latrobe Valley. This dataset provides demographic, trip and car ownership information from randomly-selected residential properties. A total of 16,411 households comprising 42,002 individuals responded, with a response rate of 47%. Since the WAI is only calculated for the Melbourne region, only residents within the MSD (22,201 individuals) were considered.

7.2.2 Approach

The aim of the present study was to measure the level of accessibility for Melbourne’s SA1s. For this purpose, weighted centroids of SA1s which were selected based on the mesh block population were considered as origins and POIs were defined as destinations. The index provides an accurate measurement of the accessibility of POIs to the weighted SA1s’ centroid. Then, using OD-cost
network analysis, the average distances from each SA1 weighted centroid to all the available destinations within acceptable walking distance were calculated. As Table 7.1 indicates, POIs are categorised into six groups of destinations. Travel impedance is defined based on the desirable and maximum travel time/distance. Origins and destinations and the approach are described in more detail in the following sections.

Origins (SA1s’ weighted centroid)

A database of mesh blocks from the 2011 Census for the Melbourne Region was accessed from the ABS (ABS, 2011). 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 (the smallest geographical unit released by the ABS) and all other statistical areas, including SA1s. According to the ABS (2011), the Melbourne region contains 53,074 mesh blocks and 9,510 SA1s. SA1s have an average population of 414 persons and an average area of about one square km. They are built up from, or approximated by, the mesh blocks. Each SA1 contains five mesh blocks on average. The mesh block with the highest population within the corresponding SA1 is defined as a weighted centroid of the SA1 and it is considered as an origin. Figure 7.3 illustrates mesh blocks, SA1s and weighted centroids. As the figure shows, the centroid for the selected SA1 is placed on the mesh block with the highest population of 87 people.

Figure 7.3 Illustration of the weighted centroid for SA1s

Destinations (POI categories)

As described above, POIs are categorised into six major destination groups, including primary and secondary schools, tertiary institutions, child care centres, medical centres, community services and libraries and retail and recreation centres. OD-cost matrix analysis was applied to each set of
destinations separately. For each category two thresholds, including the desirable and maximum travel times/distances, were defined. These values were adopted from a study undertaken by the Association of Australian and New Zealand Road Transport and Traffic Authorities (Austroads), which examined how travel time/distance impacts accessibility (Austroads, 2011). The present study mainly adopted the values from the Department for Transport (DfT) in the UK (2011). The values adopted are also consistent with research conducted by Millward et al. in the U.S.A. (Millward et al., 2013), Rattan et al. in Canada (Rattan et al., 2012), and Rendall et al. in New Zealand (Rendall et al., 2011). The median desirable travel time is the value that satisfies half of the road users, while the maximum desirable travel time/distance is the value at which a significant percentage of people would find it unfeasible to regularly travel and they may be forced to relocate their residence closer to the destination or find a less suitable destination but one that is closer. This study employs both the median and maximum desirable travel time/distance to calculate the WAI. Table 7.2 shows the acceptable travel times and distances as well as the median desirable walking travel times. These values have been adopted from the Austroads network operation planning framework (Espada et al., 2015; Espada and Luk, 2011).

Table 7.2 Median desirable walking travel times and distances for activities

<table>
<thead>
<tr>
<th>Destination Categories</th>
<th>Travel Time (min)</th>
<th>Travel Distance (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Desirable*</td>
<td>Maximum</td>
</tr>
<tr>
<td>Primary and Secondary Schools</td>
<td>&lt; 10</td>
<td>&lt; 20</td>
</tr>
<tr>
<td></td>
<td>&lt; 800</td>
<td>&lt; 1,600</td>
</tr>
<tr>
<td>Tertiary Institutions</td>
<td>&lt; 15</td>
<td>&lt; 30</td>
</tr>
<tr>
<td></td>
<td>&lt; 1,200</td>
<td>&lt; 2,400</td>
</tr>
<tr>
<td>Child Care Centres</td>
<td>&lt; 10</td>
<td>&lt; 20</td>
</tr>
<tr>
<td></td>
<td>&lt; 800</td>
<td>&lt; 1,600</td>
</tr>
<tr>
<td>Medical Centres</td>
<td>&lt; 10</td>
<td>&lt; 20</td>
</tr>
<tr>
<td></td>
<td>&lt; 800</td>
<td>&lt; 1,600</td>
</tr>
<tr>
<td>Retail and Recreation Centres</td>
<td>&lt; 10</td>
<td>&lt; 20</td>
</tr>
<tr>
<td></td>
<td>&lt; 800</td>
<td>&lt; 1,600</td>
</tr>
<tr>
<td>Community Services and Libraries</td>
<td>&lt; 15</td>
<td>&lt; 30</td>
</tr>
<tr>
<td></td>
<td>&lt; 1,200</td>
<td>&lt; 2,400</td>
</tr>
</tbody>
</table>

*Desirable travel distance is defined as the median desirable travel distance which is one that satisfies half of the road users.

Walking times were converted to distances assuming an average walking speed of 4.8 kilometres/hour or 80 meters/minutes (London, 2010). Walking distances using network analysis by ArcGIS 10.2 were calculated for each SA1’s weighted centroid to all available POIs within the acceptable travel distances. It should be noted that maximum travel distances are defined as cut-off values for each category. Then, average walking distances were computed for each centroid/origin. Table 7.2 shows that for primary and secondary schools, child-care centres medical centres and retail and recreation centres, the desirable and maximum travel distances are 800m and 1600m, respectively.

7.2.3 WAI Index

The formula given in Equation 7.1 is used to calculate the Walking Access Index (WAI):

\[
WAI = \frac{\text{Desirable travel time/distance \times Desirable travel distance}}{\text{Maximum travel time/distance \times Maximum travel distance}}
\]
\[ WAI_{SA1i} = \sum_{j=1}^{m} N_i \times \left( \frac{D^M_j - D^A_{ij}}{D^P_j} \right) \]  \hspace{1cm} (7.1)

where, \( WAI_{SA1i} \) is the Walking Access Index for SA1 \( i \), \( N_i \) is the number of POIs available within the acceptable walking distance, \( D^M_j \) is the maximum walking distance to destination type \( j \), \( D^P_j \) denotes the desirable walking distance to destination type \( j \), and \( D^A_{ij} \) represents the average walking distance from a SA1 weighted centroid \( i \) to destination type \( j \). The index can be grouped into six categories of accessibility levels, where category 1 represents a very poor level and level 6 represents an excellent level of accessibility (Table 7.3). A value of 0 indicates no accessibility in terms of the availability of destinations within the acceptable distance (cut-off value). The index reflects both the diversity and intensity of uses, while considering the availability of a number of destinations as well as the number of activities. A higher value of the WAI indicates a higher level of accessibility. Figure 7.4 provides an example of the calculation of the WAI and shows how the value of the WAI changes for different levels of diversity and intensity of land use.

\[ \text{Figures 7.4(a) and 7.4(b) illustrate how the WAI implies the intensity of land use. In Figure 7.4(a),} \]

![Diagram](image)
only one destination from category j is available within the acceptable distance. In contrast, in Figure 7.4(b), one more destination from the same category is added. Assuming a desirable distance of 800m and a maximum distance of 1600m, the WAI is calculated to be 1 (\( \text{WAI}_{ij} = 1 \times \left( \frac{(1600 - 800)}{800} \right) = 1 \)) for Figure 7.4(a) and 1.5 (\( \text{WAI}_{ij} = 2 \times \left( \frac{(1600 - 1000)}{800} \right) = 1.5 \)) for Figure 7.4(b). Note that in Figure 7.4(b), because of the availability of two destinations, the average distance of 1000m is deducted from the maximum distance (see Equation 7.1). Hence, this example shows that considering one destination category, as the number of available destinations increases, the WAI value also increases. In other words, this indicates that in areas with a higher intensity of land use, walking accessibility is higher.

Figure 7.4(c) illustrates the same situation as Figure 7.4(b) with the exception of \( dj'1 \), which has an additional POI from another destination category (\( j' \)). In this case, assuming a walking distance of 600m for this POI, the total value of the WAI for the origin (Oi) increases to 2.75 (\( \text{WAI}_{ij} = 1 \times \left( \frac{(1600 - 600)}{800} \right) = 1.25; \text{WAI}_i = 1.5 + 1.25 = 2.75 \)). Therefore, the availability of different destination categories or diversity of land use contributes to a higher value for WAI.

Table 7.3 presents the ranges and categories of the WAI. The index is grouped into six main categories including very low, low, moderate, good, very good and excellent plus a zero group. The classification method used for the WAI categories is quantiles. These are of the best methods for simplifying comparison as well as aiding general map-reading (Brewer and Pickle, 2002). Zero accessibility is provided for 43,082 residents or 1.10% of SA1s. This category represents situations where there are either no destination groups or activities (POIs) within the acceptable walking distance. Very low areas are mostly in the outer areas of Melbourne. Overall, 51.1% of SA1s, or 51.3% of the total population, have either a zero or moderate level of walking accessibility.

<table>
<thead>
<tr>
<th>WAI Categories</th>
<th>Ranges</th>
<th>Number of SA1s</th>
<th>Population</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No.</td>
<td>%</td>
</tr>
<tr>
<td>Zero/NA</td>
<td>0</td>
<td>139</td>
<td>1.46</td>
</tr>
<tr>
<td>Very Low</td>
<td>&lt; 8</td>
<td>1,391</td>
<td>14.63</td>
</tr>
<tr>
<td>Low</td>
<td>8 – 14</td>
<td>1,563</td>
<td>16.44</td>
</tr>
<tr>
<td>Moderate</td>
<td>14 – 20</td>
<td>1,765</td>
<td>18.56</td>
</tr>
<tr>
<td>Good</td>
<td>20 – 25</td>
<td>1,122</td>
<td>11.80</td>
</tr>
<tr>
<td>Very good</td>
<td>25 – 37</td>
<td>1,891</td>
<td>19.88</td>
</tr>
<tr>
<td>Excellent</td>
<td>&gt;37</td>
<td>1,639</td>
<td>17.23</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>9,510</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Figure 7.5 illustrates the distribution of WAI categories in the Melbourne region. The WAI is categorized into six bands, where the first category represents very low walking accessibility while the last category signifies an excellent level of walking accessibility. The first and last categories have
been further sub-divided into sub-levels to increase clarity. High levels of accessibility from good to excellent are mostly concentrated in the inner parts of the Melbourne region.

![Distribution of WAI categories in the Melbourne region](image)

**Figure 7.5 Distribution of WAI categories in the Melbourne region**

Table 7.4 shows a summary of the descriptive statistics of the index components. The table shows that on average there are 414 residents in each SA1 with an average area of 0.93 km$^2$. The average number of POIs per SA1 is 2.8. Average distances are also presented for each group of destinations. The output index (WAI) has an average of 24.1 with a maximum value of 221.4.

**Table 7.4 Descriptive statistics of indicators of the index components**

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Mean</th>
<th>Std. D</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA1’s Area (km$^2$)</td>
<td>0.93</td>
<td>10.2</td>
<td>0.002</td>
<td>854.3</td>
</tr>
<tr>
<td>SA1’s Population</td>
<td>414</td>
<td>209.5</td>
<td>0</td>
<td>6,224</td>
</tr>
<tr>
<td>Number of POIs per SA1</td>
<td>2.8</td>
<td>4.2</td>
<td>1</td>
<td>205</td>
</tr>
<tr>
<td>Distance of Primary and Secondary Schools</td>
<td>1,063.0</td>
<td>259.5</td>
<td>0</td>
<td>1,599.4</td>
</tr>
<tr>
<td>Distance of Tertiary Institutions</td>
<td>1,649.7</td>
<td>519.4</td>
<td>0</td>
<td>2,398.9</td>
</tr>
<tr>
<td>Distance of Child Care Centres</td>
<td>1,068.7</td>
<td>195.8</td>
<td>5.1</td>
<td>1,598.6</td>
</tr>
<tr>
<td>Distance of Medical Centres</td>
<td>1,111.7</td>
<td>272.4</td>
<td>17.2</td>
<td>1,599.6</td>
</tr>
<tr>
<td>Distance of Retail and Recreation centres</td>
<td>1,090.5</td>
<td>191.5</td>
<td>43.7</td>
<td>1,599.7</td>
</tr>
<tr>
<td>Distance of Community Services and Libraries</td>
<td>1,615.3</td>
<td>276.8</td>
<td>78.2</td>
<td>2,398.8</td>
</tr>
<tr>
<td>WAI</td>
<td>24.1</td>
<td>20.5</td>
<td>0</td>
<td>221.4</td>
</tr>
</tbody>
</table>
7.2.4 Walkability Index (WI)

As explained above, the WI is one of the most common approaches used for calculating walkability (Giles-Corti et al., 2015; Peiravian et al., 2014; Sundquist et al., 2011; Frank et al., 2010; Owen et al., 2007; Frank et al., 2006; Frank et al., 2005). The typical form of the WI expression is as follows:

\[ WI = (Z_{\text{score}_{LUMIX}}) + (Z_{\text{score}_{\text{Residential Density}}}) + (\alpha Z_{\text{score}_{\text{Connectivity}}}) \]  (7.2)

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. The land-use mix, or entropy score (LUMIX), indicates the degree to which a diversity of land use types is present. Six different land use categories, including residential, commercial, industrial, transport and infrastructure, community services and sport and recreation centres, were chosen to calculate the entropy index, using Equation 7.3. These categories are defined from ten main land use categories defined by the Australian Valuation Property Classification Codes (AVPCC) (Morse-McNabb, 2011).

\[ LUMIX = -\left( \sum_{j=1}^{J} \frac{P_j \cdot \ln P_j}{\ln J} \right) \]  (7.3)

where, \( LUMIX \) indicates the entropy index within a buffer i, \( P_j \) 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 Equation 7.2. Finally, the z-score of connectivity shows the intersection density within SA1s.

The Australian Urban Research Infrastructure Network (AURIN) (Sinnott et al., 2011) developed the WI for areas within the Melbourne region using the above equation. The network provides 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 defines \( \alpha \) as equal 1. The calculated WIs for SA1s vary from 1.8 to 50.8.

7.3 Data Analysis

As we were able to run the statistical analysis on the VISTA dataset, both the proposed measure (WAI) and the WI were combined with the VISTA dataset using the SA1 codes. In other words, the WAI and WI values were computed for the spatial areas and compared with the travel data. The VISTA dataset contains trip record information for 22,184 individuals from households randomly
selected from 1,822 SA1s. The total number of trip stages reported by participants was 93,902, of which 17,089 were walking trips. The reason for using the trip stages for analysis is that walking trips are considered as the shortest, while covering all trip purposes including changing transport modes. Table 7.5 shows the basic statistics on the walking trips.

Table 7.5 Basic statistical measures of walking trips

<table>
<thead>
<tr>
<th>Location</th>
<th>Variability</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>26.796</td>
<td>Std Deviation</td>
</tr>
<tr>
<td>Median</td>
<td>22.000</td>
<td>Variance</td>
</tr>
<tr>
<td>Mode</td>
<td>8.000</td>
<td>Range</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Interquartile Range</td>
</tr>
</tbody>
</table>

N= 16474 (Outliers were removed from analysis).

7.3.1 Measures of Association

Before applying the models, the strength of association between each of the indices and walking trip categories was examined. For this purpose, statistical measures of association were used for WAI/WI categories and walking trips. The results are presented in Table 7.6. The table indicates that the WAI has a stronger association with higher values of symmetric measures. The Somers’ D, Gamma and Spearman tests are asymmetric measures of association between two variables, which plays a central role as a parameter in rank or non-parametric statistical methods (Newson, 2006). All the three tests ranged from -1.00 to 1.00, where 0 reflects no association, 1 reflects a positive and -1 indicates a negative perfect relationship between variables (Agresti and Kateri, 2011; Sprinthall, 2011). Table 7.6 presents the results of the tests, and shows that the WAI has a better association than the WI. The following sections present the results of the models applied to the data while comparing the WAI with previous measurements.

Table 7.6 Tests of association between WAI/WI and walking trips

<table>
<thead>
<tr>
<th>Symmetric Measures</th>
<th>WAI</th>
<th>WI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Stat.</td>
<td>p-value</td>
</tr>
<tr>
<td>Somers’ D</td>
<td>0.295</td>
<td>0.000</td>
</tr>
<tr>
<td>Gamma</td>
<td>0.365</td>
<td>0.000</td>
</tr>
<tr>
<td>Spearman Correlation</td>
<td>0.366</td>
<td>0.000</td>
</tr>
<tr>
<td>N of Valid Cases</td>
<td>16474</td>
<td>-</td>
</tr>
</tbody>
</table>

* Significant at 0.99 confidence level

7.3.2 Modelling and interpretation

Models for this study were estimated using negative binomial (NB) regression techniques, which model count data and require non-negative integers for the dependent variable. Since the number of
trips is always a positive integer, this study adopted the NB regression technique (Coruh et al., 2015).

NB regression was used to analyse the effects of socioeconomic characteristics as well as walkability indexes on walking trips. Linear regression techniques have been widely used to examine travel behaviour (Krizek, 2003; Kitamura et al., 1997; Frank and Pivo, 1994). However, linear regression analysis requires model residuals to follow the normal distribution (Nachtsheim et al., 2004), while distributions of trip frequencies are often skewed to the right, and deviate from the normality assumption (Cao et al., 2006). The walking trips used in this study follow this pattern (see Figure 7.6).

![Histogram of walking trips](image)

**Figure 7.6 Histogram of walking trips**

In Poisson regression, it is assumed that the dependent variable $Y$ (the frequency of walking trips in this study) is Poisson-distributed, given the explanatory variables $X_1, X_2, ..., X_p$. This means that the probability of observing $Y = k$ trips, can be obtained by the Poisson distribution function (Cao et al., 2006):

$$
P(Y = k | X_1, X_2, ..., X_p) = \frac{e^{-\lambda} \lambda^k}{k!}, \quad k = 0, 1, 2, 3, ... \quad (7.4)$$

where, the conditional mean $k$ is an exponential function of the explanatory variables. That is,

$$\lambda = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p) \quad (7.5)$$

where, the fitted value of $Y$ for the $i$th case, $\hat{Y}_i (i = 1, 2, ..., N)$, is denoted $\hat{\lambda}_i$.

Poisson regression assumes the equality of mean variance. However, this assumption is frequently violated in empirical data. As shown in Figure 7.6, there is some evidence of over-dispersion (variance > mean) in walking trips. Alternatively, the NB regression model captures the over-dispersion effect by introducing an unobserved effect into the conditional mean, $\lambda$, of the Poisson
model:

\[ \lambda = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon) \]  

(7.6)

where, \( \exp(\varepsilon) \) has a gamma distribution with mean 1 and variance \( \alpha \) (also called the dispersion parameter). Poisson regression is a special case of NB regression in which \( \alpha \) equals 0. Two separate NB regression models were generated for walking trips using a different walkability measure (WAI and WI) in every run, while keeping other variables in the model specification constant. M1 presents the results of a NB regression model considering all the predictor variables and the WAI, and M2 denotes the model with all the variables used in M1 and WI for the walkability measure. Walking trips are defined as a count-dependent variable. Age, gender, car licence, employment type, household size, household (HH) structure, and the number of cars in the HH were employed as socioeconomic variables (Lee et al., 2014; Jun et al., 2012; Shay and Khattak, 2012; Ewing and Cervero, 2010; Winters et al., 2010). Table 7.7 shows the list of independent variables and their description as well as the hypothesised relationship with the dependent variable.

**Table 7.7 Independent variables and their expected associations with walking trips**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>Expected relationship</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Socio-demographic</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>Age of respondent</td>
<td>+/-</td>
</tr>
<tr>
<td>Sex</td>
<td>Gender</td>
<td>+/-</td>
</tr>
<tr>
<td>Licence</td>
<td>Driver licence</td>
<td>-</td>
</tr>
<tr>
<td>Employment Type</td>
<td>Type of work</td>
<td>+/-</td>
</tr>
<tr>
<td>HH Size</td>
<td>Usual number of residents in household</td>
<td>+/-</td>
</tr>
<tr>
<td>HH Structure</td>
<td>Demographic structure of household</td>
<td>+/-</td>
</tr>
<tr>
<td>Car No.</td>
<td>Number of vehicles in the household</td>
<td>-</td>
</tr>
<tr>
<td><strong>Built Environment</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WAI</td>
<td>Walking Access Index</td>
<td>+</td>
</tr>
<tr>
<td>WI</td>
<td>Walkability Index</td>
<td>+</td>
</tr>
</tbody>
</table>

Note: HH structure is converted to five dummy variables: sole person, couple no children, couple with children, one parent and other. Employment type is converted into five dummy variables: full-time, part-time, casual, unemployed and not working; sex and driver’s licence are defined as binary variables.

Table 7.8 presents the descriptive statistics for the variables used in the models. These statistics were calculated for 16,474 records of trip stages. In terms of socio-demographic characteristics, respondents were 38 years old on average and equally distributed in terms of gender. The average HH size shows that respondents were mostly from households with the usual number of about three residents.
### Table 7.8 Descriptive Statistics of Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walking Trips</td>
<td>26.80</td>
<td>20.09</td>
<td>1.00</td>
<td>108.00</td>
</tr>
<tr>
<td>Age</td>
<td>36.88</td>
<td>19.31</td>
<td>0.00</td>
<td>90.00</td>
</tr>
<tr>
<td>Gender</td>
<td>1.54</td>
<td>0.50</td>
<td>1.00</td>
<td>2.00</td>
</tr>
<tr>
<td>Licence</td>
<td>1.29</td>
<td>0.45</td>
<td>1.00</td>
<td>2.00</td>
</tr>
<tr>
<td>HH Size</td>
<td>3.00</td>
<td>1.37</td>
<td>1.00</td>
<td>6.00</td>
</tr>
<tr>
<td>Employment Type</td>
<td>2.89</td>
<td>1.78</td>
<td>1.00</td>
<td>5.00</td>
</tr>
<tr>
<td>HH Structure</td>
<td>2.80</td>
<td>1.13</td>
<td>1.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Car No.</td>
<td>1.78</td>
<td>0.85</td>
<td>1.00</td>
<td>4.00</td>
</tr>
<tr>
<td>WAI</td>
<td>31.35</td>
<td>18.94</td>
<td>0.00</td>
<td>109.63</td>
</tr>
<tr>
<td>WI</td>
<td>0.61</td>
<td>1.76</td>
<td>-1.78</td>
<td>12.42</td>
</tr>
</tbody>
</table>

n=16,474 trip stages

In order to examine the applicability of the WAI compared to the most common existing approach, two NB regression models were estimated. All the variables were considered to be constant in the models, with the exception of the walking accessibility measures. The WAI and other variables were employed to run the M1 model and the WI in model M2 (see Table 7.9).

The NB regression models predicted walking trips with age, gender, licence, work type, HH structure, HH size, car ownership, and walkability measurements. With the exception of gender, couple with children and couple without children, other variables were statistically significant. As shown in Table 7.9, the dispersion parameters of the models are greater than zero (about 0.5), which indicates that the response variable is over-dispersed, hence the NB regression model was found to be more appropriate for the data. If the dispersion parameter equals zero, the model reduces to the simpler Poisson model (Hilbe, 2011).

The Incident Rate Ratio (IRR) was also calculated for the confidence level. IRR describes the percentage change in the incident rate of the response variable for every unit increase in the corresponding explanatory variable (Hilbe, 2008). Therefore, according to the results, there is a 33% increase in walking trips for every unit increase in WAI, while this number is 25% for WI. As the age increases by one unit, the incident rate of walking trips decreases by 1%. There is a 10% decrease in walking trips by one unit increase in number of cars in the household. People with part-time jobs have 12% more walking trips than those who are not working. People who live alone have 13% fewer walking trips than others.

Regarding the criteria for assessing goodness of fit of the data, the ratio of the deviance to the degree of freedom (Value/DF), should be about one. According to Table 7.9, the Value/DFs for M1 and M2 are 1.0679 and 1.0706, respectively. Furthermore, M1 has the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which are measures of the relative quality of statistical models for a given set of data. Given a series of models for the data, these criteria estimate
the quality of each model, relative to each of the other models (Boisbunon et al., 2014; Hu, 2007; Aho et al., 2014). In this study, both AIC and BIC were smaller for M1 than M2.

After estimating and comparing the models, the standard difference-of-means test (Equation 7.7) was also used to test for any statistical difference in the estimated coefficients obtained from the NB regression models. The reason was to investigate whether there were any significant differences between the coefficients estimated by the two models.

$$t = \frac{\hat{\beta}_i - \hat{\beta}_j}{SE|\hat{\beta}_i - \hat{\beta}_j|}$$ (7.7)

where, $\hat{\beta}_i$ is the estimated coefficient of a built environment variable, $i$, and SE denotes the standard error (Mitra and Buliung, 2012). The estimated coefficients from the models were compared with each other, and the results are presented in Table 10. The t-statistics results indicate that there is a significant difference between the coefficients of walking accessibility measurements estimated by the two models.
Table 7.9 Outputs of the NB regression model for walking trips

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>IRR</th>
<th>Std. Error</th>
<th>Wald Chi-Square</th>
<th>Estimate</th>
<th>IRR</th>
<th>Std. Error</th>
<th>Wald Chi-Square</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.2946***</td>
<td>0.0388</td>
<td>7228.51</td>
<td>3.2408***</td>
<td>0.0393</td>
<td>6804.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.0008**</td>
<td>0.9992</td>
<td>0.0004</td>
<td>4.36</td>
<td>-0.0008**</td>
<td>0.9992</td>
<td>0.0004</td>
<td>3.94</td>
</tr>
<tr>
<td>Gender (Male)</td>
<td>-0.0134</td>
<td>0.9867</td>
<td>0.012</td>
<td>1.25</td>
<td>-0.0224</td>
<td>0.9778</td>
<td>0.0122</td>
<td>3.4</td>
</tr>
<tr>
<td>License (Yes)</td>
<td>0.0773***</td>
<td>1.0804</td>
<td>0.0189</td>
<td>16.74</td>
<td>0.0738***</td>
<td>1.0766</td>
<td>0.0192</td>
<td>14.85</td>
</tr>
<tr>
<td>HH Size</td>
<td>0.0300***</td>
<td>1.0304</td>
<td>0.0074</td>
<td>16.31</td>
<td>0.0433***</td>
<td>1.442</td>
<td>0.0075</td>
<td>33.05</td>
</tr>
<tr>
<td>Employment Type</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full Time</td>
<td>0.0504**</td>
<td>1.0517</td>
<td>0.0163</td>
<td>9.62</td>
<td>0.0731***</td>
<td>1.0759</td>
<td>0.0165</td>
<td>19.67</td>
</tr>
<tr>
<td>Part Time</td>
<td>0.1162***</td>
<td>1.1233</td>
<td>0.0198</td>
<td>34.58</td>
<td>0.117***</td>
<td>1.1242</td>
<td>0.0201</td>
<td>33.86</td>
</tr>
<tr>
<td>Casual</td>
<td>0.0486**</td>
<td>1.0498</td>
<td>0.0249</td>
<td>3.83</td>
<td>0.0802**</td>
<td>1.0835</td>
<td>0.0252</td>
<td>10.14</td>
</tr>
<tr>
<td>Unemployed</td>
<td>0.106**</td>
<td>1.1118</td>
<td>0.0474</td>
<td>5.01</td>
<td>0.2055***</td>
<td>1.2281</td>
<td>0.048</td>
<td>18.33</td>
</tr>
<tr>
<td>HH Structure</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sole Person</td>
<td>-0.1346***</td>
<td>0.8740</td>
<td>0.0326</td>
<td>17.08</td>
<td>-0.0309</td>
<td>0.9695</td>
<td>0.0329</td>
<td>0.89</td>
</tr>
<tr>
<td>Couple with kids</td>
<td>0.0048</td>
<td>1.0045</td>
<td>0.0247</td>
<td>0.04</td>
<td>0.0299</td>
<td>1.0303</td>
<td>0.0249</td>
<td>1.44</td>
</tr>
<tr>
<td>Couple without kids</td>
<td>-0.0019</td>
<td>0.9981</td>
<td>0.0211</td>
<td>0.01</td>
<td>0.0102</td>
<td>1.0103</td>
<td>0.0215</td>
<td>0.22</td>
</tr>
<tr>
<td>Single parent</td>
<td>-0.2031***</td>
<td>0.8162</td>
<td>0.0288</td>
<td>49.66</td>
<td>-0.1992***</td>
<td>0.8194</td>
<td>0.0292</td>
<td>46.5</td>
</tr>
<tr>
<td>Car No.</td>
<td>-0.0966***</td>
<td>0.9079</td>
<td>0.008</td>
<td>145.08</td>
<td>-0.1099***</td>
<td>0.8959</td>
<td>0.008</td>
<td>186.65</td>
</tr>
<tr>
<td>WAI</td>
<td>0.2879***</td>
<td>1.3337</td>
<td>0.0073</td>
<td>1567.77</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>WI</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.2240***</td>
<td>1.2511</td>
<td>0.0068</td>
<td>1098.17</td>
</tr>
<tr>
<td>Dispersion</td>
<td>0.4706</td>
<td>0.0058</td>
<td>-</td>
<td>-</td>
<td>0.4856</td>
<td>-</td>
<td>0.0059</td>
<td>-</td>
</tr>
</tbody>
</table>

Notes: (1) number of walking trips is defined as a dependant variable.
(2) To be able to compare the walkability indexes with different measurement scales, WAI and WI were standardized. The dependent variable was not standardized, since NB regression requires the dependent variable to be a count value (non-negative integer).
(3) The NB dispersion parameter was estimated by maximum likelihood.
(4) For WAI and WI z-values of the variables used in the model.
(5) Significance codes: p < 0.001 "***", 0.01 **", 0.1 *."
(6) Overall goodness-of-fit:
M1: Value/DF = 1.0679; AIC = 119393.18; BIC = 119514.44,
M2: Value/DF = 1.0706; AIC = 119860.78; BIC = 119982.04.

Table 7.10 Results of the standard difference-of-means test

<table>
<thead>
<tr>
<th>Measurements</th>
<th>Coeff. (S.E.)</th>
<th>t.diff</th>
</tr>
</thead>
<tbody>
<tr>
<td>WAI</td>
<td>0.2879 (0.0075)</td>
<td>-</td>
</tr>
<tr>
<td>WI</td>
<td>0.2240 (0.0068)</td>
<td>-</td>
</tr>
<tr>
<td>M1/M2</td>
<td></td>
<td>91.2857***</td>
</tr>
</tbody>
</table>

*** Significance codes: p < 0.001 "***"

7.4 Discussions and Conclusions

The method developed in this study can be used to compare neighbourhoods within the same study area in terms of their walkability. Using this approach, planners and policy makers can compare and
rank areas already built, and identify new areas where investment might improve walking accessibility. The way urban areas are configured can influence pedestrian behaviour because it can make the built environment more attractive, safer and more accessible, by bringing together shops and services and recreation centres (Peiravian et al., 2014). The method proposed in this study not only considers the proximity of different uses, but also the intensity of uses in terms of the number of activities within different destination categories. Walkable communities and active living are related to sustainable living. Changes in the physical environment affect urban mobility, particularly in metropolitan areas. People tend to use motorized vehicles more in developed countries (Cubukcu, 2013). The promise of 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 (Dong et al., 2016; Kim et al., 2014). As Randall and Baetz (2001) argue, neighbourhoods should be constructed with sustainability concepts in mind. Those providing good pedestrian and cycling environments and more green space enhance the level of physical activity. In urban and transport planning, much effort is currently being put into providing safe and friendly environments that encourage walking in cities. According to Peiravian et al. (2014), measuring the friendliness of neighbourhoods as a policy tool to promote more walking and cycling remains important, and requires more research. This study provides a starting point for such a task.

This paper introduces a new approach to the measurement of walking accessibility, the WAI. Moreover, one of the most common approaches for measuring walkability was generated for statistical areas (SA1s) and compared to the WAI to understand how these measures are related to actual observed travel behaviour. The approach included the production of walking accessibility measures associated with 9,510 Melbourne SA1s. The SA1s’ weighted centroids were considered as origins and POIs were grouped into four destination categories. The WAI was assessed, using the VISTA dataset, to determine whether there was any significant difference between the level of accessibility and number of walking trips. The proposed index was also compared with one of the most common approaches to measuring walkability. Overall, a statistically significant association between variables was found. In other words, the WAI was evaluated as a more valid measure of walking trips in the Melbourne region based on the VISTA database.

The results indicate that 1.5% of SA1s representing 1.1% of Melbourne residents have no walking access to different destinations, while 15.2% and 16.6% of residents have very low or low walking access. These WAI categories are mainly in the outer parts of the Melbourne region (see Figure 7.5). However, these levels of accessibility are not exclusive to the outer areas. The inner area of Melbourne covers approximately 3,504 km², of which approximately 1,457 km² (42% of the inner area) is covered by zero to moderate levels of walking accessibility. These numbers imply that a considerable number of SA1s have a low to average levels of walking accessibility. These findings
signify the high concentration of POIs in the inner part of Melbourne and the CBD, and that the inner areas of Melbourne have better walking access than the outer areas. In addition, the outer suburbs are characterised by dispersed patterns, which may result in increasing the distances and decreasing the odds of walking. This study used the VISTA data set to evaluate the index developed for measuring accessibility, and the WAI was assessed using tests of association. The results indicate that there is a statistically significant relationship between the WAI categories and walking trips.

One of the most common approaches, the WI, was calculated for SA1s in the Melbourne region. Both indexes, the WAI and the WI, along with socioeconomic characteristics, were used in two separate NB regression models. The M1 model included the WAI with other predictor variables, whilst the M2 model used the WI as the measure of walking accessibility. A comparison of the results revealed that M1 had the lowest AIC ($AIC_{M1}=119393.18 < AIC_{M2}=119860.78$) and BIC ($BIC_{M1}=119514.44 < BIC_{M2}=119982.04$), while showing a better fit for the data. The IRR for WAI in M1 ($IRR_{WAI}=1.33$) was higher than the coefficients estimated for WI ($IRR_{WI}=1.25$) in M2. These figures indicate that more walking trips are expected when there is a one-unit increase in the WAI compared to the WI. Tests of association were also generated to examine whether there is a stronger relationship between the new index and the number of walking trips compared to the existing WI. These findings show that the association values for WAI both in ordinal and interval tests were higher than those for the WI. Therefore, WAI is evaluated as a valid means of measuring walkability in the Melbourne region based on the VISTA database.

### 7.5 Future Research Directions

The literature commonly reports that built environment features such as density, diversity, and road connectivity can promote walking trips. This study hypothesised the distance thresholds of built environment features to develop a walking access index, and then examined the effects of levels of the walkability of areas on walking trips. In other words, the main focus of this study was to investigate whether distance thresholds overcome features considered in other measures, such as connectivity and/or urban design factors. The results of the analysis revealed that people are more likely to walk when their desired destination is located within the distance threshold. In terms of numbers of walking trips, the findings show that the average number of walking trips within SA1s (the second smallest of Melbourne’s geographical areas) is higher with higher levels of WAI categories.

The techniques presented are straightforward to apply. The WAI shows greater accuracy than the WI for measuring walkability based on the VISTA dataset. The quantitative approach developed can be applied to other cities around the world. It is designed to be applied with available census data and network modelling tools. Furthermore, the analysis provides reliable and defendable results, which can be computed for 98.5% of SA1s. Nonetheless, the accuracy can be accomplished in greater detail.
to achieve more accurate results.

One of the limitations of the study is that several of the categories are likely to be single buildings, such as child care centres and libraries, which may be less powerful attractants than retail centres, which are collections of multiple shops. An additional limitation is that, as many authorities are not likely to have a similar POI database, widespread use may be limited. However, as long as land-use maps are available, a POI database can be created by turning features into points. Hence, future work may consider these factors.

7.6 References


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NEWSON, R. 2006. Confidence intervals for rank statistics: Somers' D and extensions. Stata Journal,


CHAPTER 8

SUSTAINABLE TRANSPORT: ACCESSIBLE NEIGHBOURHOODS AND ACTIVE TRANSPORTATION
Abstract

A growing number of recent studies have focused on improving the sustainability of transportation systems by converting routine motorised travel to walking and cycling. The importance of physical activity and its impact on health have not only attracted the attention of practitioners, but also turned the attention of planners and policy-makers to the achievement of more sustainable transportation by promoting active travel. In order to identify effective strategies for increasing pedestrian and bicycle transportation in local areas, planners need to identify how current levels of accessibility in neighbourhoods affect walking and cycling trips. Although a substantial amount of research has been conducted on modelling active transportation, the importance of accessibility in terms of availability of activities for pedestrians and cyclists has been neglected. Hence, this chapter employs new approaches for measuring cycling and walking accessibility against land use features in separate models to examine how accessibility can affect participation in active transportation. Key findings indicate that more accessible neighbourhoods have more walking and cycling trips, while models using accessibility measurements show greater accuracy. Therefore, the results suggest that awareness of accessibility levels in neighbourhoods of existing and developing areas could provide a better perspective for planners and policy-makers to promote active transportation.

Keywords: Built environment, accessibility, active transportation, walkability and cycleability

8.1 Introduction

Planners around the world are attempting to implement transport policies to reduce the dramatic environmental impacts of motorised modes of transport, and enhance individual health by promoting greater levels of physical activity. Recent mobility patterns favouring single-occupancy vehicles and sprawling metropolitan areas have led to many problems, including long unproductive hours spent in traffic, air pollution, and different types of diseases due to sedentary travel behaviour (Ermagun and Samimi, 2015; Mercier et al., 2016). Sedentary travel behaviour not only affects the quality of life for citizens, but creates substantial social and economic externalities (Mayeres, 2000; Hallgrimsdottir et al., 2016).

Whilst the integration of transport and land-use planning is widely recognized as an essential requirement for sustainable development, the concept of accessibility is believed to provide a central framework for this integration (Bertolini et al., 2005; Wang et al., 2011; Silva et al., 2017). A variety of concepts and tools exist for addressing the theoretical and methodological aspects of the definition and measurement of accessibility (Iacono et al., 2010; Geurs et al., 2015; Shliselberg, 2015; Silva et al., 2017). However, these concepts and tools have not yet been extensively used in professional planning practice. Hence, as Brömmelstroet (2010) argues, there is a significant gap between advances in scientific knowledge regarding accessibility and its application in planning practice.

Accessibility can be directly related to both the quality of the transport system and the land-use system, such as the functional density and the land-use mix. At the same time, it can be directly related to economic and social goals as well as environmental goals in terms of the resource-efficiency of activity and mobility patterns. In other words, auto-oriented suburban areas have been found to decrease the degree of accessibility to more sustainable travel options such as walking and cycling (Bertolini et al., 2005).

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

The next section presents the methods of the study, and describes the dataset, study area and explanatory variables. This is followed by analysis from the perspective of planning practitioners focusing on the usefulness of accessibility measures (Section 8.3). Thereafter, in Section 8.4, the results of the analysis are discussed, while in the final section, conclusions and future directions for study are outlined (Section 8.5).
8.2 Methods

This study used two new indexes which measure walking and cycling accessibility together with other built environment measures to examine the importance of accessibility to active transportation. The following sections describe the data sources and study area as well as the process of calculating independent variables.

8.2.1 Datasets and Study Area

Travel Data

The travel dataset used was provided by the Victorian Integrated Survey of Travel and Activity (VISTA) (2009). This cross-sectional survey was conducted from 2009 to 2010. It covers the Melbourne Statistical Division (MSD) as defined by the Australian Bureau of Statistics (ABS), and the regional cities of Geelong, Ballarat, Bendigo and Shepparton and the Latrobe Valley. The data include demographic information, and trip and car ownership information from randomly-selected residential properties, and take into consideration the consistency of the distribution of survey responses and population. 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) were considered. This study used walking and cycling trip stages, which are one-way travel movements from an origin to a destination for a single purpose (including change of mode) by a single mode. The reason for using trip stages for analysis is that walking/cycling trips are considered to be the shortest modes and they cover all trip purposes and changing transport modes.

Spatial Data

A database of mesh blocks from the 2011 Census for the Melbourne Region was accessed from the Australian Bureau of Statistics (ABS, 2011). 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, the Melbourne region contains 53,074 mesh blocks, 9,510 SA1s, 277 Statistical Areas level 2 (SA2s) and 31 Local Government Areas (LGAs). Figure 8.1 presents the statistical geographical 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 the present study, SA1s were chosen as the geographical scale for analyses and calculating the built environment factors. SA1s are the second smallest geographic areas defined in the Australian Statistical Geography Standard (ABS, 2011). Furthermore, SA1 districts have the closest conformity to the definition of neighbourhoods compared to other available geographical units for the Melbourne region, with an average area and population of approximately one km² and 414, respectively.
8.2.2 Explanatory Variables

Independent variables were mainly considered in two groups, socioeconomic characteristics and built environment measurements. Age, gender, car licence, dwelling type and ownership, work arrangement, household size, household structure, and number of cars as well as bicycles in the household were the socioeconomic variables investigated (Nilsson and Küller, 2000; Cao et al., 2009; Ewing and Cervero, 2010; Winters et al., 2010, Jun et al., 2012; Lee et al., 2014).

With respect to built environment measures, three dimensions of factors were examined: land use, design, and accessibility. Land-use factors included population density and a land-use mix entropy index. Design factors covered connectivity and roadway measures, while accessibility factors encompassed both a cycling accessibility index and a walking access index. Using GIS techniques, all built environment measures were calculated for SA1s.

8.2.2.1 Land use measures

*Land-Use Mix Entropy Index (LUMIX)*

The LUMIX was computed with the numerator being normalized by the natural logarithm of the number of land-use types. Six types of uses were considered, including residential, commercial, industrial, transport and infrastructure, community services and sport recreation centres. These
categories were defined from the ten main use categories defined by the Australian Valuation Property Classification Codes (AVPCC) (Morse-McNabb, 2011). The values vary from 0 to 1, where 1 indicates a perfect balance among different types of land use and 0 represents homogeneity. Equation 8.1 presents one of the most common approaches to the measurement of mixed used development in spatial areas (Nilsson and Küller, 2000; Cerin et al., 2007; Duncan et al., 2010; Song et al., 2013; Lee et al., 2014).

\[
LUMIX_i = \left( \sum_{j=1}^{J} \frac{P_j \cdot \ln P_j}{\ln J} \right)
\]

where, \(LUMIX_i\) indicates the entropy index within buffer i (SA1), \(P_j\) represents the proportion of a type of land use \(j\) and \(J\) is the number of land use categories. The six different land-use categories chosen to calculate the Land-Use Mix Entropy Index were residential, commercial, industrial, transport and infrastructure, community services and sport and recreation centres.

**Population Density (DNSY)**

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

**8.2.2.2 Design measures**

Two design variables related to street patterns, connectivity and roadways were used in this study. Other design measures were not considered mainly due to the unavailability of data.

**Roadway Measure (RDW)**

The roadway measure considers how far the road network is spread over a buffer area, which is defined as an SA1 in this study. It is estimated by the total roadway length divided by total area, and the distance is normalized by a unit area of 100m\(^2\) (Lee et al., 2014).

**Connectivity (CON)**

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

### 8.2.2.3 Accessibility measures

**Walking Access Index (WAI)**

The WAI is used to measure walkability within Melbourne’s 9510 SA1s (Saghapour et al., 2017a), and measures the walking distances to different destinations as one of the main barriers to active transport. Walking distances were calculated as the average distance from a SA1 weighted centroid to all available points of interest (POIs) or destinations within acceptable walking distance. POIs were categorised into six groups of destinations, including primary and secondary schools, tertiary institutions, child care centres, medical centres, retail and recreation centres, and community services and libraries. The WAI reflects travel impedance in terms of median desirable and maximum desirable travel time/distance. Equation 8.2 presents the formula used to calculate the Walking Access Index (WAI) for SA1s. For each SA1, the index is computed as:

$$\text{WAI}_{SA1} = \sum_{j=1}^{m} N_i \times \left( \frac{D^M_j - D^D_j}{D^M_j} \right)$$

(8.2)

where, WAI\textsubscript{SA1} is the Walking Access Index, \(N_i\) is the number of POIs within the acceptable walking distance, \(D^M_j\) is the maximum desirable walking distance to destination type \(j\), \(D^D_j\) denotes the median desirable walking distance to destination type \(j\), and \(D^A_j\) represents the average walking distance from a SA1 weighted centroid \(i\) to destination type \(j\). The new index reflects both the diversity and intensity of land use, while considering the availability of destinations as well as the number of activities. A higher value of the WAI indicates a higher level of accessibility. A value of 0 indicates no accessibility in terms of the availability of destinations within the acceptable distance (cut-off values). The WAI ranges from 0 to 222.43 with an average value of 24.08. Table 8.1 presents the ranges and categories of the WAI. The index is grouped into six main categories including very low, low, moderate, good, very good and excellent and a zero group. The classification method used for the WAI categories is quantiles, as they are one of the best methods for simplifying comparisons and aiding general map-reading (Brewer and Pickle, 2002). Zero accessibility is provided for 43,082 residents or 1.46% of SA1s. This category represents situations where there are either no destination groups or activities (POIs) within acceptable walking distance. Areas with very low values are mostly in the outer areas of Melbourne. Overall, 51.1% of SA1s or 51.3% of the total population have either a zero or moderate

\[\text{Median desirable walking distance is a value that satisfies half of the travellers.}\]

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

Table 8.1 WAI Ranges and Categories

<table>
<thead>
<tr>
<th>WAI Categories</th>
<th>Ranges</th>
<th>Number of SA1s</th>
<th>Population</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No.</td>
<td>%</td>
</tr>
<tr>
<td>Zero/NA</td>
<td>0</td>
<td>139</td>
<td>1.46</td>
</tr>
<tr>
<td>Very Low</td>
<td>&lt; 8</td>
<td>1,391</td>
<td>14.63</td>
</tr>
<tr>
<td>Low</td>
<td>8 – 14</td>
<td>1,563</td>
<td>16.44</td>
</tr>
<tr>
<td>Moderate</td>
<td>14 – 20</td>
<td>1,765</td>
<td>18.56</td>
</tr>
<tr>
<td>Good</td>
<td>20 – 25</td>
<td>1,122</td>
<td>11.80</td>
</tr>
<tr>
<td>Very good</td>
<td>25 – 37</td>
<td>1,891</td>
<td>19.88</td>
</tr>
<tr>
<td>Excellent</td>
<td>&gt;37</td>
<td>1,639</td>
<td>17.23</td>
</tr>
<tr>
<td>Total</td>
<td>–</td>
<td>9,510</td>
<td>100.00</td>
</tr>
</tbody>
</table>

As explained above, the WAI is categorized into six bands. The first category represents very low walking accessibility, while the last category signifies an excellent level of walking accessibility. High levels of accessibility from good to excellent are mostly concentrated in the inner parts of the Melbourne region. The distribution of WAI categories is presented in Figure 8.2 for the Melbourne region. The first and last categories are further sub-divided into sub-levels to increase clarity. High levels of accessibility from good to excellent are mostly concentrated in the inner parts of the Melbourne region.

![Figure 8.2 Distribution of WAI categories in the Melbourne region](image)

**Cycling Accessibility Index (CAI)**

The CAI measures cycling for SA1s and reflects cycling catchments as well as travel impedance.
between origins and destinations. The weighted centroids of SA1s were defined as origins and distinct categories of activities were considered as destinations of trips. Destinations were categorized into four groups of activities including education centres, health and care facilities, retail and recreation centres and community services. For each SA1, the CAI is calculated using the formula shown in Equation 8.3. The index is a combined measure of AR and the exponential function of $X_{ij}$ given as:

$$CAI_i = AR_i + \sum_{j=1}^{4} e^{-X_{ij}} \quad (X_{ij} \neq 0) \quad \text{(8.3)}$$

where, $CAI_i$ is the Cycling Accessibility Index for each SA1, $AR_i$ represents the ratio of cycling catchment areas to the area of the corresponding SA1, and $X_{ij}$ is the distance or travel time between origin $i$ and destination $j$ divided by the total length of bicycle paths within the corresponding SA1. For areas with no bicycle network, the CAI is equal to $AR_i$. The reason for this is that cyclists may share the road with other transport modes within those areas. More details and an illustration of calculating the CAI are provided in Saghapour et al. (2017b). The CAI ranges from 0 to 44.7 with an average value of 2.98.

Table 8.2 presents the ranges and categories of the CAI. The index is grouped into four main categories, including poor, moderate, good, and excellent, and a zero group. The classification method used for determining the CAI categories is based on quintiles (Espada and Luk, 2011; TfL, 2010) since they one of the best methods for simplifying comparisons and aiding general map-reading (Brewer and Pickle, 2002).

### Table 8.2 CAI Ranges and Categories

<table>
<thead>
<tr>
<th>CAI Categories</th>
<th>CAI Ranges</th>
<th>SA1s</th>
<th>Population</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No</td>
<td>%</td>
</tr>
<tr>
<td>NA/Zero</td>
<td>0</td>
<td>246</td>
<td>2.6</td>
</tr>
<tr>
<td>Poor</td>
<td>&lt; 0.5</td>
<td>2,013</td>
<td>21.2</td>
</tr>
<tr>
<td>Moderate</td>
<td>0.5 - 2</td>
<td>2,560</td>
<td>26.9</td>
</tr>
<tr>
<td>Good</td>
<td>2 - 4.5</td>
<td>2,452</td>
<td>25.8</td>
</tr>
<tr>
<td>Excellent</td>
<td>&gt; 4.5</td>
<td>2,239</td>
<td>23.5</td>
</tr>
<tr>
<td>Total</td>
<td>NA</td>
<td>9,510</td>
<td>100.0</td>
</tr>
</tbody>
</table>

A map showing the distribution of the CAI is presented in Figure 8.3. High levels of accessibility from good to excellent are mostly concentrated in the inner parts of the Melbourne region. However, the inner suburbs are not exempt from lower levels of accessibility. The first and last categories are further sub-divided into sub-levels to increase clarity.
8.3 Data Analyses and Results

As mentioned previously, the aim of this study was to investigate the importance of walking and cycling accessibility for active transportation. For this purpose, two types of regression models were specified with socioeconomic and built environment factors. Access measures and land-use measures were included in separate models. The reason for this was that access measures are formulated in a way that reflects the land-use features. Hence, the correlation between these variables may bias the results. Active trips (walking and cycling trips) were defined as the dependent variable. Age, gender, car licence, work arrangement, household size, household structure, number of cars and bicycles, type of dwelling, dwelling ownership, and years lived at address were employed as socioeconomic variables (Ewing and Cervero, 2010; Winters et al., 2010; Jun et al., 2012; Lee et al., 2014). Three groups of variables, including accessibility (CAI and WAI), land-use measures (population density and land-use mix index) and design measures (roadway measure and connectivity), were considered as built environment measures.

8.3.1 Descriptive Statistics

When undertaking statistical analysis using the VISTA dataset, both the WAI as well as the CAI were combined with the VISTA dataset using the SA1 codes. The VISTA dataset contains a total of 18,405 walking and cycling trips, of which 17,089 are walking trips and 1,316 are reported as cycling trips. Since a significant number of the trips are walking-oriented, to avoid producing biased results, the
A data set was balanced using the SMOTE\(^5\) balancing classification method (Chawla et al., 2002). The balanced data set contains 9,212 active trips, of which 5264 and 3948 are the number of walking and cycling trips, respectively. Table 8.3 shows the list of independent variables and their descriptions, as well as the hypothesised relationships with the dependent variables.

Table 8.3 Independent variables and their hypothesised associations with walking trips

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>Hypothesized relationship</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Socioeconomic Characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>Age of the respondent</td>
<td>-</td>
</tr>
<tr>
<td>Sex(^1)</td>
<td>Gender</td>
<td>+/-</td>
</tr>
<tr>
<td>Licence(^2)</td>
<td>Driver licence</td>
<td>-</td>
</tr>
<tr>
<td>Car No.</td>
<td>Number of vehicles in the household</td>
<td>+/-</td>
</tr>
<tr>
<td>Bicycle No.</td>
<td>Number of bicycles in the household</td>
<td>+</td>
</tr>
<tr>
<td>HH Size</td>
<td>Usual number of residents in the household</td>
<td>+/-</td>
</tr>
<tr>
<td>HH Structure(^3)</td>
<td>Demographic structure of household</td>
<td>+/-</td>
</tr>
<tr>
<td>Dwelling Type(^4)</td>
<td>Type of Dwelling</td>
<td>+/-</td>
</tr>
<tr>
<td>Dwelling Ownership(^5)</td>
<td>Dwelling Ownership</td>
<td>+/-</td>
</tr>
<tr>
<td>Years Lived</td>
<td>Years lived at address</td>
<td>+</td>
</tr>
<tr>
<td>Work arrangement(^6)</td>
<td>Arrangement of the work</td>
<td>+/-</td>
</tr>
<tr>
<td><strong>Built Environment Measurements</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAI</td>
<td>Cycling Accessibility Index</td>
<td>+</td>
</tr>
<tr>
<td>WAI</td>
<td>Walking Access Index</td>
<td>+</td>
</tr>
<tr>
<td><strong>Accessibility Measures</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RDW</td>
<td>Roadway Measure</td>
<td>-</td>
</tr>
<tr>
<td>CON</td>
<td>Connectivity</td>
<td>+</td>
</tr>
<tr>
<td><strong>Design Measures</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LUMIX</td>
<td>Land use mix entropy index</td>
<td>+</td>
</tr>
<tr>
<td>DNSY</td>
<td>Population density</td>
<td>+</td>
</tr>
</tbody>
</table>

Notes: 1. Sex (male and female) and driver licence (yes and no) are defined as binary variables. 3. HH structure is converted to five dummy variables: sole person, couple no children, couple with children, one parent, and other; 4. dwelling type is converted into three dummy variables: separate house, terrace/townhouse, and flat or apartment; 5. dwelling ownership is converted into five categories: owned, being purchased, rented, rent-free and other; 6. work arrangement is converted into five dummy variables: fixed hours, flexible hours, rostered shifts, work from home and other.

Table 8.4 presents the descriptive statistics for the variables used in the regression models. These statistics were calculated for the 9212 walking and cycling trip stages. In terms of socio-demographic characteristics, the respondents were 37 years old on average and equally distributed according to gender. The average HH size shows that the respondents were mostly from households with about three residents. The average years lived at the address was 10 and households owned more than one car and bicycle. Regarding the dwelling type the mean value of 1.5 shows that majority of the respondents lived in separate houses.

---

\(^5\) SMOTE is a well-known algorithm to overcome this problem. The general idea of this method is to artificially generate new examples of the minority class using the nearest neighbours of these cases. Furthermore, the majority class examples are also under-sampled, leading to a more balanced dataset.
Table 8.4 Descriptive Statistics of variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>36.76</td>
<td>19.06</td>
<td>0.00</td>
<td>90.00</td>
</tr>
<tr>
<td>Sex</td>
<td>1.52</td>
<td>0.50</td>
<td>1.00</td>
<td>2.00</td>
</tr>
<tr>
<td>Licence</td>
<td>1.29</td>
<td>0.45</td>
<td>1.00</td>
<td>2.00</td>
</tr>
<tr>
<td>Car No.</td>
<td>1.57</td>
<td>1.02</td>
<td>0.00</td>
<td>7.00</td>
</tr>
<tr>
<td>Bicycle No.</td>
<td>1.85</td>
<td>1.91</td>
<td>0.00</td>
<td>13.00</td>
</tr>
<tr>
<td>HH Size</td>
<td>3.00</td>
<td>1.37</td>
<td>1.00</td>
<td>6.00</td>
</tr>
<tr>
<td>HH Structure</td>
<td>2.80</td>
<td>1.13</td>
<td>1.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Dwelling Type</td>
<td>1.52</td>
<td>0.80</td>
<td>1.00</td>
<td>3.00</td>
</tr>
<tr>
<td>Dwelling Ownership</td>
<td>1.97</td>
<td>0.82</td>
<td>1.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Years Lived</td>
<td>9.95</td>
<td>11.21</td>
<td>0.00</td>
<td>77.00</td>
</tr>
<tr>
<td>Work arrangement</td>
<td>2.86</td>
<td>1.78</td>
<td>1.00</td>
<td>5.00</td>
</tr>
<tr>
<td>CAI</td>
<td>4.01</td>
<td>3.91</td>
<td>0.00</td>
<td>32.75</td>
</tr>
<tr>
<td>WAI</td>
<td>32.63</td>
<td>21.63</td>
<td>0.00</td>
<td>212.02</td>
</tr>
<tr>
<td>RDW</td>
<td>1.48</td>
<td>0.86</td>
<td>0.00</td>
<td>5.57</td>
</tr>
<tr>
<td>CON</td>
<td>5.21</td>
<td>9.17</td>
<td>0.00</td>
<td>92.06</td>
</tr>
<tr>
<td>LUMIX</td>
<td>0.45</td>
<td>0.16</td>
<td>0.00</td>
<td>0.87</td>
</tr>
<tr>
<td>DNSY</td>
<td>3706.77</td>
<td>4521.05</td>
<td>0.00</td>
<td>158817.12</td>
</tr>
<tr>
<td>Walking &amp; Cycling Trips</td>
<td>28.81</td>
<td>20.91</td>
<td>1.00</td>
<td>110.00</td>
</tr>
</tbody>
</table>

\( n = 9212 \) trip stages

8.3.2 Modelling and Interpretation

Two types of regression models were employed to examine how accessibility can affect active transportation against land-use measures. In each type of regression model two separate models were run, one including land-use measures and the other containing accessibility measures. The following section provides a brief explanation of the models.

8.3.2.1 Ordered Logistic Regression (OLR) Model

OLR models estimate a single equation (regression coefficient) over the levels of the dependent variables. Estimates from the model denote the ordered log-odds (logit) regression coefficients. Interpretation of the ordered logit coefficients is that for a one-unit increase in the predictor, the response variable level is expected to change by its respective regression coefficient in the ordered log-odds scale, while the other variables in the model are held constant. Interpretations of the ordered logit estimates are not dependent on auxiliary parameters. Secondary parameters are used to differentiate the adjacent levels of the response variable. The odds ratio (OR) which is estimated in this model can be obtained by using the exponential function and the coefficient estimate (i.e. \( e^{\text{Coef}} \)).

To interpret this, persons who are in groups greater than \( k \) are compared to those who are in groups less than or equal to \( k \), where \( k \) is the number of the response variable levels (Andren et al., 1999). A typical model for the cumulative logits is shown in Equation 8.6:

\[
\text{logit}[P(Y \leq j)] = \alpha_j + \beta_1X_1 + \beta_2X_2 + \cdots + \beta_nX_n = \alpha_j + \hat{\beta}X \tag{8.6}
\]
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.

Walking and cycling trips in SA1s were classified into six ordered levels from very low, coded as 1, to excellent, coded as 5. The technique for defining the categories was quantiles which considers almost equal counts in each category. Hence, the outcome of the categories can be treated as an ordinal variable. Having an ordered dependent variable, OLR models were used to explore the effects of socioeconomic characteristics as well as walking and cycling access indices. Table 8.5 shows the frequency of active trips within SA1s categorised into five groups from very low to very high.

<table>
<thead>
<tr>
<th>Active Trips Categories</th>
<th>Number of Walking &amp; Cycling Trips</th>
<th>Frequency</th>
<th>Percentage</th>
<th>Cumulative Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Very Low</td>
<td>&lt; 10</td>
<td>1967</td>
<td>21.4</td>
<td>21.4</td>
</tr>
<tr>
<td>Low</td>
<td>11 - 19</td>
<td>1737</td>
<td>18.9</td>
<td>18.9</td>
</tr>
<tr>
<td>Average</td>
<td>20 - 29</td>
<td>1824</td>
<td>19.8</td>
<td>19.8</td>
</tr>
<tr>
<td>High</td>
<td>30 - 41</td>
<td>1853</td>
<td>20.1</td>
<td>20.1</td>
</tr>
<tr>
<td>Very High</td>
<td>&gt; 42</td>
<td>1831</td>
<td>19.9</td>
<td>19.9</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>9212</td>
<td>100.0</td>
<td>100.0</td>
</tr>
</tbody>
</table>

### 8.3.2.2 Negative Binomial Regression (NBR) Model

The other regression model used was the negative binomial regression (NBR) technique. These models are able to use count data and require non-negative integers for the dependent variable. Since the number of trips is always a positive integer, this study adopted the NBR model (Coruh et al., 2015).

NBR models were used to analyse the effects of explanatory variables on active trips. Linear regression techniques have been widely used to examine travel behaviour (Krizek, 2003; Kitamura et al., 1997; Frank and Pivo, 1994). However, linear regression analysis requires model residuals to follow the normal distribution (Nachtsheim et al., 2004), while distributions of trip frequencies are often positively skewed, and deviate from the normality assumption (Cao et al., 2006). The active trips used in this study follow this pattern (see Figure 8.4). Basic statistical measures of active trips are also presented in Table 8.6.
Figure 8.4 Histogram of active trips

Table 8.6 Basic statistical measures of active trips

<table>
<thead>
<tr>
<th>Location</th>
<th>Variability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>28.810</td>
</tr>
<tr>
<td>Median</td>
<td>24.000</td>
</tr>
<tr>
<td>Mode</td>
<td>8.00</td>
</tr>
<tr>
<td>Std. Deviation</td>
<td>20.907</td>
</tr>
<tr>
<td>Variance</td>
<td>479.933</td>
</tr>
<tr>
<td>Range</td>
<td>109.00</td>
</tr>
<tr>
<td>Interquartile Range</td>
<td>28.00</td>
</tr>
</tbody>
</table>

In Poisson regression, it is assumed that the dependent variable \( Y \) (the frequency of walk trips in this study) is Poisson-distributed given the explanatory variables \( X_1, X_2, \ldots, X_p \). This means that the probability of observing \( Y = k \) trips can be obtained by the Poisson distribution function (Cao et al., 2006):

\[
P(Y = K|X_1, X_2, \ldots, X_p) = \frac{e^{-\lambda}\lambda^k}{k!}, \quad k = 0, 1, 2, 3, \ldots,
\]  

(8.7)

where, the conditional mean \( k \) is an exponential function of the explanatory variables. That is,

\[
\lambda = \exp(\beta_0 + \beta_1X_1 + \beta_2X_2 + \cdots + \beta_pX_p)
\]  

(8.8)

where, the fitted value of \( Y \) for the \( i \)th case, \( \hat{Y}_i (i = 1, 2, \ldots, N) \), is denoted \( \hat{\lambda}_i \).

Poisson regression assumes equality of the mean variance. However, this assumption is frequently violated in empirical data. As shown in Figure 8.4, there is some evidence of over-dispersion (variance > mean) in active trips. Alternatively, the NBR model captures the over-dispersion effect by introducing an unobserved effect into the conditional mean, \( \lambda \), of the Poisson model.
\[ \lambda = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \varepsilon) \]  

(8.9)

where, \( \exp(\varepsilon) \) has a gamma distribution with mean 1 and variance \( \alpha \) (also called the dispersion parameter). Poisson regression is a special case of NBR in which \( \alpha \) equals 0.

As stated previously, two separate models were run for each type of regression model. The reason was that since both defined accessibility measures reflect the land-use mix as well as population density, their inclusion in a single model could have biased the results. Table 8.7 shows the results of correlation analysis between access measures with land use and design measures.

**Table 8.7 Correlation analysis between CAI, WAI and other built environment measures**

<table>
<thead>
<tr>
<th></th>
<th>LUMIX</th>
<th>Density</th>
<th>RDW</th>
<th>Connectivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAI</td>
<td>0.420</td>
<td>0.149</td>
<td>0.142</td>
<td>0.144</td>
</tr>
<tr>
<td>WAI</td>
<td>0.468</td>
<td>0.507</td>
<td>0.304</td>
<td>0.227</td>
</tr>
</tbody>
</table>

In the OLR and the NBR models, M1 and M1’ present the results of the models considering all the predictor variables and accessibility measures, while M2 and M2’ include all the variables used in the M1 and M1’ with accessibility measures replaced by land-use measures. Active trips are defined as an ordered variable in the OLR models and a count variable in the NBR models. Table 8.9 presents the results of the regression models. Accessibility measures (CAI and WAI) along with other variables were employed to develop models M1 and M1’ and the land-use measures in M2 and M2’. The results indicate that all built environment measures in the models were statistically significant and that active transport was positively associated with built environment measures. However, based on the Akaike information criterion (AIC) (Yamaoka et al., 1978) and the Bayesian Information Criterion (BIC) (Posada and Buckley, 2004), which are measures of the relative quality of statistical models for a given set of data, the M1 and M1’ models were found to be better models. Given a series of models for the data, AIC and BIC estimate the quality of each model, relative to each of the other models. Hence, these criteria provide a means for model selection (Aho et al., 2014; Hu, 2007; Boisbunon et al., 2014).

As Table 8.8 indicates, the outcome of the OLR models indicates that the number of cars in a household is negatively associated with walking and cycling trips and the number of bicycles in households and HH size are positively associated with walking and cycling trips. In terms of dwelling type, the log odds of having a higher level of walking/cycling trips is higher for people who live in a terrace or townhouse than for those who live in flats or apartments. The built environment features also have a significant impact on walking and cycling trips. The CAI, WAI, LUMIX and DNSY are positively associated with active trips and RDW is negatively associated with active trips. For
instance, there is an expectation of a 1.38 times increase in the log odds of a higher level of walking and cycling trips for a unit increase of the WAI. This value is 1.50 times for the CAI. In contrast, the log odds of a higher level of walking and cycling trips is 0.77 times lower when the RDW increases by one unit.

On the right-hand side of Table 8.5, the results of the NBR models are presented. The incident rate ratio (IRR) of the models indicates that for a one-unit increase in the WAI and the CAI, active trips increase by 15% and 19%, respectively. The IRR values for the LUMIX and the DNSY show that walking and cycling trips increase by 21% and 9%, respectively, for a one-unit increase in land-use mix and population density.
Table 8.8 Outputs of the OLR and the NBR models for walking and cycling trips

<table>
<thead>
<tr>
<th>Parameter</th>
<th>OLR Models</th>
<th>NBR Models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$M_1$</td>
<td>$M_2$</td>
</tr>
<tr>
<td></td>
<td>Estimate</td>
<td>OR</td>
</tr>
<tr>
<td>Intercept</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Age</td>
<td>0.0050**</td>
<td>1.0050</td>
</tr>
<tr>
<td>(Male)</td>
<td>-0.0565</td>
<td>0.9450</td>
</tr>
<tr>
<td>Licence (Yes)</td>
<td>-0.1013</td>
<td>0.9040</td>
</tr>
<tr>
<td>Car No.</td>
<td>-0.1452***</td>
<td>0.8650</td>
</tr>
<tr>
<td>Bicycle No.</td>
<td>0.0302**</td>
<td>1.0310</td>
</tr>
<tr>
<td>HH Size</td>
<td>0.0750**</td>
<td>1.0780</td>
</tr>
<tr>
<td><strong>HH Structure</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Solo Person</td>
<td>-0.8727***</td>
<td>0.4180</td>
</tr>
<tr>
<td>Couple no Children</td>
<td>-0.2521**</td>
<td>0.7770</td>
</tr>
<tr>
<td>Couple with Children</td>
<td>-0.1383**</td>
<td>0.8710</td>
</tr>
<tr>
<td>Single Parent</td>
<td>-0.2342**</td>
<td>0.7910</td>
</tr>
<tr>
<td><strong>Dwelling Type</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Separate House</td>
<td>0.0960</td>
<td>1.1010</td>
</tr>
<tr>
<td>Terrace/Townhouse</td>
<td>0.2088**</td>
<td>1.2320</td>
</tr>
<tr>
<td><strong>Dwelling Ownership</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Owned</td>
<td>0.9066**</td>
<td>2.4760</td>
</tr>
<tr>
<td>Being Purchased</td>
<td>0.8968**</td>
<td>2.4520</td>
</tr>
<tr>
<td>Rented</td>
<td>1.0520**</td>
<td>2.8630</td>
</tr>
<tr>
<td>Rent Free</td>
<td>1.3456**</td>
<td>3.8410</td>
</tr>
<tr>
<td>Years Lived</td>
<td>-0.0017</td>
<td>0.9980</td>
</tr>
<tr>
<td><strong>Work arrangement</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed Hours</td>
<td>0.0914</td>
<td>1.0960</td>
</tr>
<tr>
<td>Flexible Hours</td>
<td>0.1450**</td>
<td>1.1560</td>
</tr>
<tr>
<td>Rostered Shifts</td>
<td>0.2181**</td>
<td>1.2440</td>
</tr>
<tr>
<td>Work from Home</td>
<td>0.2046**</td>
<td>1.2270</td>
</tr>
<tr>
<td><strong>Design Measures</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RDW</td>
<td>-0.2577***</td>
<td>0.7730</td>
</tr>
<tr>
<td>CON</td>
<td>0.0297**</td>
<td>1.0300</td>
</tr>
<tr>
<td><strong>Accessibility Measures</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAI</td>
<td>0.4110***</td>
<td>1.5080</td>
</tr>
<tr>
<td>WAI</td>
<td>0.3239***</td>
<td>1.3820</td>
</tr>
<tr>
<td><strong>Land use Measures</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LUMIX</td>
<td>0.4169***</td>
<td>1.5170</td>
</tr>
<tr>
<td>DNSY</td>
<td>0.1654***</td>
<td>1.1800</td>
</tr>
<tr>
<td>Dispersion</td>
<td>0.3987</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:**
(1) Numbers of walking and cycling trips were converted to five dummy variables using level 1 (very low): less than 10 trips, level 2 (low): 11-19 trips, level 3 (average): 20-29 trips, level 4 (high): 30-41 trips, and level 5 (very high): more than 42. Level one was the reference level.
(2) Threshold coefficients for M1: $1/2$ → -1.7806, $2/3$→ -2.8145, $3/4$→ -3.7624; 4/$5$→ -4.9181; for M2: $1/2$ → -1.6172, $2/3$→ -2.6122, $3/4$→ -3.5028; 4/$5$→ -4.5895;
(3) Significance codes: $p < 0.001$ ****, $0.01$ ***, $0.1$ **.
(4) Overall goodness-of-fit:
AIC$_{M1}$ = 26,005, -2 Log L = 25947, SC = 26210;
AIC$_{M2}$ = 28,355, -2 Log L = 28,297, SC = 28,562.

**NB Models:**
Notes: (1) number of active trips is defined as a dependent variable.
(2) The NB dispersion parameter was estimated by maximum likelihood.
(3) Significance codes: $p < 0.001$ ****, $0.01$ ***, $0.1$ **.
(4) Overall goodness of fit:
AIC$_{M1'}$ = 71,941, BIC$_{M1'}$ = 72,131;
AIC$_{M2'}$ = 77,055, BIC$_{M2'}$ = 77,247.
8.4 Discussions

This study investigated the impact of accessibility on active transportation. For this purpose, three sets of built environment measures, including land-use measures, design measures and accessibility measures, were used to develop separate OLR and NBR models to examine their effectiveness and their importance. Both the CAI and the WAI were determined for Melbourne’s 9510 statistical areas level one (SA1s). These new indexes were formulated in a way that reflects the land-use mix as well as population density (tested using correlation analysis, see Table 8.8). Hence, accessibility measures and land-use measures were not used simultaneously in a single model. Conversely, accessibility measures along with design measures and socioeconomic characteristics were employed in models M1 and M1’, while models M2 and M2’ had the same variables with the exception of the accessibility measures which were replaced by land-use measures. The results indicated that both land-use measures and accessibility measures had a statistically significant effect on walking and cycling trips.

The coefficients estimated by the models indicate that higher log odds of being in a higher level of walking and cycling trips are expected when there is a one-unit increase in the associated variable compared to its counterparts. Results of the OLR models show that gender and number of years that people live in an area have no statistical significant influence on levels of walking and cycling trips. Regarding the built environment measures, the ORs for the OLR model indicate that for a one-unit increase in the WAI and the CAI the log odds of a one-unit increase in these predictor variables, and the odds of levels of active trips are 1.4 and 1.5 times higher, if the other variables are held constant. On the other hand, with a one-unit increase in the LUMIX and the DNSY, the odds of higher levels of active trips are 1.5 and 1.2 times higher, holding all other variables constant. Similar results were also obtained for the NBR models. According to the values of the IRR in models M1’ and M2’, active trips increase by 19% and 15% when there is a one-unit increase in the CAI and the WAI, respectively, holding all other variables in the model constant. Furthermore, walking and cycling trips increase by 19% and 9% when the LUMIX and the DNSY increase by one unit, holding all other variables constant. These results indicate that active trips had greater changes for the CAI and the WAI compared to land-use measures. In addition, considering the AIC ($AIC_{M1} = 26,005 < AIC_{M2} = 28,355$) of the OLR models and the AIC ($AIC_{M1} = 71,941 < AIC_{M2} = 77,055$) and BIC ($BIC_{M1} = 72,131 < BIC_{M2} = 72,247$) for the NBR models, it can be concluded that models M1 and M1’ are better models than the other two. Hence, based on the VISTA dataset, models that include access measures in both types of regression models better fit the data and can be considered better models.

The accessibility measures developed in this study can be used to compare neighbourhoods within the same study area in terms of their walkability and cycleability. Using this approach, planners and policy makers can compare and rank areas already built, and identify new areas where investment
might improve walking and cycling accessibility. The way urban areas are configured can influence pedestrian behaviour because it can make the built environment more attractive, safer and more accessible, by bringing together shops and services and recreation centres (Peiravian et al., 2014). The CAI and the WAI used in this study not only reflect the diversity of different land uses, but also consider the intensity of activities. Walkable, cycleable communities and active living are related to sustainable living. Changes in the physical environment affect urban mobility, particularly in metropolitan areas (Cubukcu, 2013). The promise of planning and policy actions to improve active travel is that walking and cycling can be encouraged by enhancing the quality of the built environment, which can affect travel distance, travel time and transport mode choice (Kim et al., 2014). As Randall and Baetz (2001) argue, neighbourhoods should be constructed with sustainability concepts in mind. Those providing good pedestrian and cycling environments and more green space can enhance the level of physical activity. All across urban and transport planning, much effort is currently being put into providing safe and friendly environments that encourage walking in cities. Using the approaches presented in this study, planners and policy makers can compare and rank areas already developed, and identify new areas where investment might improve walking and cycling accessibility. The way urban areas are configured can influence pedestrian behaviour, because it can make the built environment more attractive, safer and more accessible, by bringing together shops and services and recreation centres. In addition, awareness of walking and cycling levels in existing neighbourhoods and developing areas may affect people’s selection of living area. The methods presented in this paper can be used to achieve more and better insights into the location of different activities in proposed plans for under-developed and developing areas. Measuring the friendliness of neighbourhoods can be a policy tool for promoting more walking and cycling (Peiravian et al., 2014). This is considered important and requires more research. The present study provides a starting point for such a task.

8.5 Conclusions and Future Research Directions

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

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

In summary, based on the literature, there is a significant gap between advances in scientific knowledge of accessibility and its application in planning practice. In comparison with the limited previous work on accessibility-based analyses, the analysis presented here is distinctive, because it incorporates the impacts of both land use and accessibility on active transportation. The measurements described in this study are capable of being used by urban and transport planners as well as policy makers in relation to any proposed land-use development. Apart from the ease of understanding of both measurements, one of the greatest strengths of these measures is that they reflect the land-use features in terms of diversity and intensity of activities.

However, the current study did not consider access to public transport, which could affect the number of walking and cycling trips. According to Lei and Church (2010), public transport improves sustainability as well as being a more social means of transportation, which may lead to increasing the liveability and sustainability of cities (Mamun, 2011). Furthermore, an improved public transport system provides mobility to those who do not have access to automobiles (Mamun, 2011). In other words, use of public transport is considered within the definition of active transportation, as it often involves some walking or cycling to connect to trip origins and destinations (Taniguchi et al., 2013). Therefore, it may be useful for future studies to consider public transport accessibility.

Another limitation of this study was that since it was assumed that bicycles operated at an average speed of 16 km/h, there would be a chance of bicycle trips traversing multiple SA1s within a single trip. Therefore, bicycle activity may not only be influenced by the built environment in one SA1, but potentially also in surrounding SA1s. However, in this study some of the built environment variables such as the LUMIX and the DNSY were calculated based on the characteristics of a single SA1. Therefore, future studies may consider the effect of surrounding regions on bicycle trips to obtain more precise outcomes. In addition, due to the unavailability of data on other design factors that may affect walking and cycling, such as pedestrian and cyclist environments (Komanoff and Roelofs, 1993) including sidewalk widths, pavement quality, curb, cuts, and type of bicycle lanes, etc. were not considered in this study. Hence, future studies may take these features into account to achieve more accurate results.
8.6 References


DUNCAN, M. J., WINKLER, E., SUGIYAMA, T., CERIN, E., DUTOIT, L., LESLIE, E. & OWEN,


CHAPTER 9

ENHANCING ACTIVE TRANSPORT DEMAND MODELLING BY INCORPORATING ACCESSIBILITY MEASURES
Chapter 9: Enhancing Active Transport Demand Modelling by Incorporating Accessibility Measures

Abstract

Accessibility measures have been recognised as valuable inputs for decision support tools for land-use and transport planning. However, despite the relatively large number of available measures outlined in the literature, they are not widely used in planning practice, particularly in non-motorized transport modelling. The concept of availability of activities within acceptable walking/cycling travel distances may potentially affect the travel behaviour of pedestrians and cyclists, as distance has always been a significant barrier to travellers using active transport. Hence, the aim of this study is to investigate the benefits of incorporating accessibility in active transportation modelling. For this purpose, three non-motorized accessibility measures are used in cluster analyses for classifying levels of access. Subsequently, three separate negative binomial regression (NBR) models are applied to examine the impact of including the access measure versus land-use measures in the models. Key findings indicate that the performance of active transport demand models is enhanced by incorporating accessibility as an explanatory variable as well as land-use measures.

Keywords: Land-use measures, accessibility, access-level measure, active transportation, NBR model

9.1 Introduction

The term “accessibility” is commonly defined as the ease with which any land-use activity is reachable from a certain location and by a certain mode of transport (Dalvi and Martin, 1976; Lee and Goulia, 1997). The definition of accessibility varies depending on the goal and perspective of the study (Eizaguirre-Iribar, Igiñiz and Hernández-Minguillón, 2016). Since distance has been always a significant barrier to travellers using active transport, accessibility potentially influences the frequency of non-motorized trips (Rodríguez and Joo, 2004; Cervero and Kockelman, 1997; Greenwald and Boarnet, 2001; Cao et al., 2009b).

A growing number of studies in the past few years have investigated the link between land use and design measures, such as population density, land-use mix and connectivity, and active transport (Duncan et al., 2010; Song et al., 2013; Kim et al., 2014). According to Soria-Lara et al. (2016), six groups of land-use factors are interconnected with transport, including settlement size, urban density, land-use mix, urban design, local accessibility to public transport, and the provision of parking. More recently, transportation research has become concerned with the built-environmental determinants of “active transport”, driven mainly by the need to reduce the negative side-effects of car-related issues. Active transport is commonly defined as trips made by non-motorized modes of transport such as walking and cycling (Frank and Engelke, 2001; Sallis et al., 2004). However, the use of public transport is considered within the definition of active transport, as it often involves some walking or cycling to be connected from origins to destinations of trips (Taniguchi et al., 2013). As Sallis et al. (2004) state, two fundamental urban features that impact travel choice and active transport are the proximity of different land uses and the connectivity between complementary activities (e.g. work, shops, etc.).

There has been considerable research on the measurement of access levels of active modes of transport (Iacono et al., 2010; Krizek, 2005; Frank et al., 2005; Currie, 2010). Although non-motorised accessibility to a range of destinations has recently emerged as an important issue in transport and urban planning (Iacono et al., 2010; Krizek, 2005), accessibility as an integrated measure for non-motorized modes of transport has not been particularly considered in previous research (Iacono et al., 2010). A considerable amount of research has used land use and design measures as influential factors on non-motorized trips. However, the importance of accessibility as an explanatory variable has been neglected (Van Acker and Witlox, 2011; Ewing and Cervero, 2010b; Cervero, 1996). Therefore, the aim of this study is to define an access measure based on walking, cycling and public transport accessibility measurements and employ it to examine whether it improves the performance of active-transport demand models.

The next section presents the methods of the study, and describes the dataset, study area, and
explanatory variables. This is followed by an analysis from the perspective of planning practitioners, focusing on the usefulness of accessibility measures (Section 9.3). Thereafter, in Section 9.4, the results of the analysis are discussed, while in the last section, the conclusions and future directions of study are outlined.

9.2 Methods

The methods used in this study involve two main parts. In the first part, three measures of walking, cycling and public transport accessibility are converted into an access-level measure using cluster analysis. In the second step, three separate negative binomial regression (NBR) models that consider the importance of accessibility measures in modelling active transportation are examined. Figure 9.1 shows the conceptual framework of the study. The following sections describe the data sources and study area and the explanatory variables considered.

Figure 9.1 Conceptual framework of study

9.2.1 Datasets and study area

Travel data

The travel dataset was provided by the Victorian Integrated Survey of Travel and Activity (VISTA, 2009). This cross-sectional survey was conducted from 2009 to 2010. It covers the Melbourne Statistical Division (MSD), as defined by the Australian Bureau of Statistics (ABS), and the regional cities of Geelong, Ballarat, Bendigo and Shepparton, and the Latrobe Valley in the state of Victoria, Australia. Data collected include demographic information, trip information and car ownership from
randomly-selected residential properties. A total of 16,411 households, comprising 42,002 individuals, responded, a response rate of 47%. Since built environment features were calculated for the Melbourne region, the present research considered only residents within the MSD (22,201 individuals). For active trips, this study used walking and cycling trip stages, which are one-way travel movements from an origin to a destination for a single purpose (including change of mode) and by a single mode. The reason for the use of trip stages for analysis is that walking/cycling trips are usually the shortest trips when covering all trip purposes, even for changing transport modes. The VISTA dataset contains a total of 18,405 active transport trips.

Spatial data

A database of mesh blocks from the 2011 Census for the Melbourne region was accessed from the Australian Bureau of Statistics (ABS, 2011). 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 the Australia Bureau of Statistics (ABS, 2011), the Melbourne region contains 53074 mesh blocks, 9510 SA1s, 277 statistical areas level 2 (SA2s) and 31 local government areas (LGAs). Figure 9.2 presents the statistical geography areas of the Melbourne region. Mesh blocks are the smallest geographical units released by the ABS and all other statistical areas are built up from, or approximated by, whole mesh blocks. In this study, SA1s were chosen as the geographical scale for the analysis and calculation of the built environment factors. SA1s are the second smallest geographic areas defined in the Australian Statistical Geography Standard (ABS, 2011). In addition, SA1 districts with an average area and population of roughly one km$^2$ and 414, respectively, have the closest conformity to the definition of neighbourhood compared to other available geographical units for the Melbourne region.
Independent variables were mainly considered in two groups, socioeconomic characteristics and built environment measures. Age, gender, car licence, dwelling type and ownership, work arrangement, household size, household structure, and number of cars and bicycles in the household were employed as socioeconomic variables (Nilsson and Küller, 2000; Cao et al., 2009a; Ewing and Cervero, 2010a; Winters et al., 2010; Jun et al., 2012; Kim et al., 2014; Manaugh et al., 2010).

With respect to the built environment measurements, three dimensions of factors were examined: land use, design, and accessibility. Land use includes population density and a land-use mix entropy index; design covers connectivity and a roadway measure, while accessibility encompasses a cycling accessibility index and a walking access index. Using geographic information system (GIS) techniques, all built environment measures were calculated for SA1s.

**9.2.2.1 Land use measures**

*Land-use mix entropy index (LUMIX)*

The LUMIX is computed when the numerator is normalized by the natural logarithm of the number of land-use types. Six land uses are considered, including residential, commercial, industrial, transport and infrastructure, community services and sport recreation centres. These categories are defined from the ten main categories of uses defined by the Australian Valuation Property Classification Codes.
The LUMIX varies from 0 to 1, with 1 indicating a perfect balance among different types of land use and 0 showing full homogeneity. Equation 9.1 presents one of the most common approaches for measuring mixed-used development within spatial extents (Nilsson and Küller, 2000; Cerin et al., 2007; Duncan et al., 2010; Song et al., 2013; Kim et al., 2014):

\[
LUMIX_i = -\left( \sum_{j=1}^{J} P_j . \ln P_j \right) \quad \ln J = 1
\]  

(9.1)

where, LUMIX\(_i\) indicates the entropy index within a buffer \(i\) (SA1), \(P_j\) represents the proportion of a type of land use \(j\) and \(J\) is the number of land-use categories. Six different land-use categories, including residential, commercial, industrial, transport and infrastructure, community services and sport and recreation centres, were chosen to calculate the LUMIX.

**Population density (DNSY)**

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

**9.2.2.2 Design measures**

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

**Roadway measure (RDW)**

The roadway measure examines how far the network spreads over a buffer area, which is defined as an SA1 in this study. It is quantified by the total roadway length divided by the total area, and the distance is normalized by a unit area of 100m\(^2\) (Kim et al., 2014; Lee et al., 2014).

**Connectivity (CON)**

The connectivity measure, also called internal connectivity, is defined as the number of intersections divided by the total number of intersections and dead-ends within a certain area (Song and Knaap, 2004; Knaap et al., 2007; Kim et al., 2014). The Australian Urban Research Infrastructure Network (AURIN) (Sinnott et al., 2011) has also determined connectivity measures for areas within Melbourne. AURIN provides a web-based environment for calculating connectivity for different statistical sub-divisions in the Melbourne area. Hence, this study used this for calculating the connectivity for SA1s.
9.2.2.3 Accessibility measures

Walking Access Index (WAI)

The WAI is used to measure walkability within the 9510 SA1s in Melbourne (Saghapour et al., 2017a). The WAI measures the walking distances to different destinations as one of the main barriers to active transport. Walking distances were calculated as the average distance from a SA1 weighted centroid to all available points of interest (POIs) or destinations within acceptable walking distances. POIs were categorised into six groups of destinations, including primary and secondary schools, tertiary institutions, child care centres, medical centres, retail and recreation centres, and community services and libraries. The WAI reflects travel impedance in terms of median desirable and maximum desirable travel time/distance. Equation 9.2 presents the formula used to calculate the WAI for SA1s. For each SA1, the index is computed as:

\[
WAI_{SA1i} = \sum_{j=1}^{m} N_i \times \left( \frac{D^M_j - D^A_{ij}}{D^M_j} \right)
\]

(9.2)

where, \(WAI_{SA1i}\) is the Walking Access Index, \(N\) is the number of POIs available within acceptable walking distance, \(D^M_j\) is the maximum desirable walking distance to destination \(j\), \(D^D_j\) denotes the median desirable walking distance to destination \(j\), and \(D^A_{ij}\) represents the average walking distance from a SA1 weighted centroid \(i\) to destination \(j\). The new index reflects both the diversity and intensity of land use, while considering the availability of destinations as well as the number of activities. A higher value of WAI indicates a higher level of accessibility. A value of 0 indicates no accessibility in terms of the availability of destinations within the acceptable distance (cut-off values). The WAI ranges from 0 to 222.43 with an average value of 24.08.

Cycling Accessibility Index (CAI)

The CAI measures cycling for SA1s and reflects cycling catchments as well as travel impedances between origins and destinations. The weighted centroids of SA1s were defined as origins and distinct categories of activities were considered as destinations of trips. Destinations were categorized into four groups of activities: education centres, health and care facilities, retail and recreation centres and community services. For each SA1, the CAI is calculated using the formula shown in Equation 9.3. The index is a combined measure of \(AR\) and the exponential function of \(X_i\) given as:

---

6 Median desirable walking distance is a value that satisfies half of the travellers.
7 The maximum desirable walking distance is defined as a value at which a significant percentage of people would find it unfeasible to regularly travel and they may be forced to relocate their residence closer to the destination or find a less suitable destination that is closer.
\[ CAI_i = AR_i + \sum_{j=1}^{4} e^{-X_{ij}} \quad (X_{ij} \neq 0) \] (9.3)

where, \( CAI \) is the Cycling Accessibility Index for each SA1, \( AR_i \) represents the ratio of cycling catchment areas to the area of the corresponding SA1, and \( X_{ij} \) is the distance or travel time between origin \( i \) and destination \( j \) divided by the total length of bicycle paths within the corresponding SA1. For areas with no bicycle network, the CAI is equal to \( AR_i \). The reason for this is that cyclists may share the roads with other modes within those areas. More details and an illustration of calculating the CAI is provided in Saghapour et al. (2017b). The CAI ranges from 0 to 44.7 with an average value of 2.98.

**Public Transport Accessibility Index (PTAI)**

Public transport accessibility is calculated using the Public Transport Accessibility Index (PTAI) (Saghapour et al., 2016). The PTAI measuring the level of public transport access was calculated for Melbourne’s 9510 SA1s. This approach computes the level of access by public transport for POIs. The PTAI includes measures such as access walking time, service frequency and waiting time, as well as the population density ratio in walking catchments and SA1s, as shown in Equation 9.4:

\[
\begin{align*}
\text{if } D_{B_{ij}} = 0; & \\
PTAI_{SA1} &= \sum_{j=1}^{3} \sum_{i=1}^{l} \left( 1 + \frac{D_{B_{ij}}}{D_{SA1_i}} \right) \cdot WEF_{SA1_i} \\
\text{if } D_{B_{ij}} \neq 0; & \\
PTAI_{SA1} &= \sum_{j=1}^{3} \sum_{i=1}^{l} \left( \frac{D_{B_{ij}}}{D_{SA1_i}} \right) \cdot WEF_{SA1_i}
\end{align*}
\] (9.4)

where, \( PTAI_{SA1} \) denotes the public transport accessibility index for a given SA1, \( D_{B_{ij}} \) is the population density of buffer \( i \) for public transport mode \( j \), \( D_{SA1_i} \) is the population density of the SA1, and \( WEF_{SA1_i} \) is the weighted equivalent frequency calculated for the corresponding SA1.

In this approach, accessibility is calculated for the spatial coverage of each SA1, which is covered by walking buffers to public transport 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 both bus and tram stops, the 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. A value of 0 indicates that there is either no accessibility or no population in a SA1. The PTAI ranges from 0 to 115.68 with an average value of 10.76.
9.3 Data Analysis and Results

The data were analysed in two stages. In the first stage of the analysis three access measures outlined in the previous section, the WAI, CAI and PTAI, were converted into one access level measure using seven different clustering methods. In the next stage, three separate NBR models were developed to examine the importance of accessibility in modelling active transportation.

9.3.1 Cluster analysis

Using cluster analyses, the WAI, CAI and PTAI were classified into four categories to define an access level measure. For clustering, five hierarchical methods, including the un-weighted Pair-Group Method (PGM), the Nearest Neighbour Method (NNM), the Furthest Neighbour Method (FNM), Centroid Clustering Analysis (CCA), and Ward’s Method (WDM), and two non-hierarchical techniques, K-means Cluster Analysis (KMC) and Two-step Cluster Analysis (TSC), were applied. To select the best method, correlation analysis between the seven access level measures (ALMs) obtained from the cluster analysis and active trips, was performed.

Table 9.1 Correlation analysis between ALMs and active trips

<table>
<thead>
<tr>
<th>Kendall's tau b</th>
<th>.317**</th>
<th>.309**</th>
<th>.307**</th>
<th>.237**</th>
<th>.250**</th>
<th>.198**</th>
<th>.167**</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spearman's rho</td>
<td>.410**</td>
<td>.400**</td>
<td>.394**</td>
<td>.299**</td>
<td>.324**</td>
<td>.247**</td>
<td>.219**</td>
</tr>
<tr>
<td>Pearson's R</td>
<td>.422**</td>
<td>.417**</td>
<td>.396**</td>
<td>.333**</td>
<td>.332**</td>
<td>.276**</td>
<td>.242**</td>
</tr>
</tbody>
</table>

** Significant at 0.99 confidence level.

Since ALM_{TSC} had the higher correlation values (see Table 9.1) it was selected as the access level measure to be considered in the regression models. Table 9.2 shows the specification of the selected access level measure. Figure 9.3 presents the distribution of accessibility levels within the study area.

Table 9.2 Number and percentage of SA1s in each cluster membership

<table>
<thead>
<tr>
<th>Cluster No.</th>
<th>Categories</th>
<th>No. of SA1s</th>
<th>% of SA1s</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Poor</td>
<td>2882</td>
<td>30.3</td>
</tr>
<tr>
<td>2</td>
<td>Moderate</td>
<td>2624</td>
<td>27.6</td>
</tr>
<tr>
<td>3</td>
<td>Good</td>
<td>1873</td>
<td>19.7</td>
</tr>
<tr>
<td>4</td>
<td>Excellent</td>
<td>1231</td>
<td>22.4</td>
</tr>
</tbody>
</table>

Note: the ratio of the smallest cluster to the largest cluster is 1.5, which represents a good distribution of cluster membership.
9.3.2 Modelling and interpretation

Models for this study were estimated using NBR techniques, which are able to use count data and require non-negative integers for the dependent variable. Since the number of trips is always a positive integer, this study adopted the NBR model (Coruh et al., 2015).

NBR models were used to analyse the effects of explanatory variables on active trips. Linear regression techniques have been widely used to examine travel behaviour (Krizek, 2003; Kitamura et al., 1997; Frank and Pivo, 1994). However, linear regression analysis requires the model’s residuals to follow the normal distribution (Nachtsheim et al., 2004), while distributions of trip frequencies are often positively skewed, and deviate from the normality assumption (Cao et al., 2006). The active trips used in this study follow this pattern (see Figure 9.4). Basic statistical measures of active trips are also presented in Table 9.3.
In Poisson regression, it is assumed that the dependent variable \( Y \) (the frequency of walking trips in this study) is Poisson-distributed given the explanatory variables \( X_1, X_2, \ldots, X_p \). This means that the probability of observing \( Y = k \) trips can be obtained by the Poisson distribution function (Cao et al., 2006):

\[
P(Y = k|X_1, X_2, ..., X_p) = \frac{e^{-\lambda} \lambda^k}{k!}, \quad k = 0, 1, 2, 3, ..., \tag{9.5}
\]

where, the conditional mean \( k \) is an exponential function of the explanatory variables. That is,

\[
\lambda = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p) \tag{9.6}
\]

where, the fitted value of \( Y \) for the \( i \)th case, \( \hat{Y}_i (i = 1, 2, ..., N) \), is denoted \( \hat{\lambda}_i \).

Poisson regression assumes equality of mean variances. However, this assumption is frequently violated in empirical data. As shown in Figure 9.4, there is some evidence of over-dispersion (variance > mean) in active trips. Alternatively, the NBR model captures the over-dispersion effect by introducing an unobserved effect into the conditional mean, \( \lambda \), of the Poisson model:

\[
\lambda = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon) \tag{9.7}
\]
where, \( \exp(\varepsilon) \) has a gamma distribution with mean 1 and variance \( \alpha \) (also called the dispersion parameter). Poisson regression is a special case of NBR in which \( \alpha \) equals 0. Three separate NBR models were generated for active trips. M1 presents the results of a NBR model considering all the predictor variables, M2 denotes the model with all the variables used in M1 excluding the access measure, and in model M3 all variables were included, except the land-use measure variables. Active trips were defined as a count-dependent variable. Age, gender, car licence, employment type, household size, household (HH) structure, and the number of cars in the HH were used as socioeconomic variables (Lee et al., 2014; Jun et al., 2012; Shay and Khattak, 2012; Ewing and Cervero, 2010a; Winters et al., 2010; Engelfriet and Koomen, 2017). Table 9.4 shows the list of independent variables and their descriptions as well as the hypothesised relationship with the dependent variable.

**Table 9.4 Independent variables and their hypothesized associations with active trips**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>Hypothesized relationship</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Socioeconomic Characteristics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>Age of the respondent</td>
<td>-</td>
</tr>
<tr>
<td>Sex</td>
<td>Gender</td>
<td>+/-</td>
</tr>
<tr>
<td>Licence</td>
<td>Driver licence</td>
<td>-</td>
</tr>
<tr>
<td>Car No.</td>
<td>Number of vehicles in the household</td>
<td>+/-</td>
</tr>
<tr>
<td>HH Size</td>
<td>Usual number of residents in the household</td>
<td>+/-</td>
</tr>
<tr>
<td>HH Structure</td>
<td>Demographic structure of household</td>
<td>+/-</td>
</tr>
<tr>
<td>Work arrangement</td>
<td>Arrangement of work</td>
<td>+/-</td>
</tr>
<tr>
<td><strong>Built Environment Measurements</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Access Measure</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ALM</td>
<td>Access Level Measure obtained from two-step cluster analysis</td>
<td>+</td>
</tr>
<tr>
<td><strong>Design Measures</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RDW</td>
<td>Roadway measure</td>
<td>-</td>
</tr>
<tr>
<td>CON</td>
<td>Connectivity</td>
<td>+</td>
</tr>
<tr>
<td><strong>Land use Measure</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LUMIX</td>
<td>Land-use mix entropy index</td>
<td>+</td>
</tr>
<tr>
<td>Pop. Density</td>
<td>Population density</td>
<td>+</td>
</tr>
</tbody>
</table>

Note: HH structure is converted to five dummy variables: sole person, couple no children, couple with children, one parent and other; work arrangement is converted into five dummy variables: fixed hours, flexible hours, rostered shifts, work from home and other; sex and driver licence are defined as binary variables.

Table 9.5 describes the basic statistics of the data. As the table shows, the average age of the respondents is about 37 and females and males are almost equally distributed. The average number of residents in households is 3.
Table 9.5 Descriptive statistics of variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>36.76</td>
<td>19.06</td>
<td>0.00</td>
<td>90.00</td>
</tr>
<tr>
<td>Sex</td>
<td>1.52</td>
<td>0.50</td>
<td>1.00</td>
<td>2.00</td>
</tr>
<tr>
<td>Licence</td>
<td>1.29</td>
<td>0.45</td>
<td>1.00</td>
<td>2.00</td>
</tr>
<tr>
<td>HH Size</td>
<td>3.01</td>
<td>1.41</td>
<td>1.00</td>
<td>9.00</td>
</tr>
<tr>
<td>Work Arrangement</td>
<td>2.86</td>
<td>1.78</td>
<td>1.00</td>
<td>5.00</td>
</tr>
<tr>
<td>HH Structure</td>
<td>2.80</td>
<td>1.13</td>
<td>1.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Car No.</td>
<td>1.77</td>
<td>0.84</td>
<td>1.00</td>
<td>4.00</td>
</tr>
<tr>
<td>LUMIX</td>
<td>2.50</td>
<td>1.12</td>
<td>1.00</td>
<td>4.00</td>
</tr>
<tr>
<td>CON</td>
<td>2.00</td>
<td>1.26</td>
<td>1.00</td>
<td>4.00</td>
</tr>
<tr>
<td>RDW</td>
<td>1.47</td>
<td>0.61</td>
<td>1.00</td>
<td>3.00</td>
</tr>
<tr>
<td>DNSY</td>
<td>3.57</td>
<td>1.25</td>
<td>1.00</td>
<td>5.00</td>
</tr>
<tr>
<td>ALM</td>
<td>2.90</td>
<td>1.12</td>
<td>1.00</td>
<td>4.00</td>
</tr>
</tbody>
</table>

Table 9.6 presents the outcomes of the NBR models. The non-zero dispersion value indicates that the NBR model is a more appropriate model for the data than the Poisson regression model. As explained in the previous section, M1 includes all the explanatory variables, M2 includes socioeconomic factors along with the design and land-use measures from the built environmental features, and M3 includes the socioeconomic variables with the design and access measures. The results indicate that there is a significant association between land-use and access measures with active trips. The Incident Rate Ratio (IRR) of LUMIX denotes that for a one-unit increase in LUMIX the active trips increase by about 12%. This value is 10% and 26% for DNSY and ALM. Regarding the socioeconomic factors, the results show that age, number of cars, living as a sole person and being a single parent are negatively associated with active trips.
Table 9.6 Outputs of the NBR models for Active Trips

<table>
<thead>
<tr>
<th>Parameter</th>
<th>M1 Estimate</th>
<th>M1 IRR</th>
<th>M2 Estimate</th>
<th>M2 IRR</th>
<th>M3 Estimate</th>
<th>M3 IRR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.024**</td>
<td>2.1395**</td>
<td>2.4982**</td>
<td>0.9989</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>-0.0004</td>
<td>0.9996</td>
<td>-0.0011**</td>
<td>0.9989</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender (Male)</td>
<td>-0.0133</td>
<td>0.9867</td>
<td>0.0207**</td>
<td>0.9795</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Licence (Yes)</td>
<td>0.0361**</td>
<td>1.0368</td>
<td>0.047**</td>
<td>1.0481</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Car No.</td>
<td>-0.0548**</td>
<td>0.9467</td>
<td>-0.074**</td>
<td>0.9284</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment Type</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed Hours</td>
<td>0.0341**</td>
<td>1.0347</td>
<td>0.0605**</td>
<td>1.0624</td>
<td>0.05**</td>
<td>1.0512</td>
</tr>
<tr>
<td>Flexible Hours</td>
<td>0.0352**</td>
<td>1.0358</td>
<td>0.0899**</td>
<td>1.0941</td>
<td>0.0488**</td>
<td>1.05</td>
</tr>
<tr>
<td>Rostered Shifts</td>
<td>0.0512**</td>
<td>1.0525</td>
<td>0.0616**</td>
<td>1.0636</td>
<td>0.0594**</td>
<td>1.0612</td>
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<tr>
<td>Work from Home</td>
<td>0.0803**</td>
<td>1.0836</td>
<td>0.14**</td>
<td>1.1503</td>
<td>0.0876**</td>
<td>1.0916</td>
</tr>
<tr>
<td>HH Size</td>
<td>0.0276**</td>
<td>1.028</td>
<td>0.0383**</td>
<td>1.039</td>
<td>0.0182**</td>
<td>1.0184</td>
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<td>HH Structure</td>
<td></td>
<td></td>
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<tr>
<td>Sole Person</td>
<td>-0.0676**</td>
<td>0.9346</td>
<td>-0.0635**</td>
<td>0.9384</td>
<td>-0.1019**</td>
<td>0.9031</td>
</tr>
<tr>
<td>Couple no Children</td>
<td>0.0381**</td>
<td>1.0388</td>
<td>0.0145</td>
<td>1.0146</td>
<td>0.0227</td>
<td>1.023</td>
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<tr>
<td>Couple with Children</td>
<td>0.0295</td>
<td>1.03</td>
<td>-0.0125</td>
<td>0.9876</td>
<td>0.0097</td>
<td>1.0097</td>
</tr>
<tr>
<td>Single Parent</td>
<td>-0.105**</td>
<td>0.9003</td>
<td>-0.188**</td>
<td>0.8287</td>
<td>-0.144**</td>
<td>0.8659</td>
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<td>Design Measures</td>
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<tr>
<td>CON</td>
<td>0.0138**</td>
<td>1.0139</td>
<td>0.017**</td>
<td>1.0171</td>
<td>0.0275**</td>
<td>1.0279</td>
</tr>
<tr>
<td>RDW</td>
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<td>0.9128</td>
<td>-0.0638**</td>
<td>0.9382</td>
<td>-0.0666**</td>
<td>0.9356</td>
</tr>
<tr>
<td>Land use Measures</td>
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<tr>
<td>LUMIX</td>
<td>0.1185**</td>
<td>1.1258</td>
<td>0.1956**</td>
<td>1.2160</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>DNSY</td>
<td>0.0991**</td>
<td>1.1042</td>
<td>0.2003**</td>
<td>1.2217</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Access Measure</td>
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<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ALM</td>
<td>0.2381**</td>
<td>1.2689</td>
<td>-</td>
<td>-</td>
<td>0.3111**</td>
<td>1.3649</td>
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<tr>
<td>Dispersion</td>
<td>0.4179</td>
<td>0.4600</td>
<td>0.4350</td>
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</tbody>
</table>

Notes: (1) number of active trips is defined as a dependent variable.  
(2) The NBR dispersion parameter was estimated by maximum likelihood.  
(3) Significance codes: 0.01 "**".

Table 9.7 presents the goodness of fit criteria for the three models. Deviance has an approximate chi-square distribution with \( n-p \) degrees of freedom, where \( n \) is the number of observations and \( p \) is the number of predictor variables (including the intercept). The expected value of a chi-square random variable is equal to the degrees of freedom. The ratio of the Deviance to DF, Value/DF, about one signifies that our three models fit the data well. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are measures of relative quality of the statistical models for a given set of data (Boisbunon et al., 2014; Hu, 2007; Aho et al., 2014). Table 9.7 shows that M1 with the smallest value is the best model and M3 is positioned in second place.
Table 9.7 Criteria for Assessing Goodness of Fit

<table>
<thead>
<tr>
<th>Models</th>
<th>AIC</th>
<th>BIC</th>
<th>Deviance (Value/DF)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>134044.65</td>
<td>134198.49</td>
<td>1.07</td>
</tr>
<tr>
<td>M2</td>
<td>135558.68</td>
<td>135704.82</td>
<td>1.08</td>
</tr>
<tr>
<td>M3</td>
<td>134641.76</td>
<td>134780.21</td>
<td>1.06</td>
</tr>
</tbody>
</table>

9.4 Discussions

The aim of this study was to investigate the impacts of non-motorized accessibility on active transportation. For this purpose, three accessibility measures, the WAI, CAI and PTAI, were used in cluster analyses to obtain an access level measure for the Melbourne metropolitan region in Australia. Seven clustering methods were adopted from hierarchical and non-hierarchical cluster analysis methods. From the cluster analyses, seven access level measures were obtained, from which two-step cluster analysis was selected as the most accurate method using non-parametric correlation analysis.

Subsequently, the access level measure, along with land-use and design measures, was employed in three NBR models to explore the importance of including the accessibility measure in modelling active trips. Model M1 was run with all three categories of built environment variables, while in model M2 only land use measures were included and in model M3 land use measures were replaced by the access measure (ALM). The results of the three models indicate that both land-use measures and accessibility measures had statistically significant impacts on active trips.

The IRRs estimated in model M1 indicate that for a one-unit increase in ALM there is a 24% increase in active trips, while for a one-unit increase in LUMIX and DNSY, active trips increase by 12% and 10%, respectively. In model M2, which excludes the accessibility measure, the IRRs for the LUMIX and DNSY show that for a one-unit increase in these variables, active trips increase by about 19% and 20%, respectively. However, this amount is about a 36% increase in active trips for one-unit increase in ALM.

To assess the goodness-of-fit for the three models, two model selection measures, AIC and BIC, were used. As presented in Table 9.7, model M1 with the lowest AIC and BIC ($AIC_{M1} = 134044$, $BIC_{M1} = 134198$) was selected as the best fitting model for the data and model M3 with the second smallest values for AIC and BIC ($AIC_{M3} = 134641$, $BIC_{M3} = 134780$) showed a better fit for the data than M2. As explained previously, M1 and M3 are two models that include ALM. Hence, based on the VISTA data set, the results of the models show that predicting active transport demand can be enhanced by incorporating an accessibility measure as well as land-use measures.

Overall, the study contributes to the literature by providing evidence of the importance of considering accessibility as an explanatory variable in transportation demand modelling. The access measure...
defined in this study was obtained from the access measures of non-motorised modes of transport, including walking and cycling as well as public transport. Hence, the access levels defined for the Melbourne metropolitan area cover the concept of accessibility in terms of the availability of activities for non-motorised means of transportation. Using this approach, planners and policy makers can compare and rank already built areas, and identify new areas where investment might improve walking and cycling accessibility. The way urban areas are configured can influence pedestrian behaviour, because it can make the built environment more attractive, safer and more accessible. This is achievable by bringing together shops and services and recreation centres (Peiravian et al., 2014).

In order to promote active trips, accessibility should be considered as an important planning variable which can aid planners in deciding the location of settlements, and the maximum distances to facilities and services should be considered (Rahul and Verma, 2014). The main difference between walking and cycling and other modes of transport is that they require physical effort for their usage. Due to that effort, these modes are used mainly for short-distance trips. In this regard, accessibility in terms of the availability of services and facilities within acceptable walking and cycling distances gives an indication of this physical effort. In addition, walkable and cycleable communities and active living life styles are related to the concept of sustainability. As Lamiquiz and López-Domínguez (2015) argue, accessibility is relevant to pedestrian needs, because it makes the built environment more attractive, safer and closer, by influencing and bringing together the locations of facilities.

9.5 Conclusions and Future Directions

The literature commonly reports that built environment features such as density, diversity, and road connectivity promote active trips. This study hypothesised that accessibility measures have an impact on the level of walking and cycling trips. The results of the analysis reveal that accessibility levels have a statistically significant impact on active trips.

In summary, there is currently a significant gap between advances in scientific knowledge on accessibility and its application in planning practice (Bertolini et al., 2005). In comparison with the limited previous work on accessibility-based analyses, the analysis presented here is distinctive because it incorporates the impacts of both land-use and accessibility on active transportation.

However, the current study considered land-use diversity and population density as land-use measures, and connectivity and roadway measure as design measures. However, other factors, such as residential density, employment density, street density, street type, walking and cycling infrastructural elements (e.g. sidewalks, lighting, etc.) may also affect active travel (Etminani-Ghasrodasht and Ardeshiri, 2016; Etminani-Ghasrodasht and Ardeshiri, 2015; Aziz et al., 2017; Ramezani et al., 2017). Furthermore, in defining the access measure, this study adopted non-model-based clustering methods, while the use of model-based clustering analysis may enhance the accuracy of the results.
Hence, future studies may take these features into account to achieve more defendable results.

9.6 References


KRIZEK, K. J. 2005. Perspectives on accessibility and travel.


CHAPTER 10

CONTRIBUTIONS, CONCLUSIONS AND FUTURE RESEARCH
DIRECTIONS
Chapter 10: Contributions, Conclusions and Future Research Directions

10.1 Contributions

The literature commonly reports that built environment features such as density, diversity of land use, and road connectivity can promote active transportation. This study confirms the hypothesis that accessibility affects the level of walking and cycling trips, and proposes and applies new methods for measuring accessibility. The results of the analysis revealed that people are more likely to walk and cycle when their desired destination is located within distance thresholds.

A major methodological challenge when working with accessibility measures in land use and transport planning is to find a measure that is both theoretically and empirically complete and sufficiently simple enough to be implemented in practice. The accessibility measures developed in this study are simple and straightforward approaches that can be applied with different databases and at different geographical scales. Furthermore, they are sufficiently comprehensive to be used in transport modelling. In addition, the introduced measures are updatable. In other words, three accessibility measures used in this study have been built using spatial data bases such as land uses and street networks. Therefore, by any changes occur in land uses or network; the measurements can be easily updated.

In summary, there is a significant gap between advances in scientific knowledge of accessibility and its application in planning practice. In comparison with the limited previous work on accessibility-based analyses, the analysis presented here is distinctive because it incorporates the impacts of both land-use and accessibility on active transportation. The measurements described in this study are capable of being used by urban and transport planners as well as policy makers for any proposed land-use development. Apart from the ease of understanding of accessibility measurements, one of the greatest strengths of these measures is that they reflect the land-use features in terms of diversity and intensity of activities.

In urban and transport planning, much effort is currently being devoted to the provision of safe and friendly environments that encourage walking in cities. Using the approaches presented in this study, planners and policy makers can compare and rank areas already developed, and identify new areas where investment might improve walking and cycling accessibility. The way urban areas are configured can influence pedestrian behaviour, because it can make the built environment more attractive, safer and more accessible, by bringing together shops and services and recreation centres. Furthermore, an awareness of walking and cycling levels in existing neighbourhoods as well as developing areas may affect people’s selection of living areas. Therefore, the methods presented in
this thesis can be used to achieve more and better insights into the location of different activities in proposed plans for underdeveloped and developing areas. Measuring the friendliness of neighbourhoods can be a policy tool for promoting more walking and cycling. This is important and requires more research to be undertaken. This study provides a starting point for such a task.

10.2 Conclusions

This study presents three accessibility indexes developed for the Melbourne metropolitan area. These indices measure public transport, walking and cycling accessibility for 9,510 Melbourne SA1s. The PTAI, which is extended from two common existing approaches, was applied for statistical areas and mapped to improve the visual understanding of access levels within the Melbourne region. The PTAI was also compared with the PTAL and the SI, the most common approaches to the measurement of public transport accessibility. Statistical analyses indicated that the PTAI had the highest correlation with the number of public transport trips compared to the PTAL and the SI. All three indices were also employed in separate regression models to investigate how the proposed index performs in transport modelling. Based on the model selection criteria (AIC), the PTAI was a better fit of the data and the model in which the PTAI was included as an explanatory variable performed better than the models including the PTAL or the SI. The techniques presented are straightforward to apply, and provide better and more accurate measurements of accessibility based on the VISTA (2009) dataset. The quantitative approaches developed can be employed for any number of public modes in other cities around the world. They are designed to be applied with available census and transport modelling tools. Furthermore, the analysis provides reliable and defendable results that enable the accessibility for about 99% of the SA1s to be calculated. However, the methods can be enhanced by greater detail to achieve even more accurate results.

The CAI was developed as a new approach to measuring cycling accessibility within Melbourne SA1s. This index is based on the gravity model and considers travel impedance as well as cycling catchments. The CAI was assessed using real travel data and included in regression models to examine its importance as an explanatory variable. In this study, due to the availability of data, travel distances were calculated based only on segment length, and consideration of the other factors could enhance the accuracy of the results. In developing the cycling measure of accessibility, a balance between practical considerations and theoretical rigour has been found. The index is based on gravity-based measures and these kinds of measures are operational, and relatively easy to interpret and communicate.

This study also introduced a new approach for measuring walking accessibility within the Melbourne region. The WAI was computed based on the walking distance thresholds. The WAI was assessed and compared to a common walkability index using statistical analyses. The results indicated that the WAI
performed better than the existing approach.

All three indices were combined to produce an access level measure for the Melbourne region using cluster analysis. The Melbourne region was also mapped based on the access levels from poor to excellent levels of accessibility. The access level measure was then used in regression models versus land-use measures to examine the importance of including the accessibility measurement in transport modelling. The findings indicated that the models which included the access measure provided a better fit for the data than those including land-use measures.

The methods developed in this study can be used to compare neighbourhoods within the same study area in terms of their access to public transport, walkability and cycleability. Using these approaches, planners and policy makers can compare and rank areas already built, and identify new areas where investment might improve walking accessibility.

10.3 Future Research Directions

The approaches developed in this study for computing accessibility are simple and easy to apply. Furthermore, their application is not restricted to Melbourne, but can be implemented for any other cities or metropolitan region all around the world. They are based on spatial/land-use data using network analyses. The application of these indices will enable planners and policy makers to have a clearer understanding of the level of accessibility of developed as well as newly-planned areas. They will also enable the level of active transportation in existing and newly-built areas to be estimated.

However, the inclusion of more details in calculating the indices may enhance their accuracy. For instance, information regarding bicycle lanes is limited and infrastructure elements such as the width, pavement, and quality of the lanes was not considered in computing the CAI or the WAI. Therefore, future studies should include these elements.

With respect to the PTAI, this study has not focused on off-peak periods which tend to have lower public transport service frequencies and public transport users encounter lower levels of service and consequently lower mobility. In addition, in the calculation of the average waiting times it was assumed passengers arrive at stops/stations randomly. Future studies may consider these points when measuring accessibility. Besides, public transport crowding might be an important factor reducing accessibility which not considered in this research. This study has not also focused on differences in perceived accessibility by different population groups.

On the other hand, in defining the access measure, this study adopted a non-model-based clustering method and the use of model-based clustering analysis may have affected the results. Hence, future work may take these features into account to achieve more defendable results.
Overall, although all measurements presented in this study can be updated by changes in land-uses, big developments in transport networks such as shared transport, autonomous driving etc. may impact accessibility perceptions. Therefore, future studies may consider these points.