A Section 508–conformant HTML version of this article is available at https://doi.org/10.1289/EHP3395.

Daily Walking among Commuters: A Cross-Sectional Study of Associations with Residential, Work, and Regional Accessibility in Melbourne, Australia (2012–2014)

Alison Barr,[1] Koen Simons,[1] Suzanne Mavoa,[1] Hannah Badland,[2] Billie Giles-Corti,[2] Jan Scheurer,[2] Elizabeth Korevaar,[1] Josh Stewart,[3] and Rebecca Bentley[1]

[1]Melbourne School of Population and Global Health, University of Melbourne, Melbourne, Victoria, Australia
[2]Centre for Urban Research, Royal Melbourne Institute of Technology, Melbourne, Victoria, Australia
[3]Department of Economic Development, Jobs, Transport and Resources, State Government of Victoria, Melbourne, Victoria, Australia

BACKGROUND: Most research on walking for transport has focused on the walkability of residential neighborhoods, overlooking the contribution of places of work/study and the ease with which destinations outside the immediate neighborhood can be accessed, referred to as regional accessibility.

OBJECTIVES: We aimed to examine if local accessibility/walkability around place of work/study and regional accessibility are independently and interactively associated with walking.

METHODS: A sample of 4,913 adult commuters was derived from a household travel survey in Melbourne, Australia (2012–2014). Local accessibility was measured as the availability of destinations within an 800-m pedestrian network from homes and places of work/education using a local living index [LLI; 0–3 (low), 4–6, 7–9, and 10–12 (high) destinations]. Regional accessibility was estimated using employment opportunity, commute travel time by mode, and public transport accessibility. Every individual's potential minutes of walking for each level of exposure (observed and counter to fact) were predicted using multivariable regression models including confounders and interaction terms. For each contrast of exposure levels of interest, the corresponding within-individual differences in predicted walking were averaged across individuals to estimate marginal effects.

RESULTS: High LLI at home and work/education was associated with more minutes walking than low LLI by 3.9 [95% confidence interval (CI): 2.3, 5.5] and 8.3 (95% CI: 7.3, 9.3) min, respectively, in mutually adjusted models. Across regional accessibility measures, an independent association with walking and an interactive association with LLI at work/education was observed. To take one example, the regional accessibility measure of "Jobs within 30 min by public transport" was associated with 4.3 (95% CI: 2.9, 5.7) more mins walking for high ($\geq$30,000 jobs) compared with low ($<$4,000 jobs) accessibility in adjusted models. The estimated difference for high vs. low LLI (work/education) (among those with low regional accessibility) was 3.6 min (95% CI: 2.3, 4.8), while the difference for high vs. low regional accessibility (among those with low LLI) was negligible (-0.01; 95% CI: -1.2, 1.2). However, the combined effect estimate for high LLI and high regional accessibility, compared with low on both, was 12.8 min (95% CI: 11.1, 14.5), or 9.3 (95% CI: 6.7, 11.8) min/d walking more than expected based on the separate effect estimates.

CONCLUSIONS: High local living (work/education) and regional accessibility, regardless of the regional accessibility measure used, are positively associated with physical activity. High exposure to both is associated with greater benefit than exposure to one or the other alone. https://doi.org/10.1289/EHP3395

Introduction

A large body of public health research has investigated the relationship between local accessibility—the ease of accessing local destinations or the relative walkability of neighborhoods—and walking. The spatial extent of the local neighborhood has commonly been operationalized as a 400-m or 800-m distance from an origin (Giles-Corti et al. 2016). There is a wealth of evidence showing that greater local walkability and accessibility of neighborhood destinations are associated with increased active travel (i.e., walking and cycling for transport purposes), walking, and physical activity (Badland and Schofield 2005; Bauman and Bull 2007; Ewing and Cervero 2001, 2010; Owen et al. 2004; Saelens et al. 2003; Saelens and Handy 2008; Sugiyama et al. 2012; Witten et al. 2012). However, this research has predominantly focused on one spatial domain: the residential environment around people's homes.

Address correspondence to Associate Professor Rebecca Bentley, Centre for Health Equity, Melbourne School of Population and Global Health, Room 355 (Level 3), 207 Bouverie St., University of Melbourne, Victoria 3010, Australia. Telephone: 8344 0639. Email: Brj@unimelb.edu.au

Supplemental Material is available online (https://doi.org/10.1289/EHP3395).

The authors declare they have no actual or potential competing financial interests.

Received 23 January 2018; Revised 19 August 2019; Accepted 22 August 2019; Published 18 September 2019.

Note to readers with disabilities: *EHP* strives to ensure that all journal content is accessible to all readers. However, some figures and Supplemental Material published in *EHP* articles may not conform to 508 standards due to the complexity of the information being presented. If you need assistance accessing journal content, please contact ehponline@niehs.nih.gov. Our staff will work with you to assess and meet your accessibility needs within 3 working days.

The concentration of research effort on the residential environment, in isolation from other spaces in which people spend their lives, creates potential for "residential effect fallacy" (Chaix et al. 2017). Residential neighborhood–outcome associations may overestimate the effects that interventions have on health due to confounding effects from time spent in other important spatial domains (Chaix et al. 2017), particularly secondary activity spaces such as neighborhoods around school or work. People are in a range of different places throughout their day, and for some, notably workers, only a small number of their waking hours may be spent in their residential neighborhood. Studies have shown that around 30–60% of walking and physical activity takes place outside the home neighborhood (Giles-Corti et al. 2008; Hillsdon et al. 2015; Hurvitz et al. 2014; Troped et al. 2010), and local neighborhood infrastructure at both home origin and other destinations appears important for facilitating active travel opportunities, as our work (Badland et al. 2014) and others (Ewing and Cervero 2010; van Heeswijck et al. 2015) have shown. The comparatively few studies examining the walkability of local work environments and other secondary activity spaces have found positive associations between characteristics of the built environment (including population density, the accessibility of destinations, and street connectivity) and walking, active commuting, transport-related physical activity, and cardiorespiratory fitness (Barrington et al. 2015; Frank et al. 2008; Hoehner et al. 2013; Howell et al. 2017; Lachapelle and Frank 2009; Troped et al. 2010; Yang et al. 2015).

In addition to the gap in research evidence on local accessibility around work environments, little attention has been given to understanding associations between regional accessibility and walking. Regional accessibility relates to the ease with which destinations outside the immediate neighborhood, or across wider areas of the metropolis, can be accessed (Giles-Corti et al. 2016). Regional accessibility has been defined as a site's "location relative to the regional urban centre ... or the number of jobs and public services available within a given travel distance or time" (Litman 2017). As this definition suggests, the purpose of regional travel is often the commute between the primary and secondary activity spaces of home and work or education. If undertaken as part of a commute, regional travel may be more likely than local travel to be nondiscretionary, habitual, and fixed in time (Lovelace et al. 2014), and these characteristics may increase the potential for routine physical activity through regular walking.

Greater distances involved in regional travel may require motorized transport and preclude travel solely by walking or cycling. Accessing regional destinations by public transport may provide more opportunity for walking than using a car. Indeed, those who use public transport walk more than private transport users (Rissel et al. 2012; Sener et al. 2016), with most estimates in the range of an additional 12–15 min more walking per day (Rissel et al. 2012). Higher levels of walking are directly associated with accessing and egressing public transport (Saelens et al. 2014); however, public transport users may also walk more around their workplace (Lachapelle et al. 2011). Public transport effectively separates users from their vehicle at origin, delivering them as pedestrians at their destination, which in turn requires them to walk between other intermittent destinations throughout the day (e.g., out to lunch).

Regional accessibility indicators associated with mode choice, active travel, walking, or meeting physical activity recommendations include commute distance (Hoehner et al. 2012; Targa and Clifton 2005; Yang et al. 2015), distance to the Central Business District (Beavis and Moodie 2014; Ewing and Cervero 2010; Næss 2005), job accessibility by automobile and transit (Ewing and Cervero 2010), and accessibility to activity centers by public transport (Frank et al. 2010), with increased accessibility being positively associated with active travel and/or physical activity outcomes.

Although there is little consensus on how best to define and measure regional accessibility, research in the fields of transport, planning, and geography has spawned a range of alternative models and measures (Lei and Church 2010; te Brömmelstroet et al. 2014), which all provide different perspectives on regional accessibility. These include:

- contour or cumulative threshold measures that identify the number of potential or possible social and economic opportunities (e.g., jobs) within service areas defined by specific travel times from an origin (e.g., home) (Niedzielski and Eric Boschmann 2014; te Brömmelstroet et al. 2014)
- comparative travel time measures that capture relative differentials in the accessibility offered by private motorized and public transport (Kwok and Yeh 2004; Salonen and Toivonen 2013; Kawabata 2009)
- network analysis measures that capture the capacity of a city's overall land use and transport system to enable reliance on noncar travel.

The importance of taking a broader view of accessibility, being one that incorporates the local accessibility around, and regional accessibility between, home, work, and education environments, is being increasingly articulated in theoretical and urban policy frameworks (Department of Environment, Land, Water and Planning 2017; Department of Infrastructure, Transport, Cities and Regional Development 2016; Giles-Corti et al. 2016). However, health research has yet to fully engage with this broader policy framework on accessibility. In particular, better definitions and measures of local and regional accessibility are needed to understand how accessibility provided by city planning and transport systems relates to active travel and walking, and how these relationships can inform policy levers.

To broaden our understanding of the relationship between accessibility afforded by land use and transport systems and walking, we explored associations between three spatial domains of accessibility (local accessibility around the home, local accessibility around the place of work or education, and regional accessibility between home and work, education, and other opportunities) and walking in a sample of Melbourne adult commuters who traveled to a place of work or education. Several measures were used to capture different elements of regional accessibility, as argued above, allowing for comparison of effect estimates across multiple measures. Finally, as it is plausible that good regional access is more important in the context of good local access, we examined the relationship between local and regional access in relation to their association with walking by testing their interaction.

Specifically, this study of adult commuters sought to address four research questions.

1. Is local accessibility around home and place of work/education associated with minutes of daily walking?
2. Is regional accessibility of employment and education opportunities (measured across a number of dimensions, including networks, comparative travel time, and cumulative opportunity thresholds/contours) associated with minutes of daily walking?
3. Are associations between accessibility in these three spatial domains (local accessibility at home and place of work/education and regional accessibility) and minutes of daily walking independent of one another?
4. Does the association between regional accessibility and minutes of daily walking vary by local accessibility around home and place of work/education?

Methods

Sample

The sample was derived from 22,934 people from 8,994 households who responded to the Victorian Integrated Survey of Travel and Activity (VISTA) in 2012 to 2014. VISTA is a household travel survey of a stratified, clustered, random sample of residents in private households in Mesh Blocks in the Greater Melbourne and Greater Geelong metropolitan areas, Victoria, Australia, as described elsewhere (Ipsos 2016). Mesh Blocks are the smallest geographical area in the Australian Bureau of Statistics Australian Statistical Geography Standard, on average containing 30 to 60 dwellings (ABS 2016). VISTA runs continuously throughout the year. Individual households are surveyed on their travel and activity patterns for one nominated travel day.

The representativeness of the sample was checked against data from the 2011 Australian Census of Population and Housing (ABS 2012a, 2012b). Descriptive analysis was conducted using the tabulate command.

VISTA records self-reported characteristics of all travel trips undertaken through the day including trip origin and location, departure time, main mode of travel, destination type and destination, arrival time, trip distance and duration, trip purpose, and accompaniment by another person. The street addresses of origins and destinations are geocoded using geographic information systems (GIS), and travel data are linked to an individual's demographic, socioeconomic, and vehicle ownership data. Survey data are validated through an iterative process of data logic and quality checks and participant callback, and missing data remediated through imputation (Ipsos 2016).

For the purposes of this research, we sought to study only commuters who were undertaking travel to a place of work or education outside of their home, as these two destinations best represented: *a*) secondary activity spaces where people would be likely to spend a significant amount of time, and *b*) regional destinations that people regularly or habitually traveled to with less discretion over their travel, compared with other regional destinations (e.g., shopping centers). This set of commuters therefore represented the sample for whom exposures for local accessibility outside the home neighborhood and regional accessibility could be most tightly defined. Accordingly, the following groups were excluded from the sample: people who did not do any travel on the survey day (primarily because we could not identify if they had a place of work or education and therefore calculate their exposures) ($n = 5,240$), children under 18 years of age ($n = 3,701$), people who did not commute to work or education ($n = 8,111$), people who commuted on a weekend day ($n = 352$), people who lived in or commuted to an area outside of the Melbourne metropolitan region and/or had missing or outlier exposure data ($n = 526$), people whose main activity was secondary education or retirement ($n = 71$), and people who commuted to a primary school for the purpose of education rather than employment ($n = 20$). The final sample consisted of 4,913 adults ≥18-y-old, 247 (5.0%) of whom commuted to tertiary education and 4,666 (95.0%) to work in the Melbourne metropolitan region.

Ethics approval was granted by the University of Melbourne (Ethics ID: 1,442,864.1). As the VISTA survey data used in this analysis were secondary data obtained from transport authorities, the research team did not need to obtain informed consent from participants.

Exposures. ArcGIS (version 10.4; ESRI) GIS software was used for all spatial analysis.

Local Accessibility Measures

For confidentiality purposes, respondents' home addresses were reassigned to a random set of coordinates within a 100-m radius from their home. Work and place of education addresses coordinates were not randomized. Local accessibility measures were calculated at 800-m street network buffers from the home address (primary activity space) and work or education address (secondary activity space), reflecting a 10-min walk in any direction.

Local accessibility was measured using a local living score (ranging from 0 to 12), which comprised the sum of the absence (scored 0) or presence (scored 1) of twelve destination types within an 800-m street network buffer. These destinations were sourced from a range of databases and were selected based on their conceptual importance for supporting the ability to live locally. They included: supermarket, convenience store, public transport stop, specialty food (butcher, greengrocer), general practitioner, pharmacy, dentist, community center, library, post office, bank/financial institution, and child care (Badland et al. 2017). As described in Mavoa et al. (2018), data about stores and other commercial destinations were obtained from a commercial database (Axiom Business Points, Pitney Bowes Ltd and Supermarkets, Pitney Bowes Ltd), and data about public transport stops, medical centers, libraries, child care facilities, and community centers were from local and Victorian government sources (including Public Transport Victoria, Victorian Health Services Directory, Public Libraries Victoria, Australian Children's Education and Quality Care Authority, VicMaps Features of Interest).

Our measure of local accessibility reflects the spatial arrangement of destinations (density and land use) and the ease by which the distance between them could be traversed (connectivity)—such an approach has been recommended by others (Lee and Moudon 2006). The local living score was categorized into two four-level local living indices (LLIs) named LLI: Home and LLI: Work/Education (1: 0–3 destinations, 2: 4–6 destinations, 3: 7–9 destinations, 4: 10–12 destinations). The local living scores (and the categorical LLIs) measure local accessibility in which local accessibility is a proxy measure for walkability. When used as a binary variable, categories 1 and 2 were combined such that 0 to 6 destinations constituted the new category 1, and category 3 and 4 were combined such that 7 to 12 destinations constituted the new category 2. When estimating contrasts (described under "Analysis" below), low local living was considered as category 1 (0 to 3 destinations), and high local living was considered as category 4 (10 to 12 destinations).

Regional Accessibility Measures

Given the rational outlined in the three regional accessibility measures that were selected for this research (Table 1), the last of which was calculated from both the home and work/education address, there was a total of four regional measures used in models:

1. Number of jobs available within 30 min by public transport: This measure used Victorian Integrated Transport Model (VITM) data to estimate the accessibility of employment from the respondent's home using public transport in a midweek morning peak period. VITM is a multimodal strategic transport planning model for the State of Victoria (Sinclair Knight Merz and AECOM 2010), which determines travel times by car and public transport between 3,098 different transport zones, the smallest areas for which data are available in the Greater Melbourne Metropolitan area. The number of jobs in zones within a 30 min public transport travel time from the respondent's home zone in the midweek morning peak period were summed to calculate a 30-min total employment travel time contour. These were divided into four categories reflecting the distribution of the measure (<4,000; 4,000–9,999; 10,000–29,999, and ≥30,000 jobs available). The 30-min travel time contour reflects the upper threshold of a desirable commute time for a smart city in current Australian policy documents (Department of Infrastructure, Transport, Cities and Regional Development 2016).
2. Commute time by car compared with public transport: Using VITM data, commute times were calculated by car and public transport between the zones in which respondents' homes and their place of work/study were located. Commute times were modeled for midweek using the VITM model time period corresponding to the departure time reported in the VISTA survey: A.M. peak (0700 to 0859 hours), interpeak (0900 to 1459 hours), P.M. peak (1500 to 1759 hours), and off-peak (1800 to 0659 hours). Public transport access and egress were modeled by the fastest mode (walk, park, and ride, or ride and park). The ratio of the travel time by car/public transport was converted into four categories (0.0–0.24, 0.25–0.49, 0.50–0.74, and ≥0.75), reflecting the relative public transport efficiency for the commute. Ratios approaching 1.00 indicate the public transport commute was comparable in time to car.
3. Spatial Network Analysis for Multimodal Urban Transport Systems Level of Public Transport Service: Home.
4. Spatial Network Analysis for Multimodal Urban Transport Systems Level of Public Transport Service: Work/Education.

The Spatial Network Analysis for Multimodal Urban Transport Systems (SNAMUTS) approach uses network analysis to measure the integral characteristics and efficiency of public transport networks. The level of service index adapted here summarizes three

Table 1. Regional accessibility measures.

Measure	Description	Type of measure	Type of accessibility	Strengths
Number of jobs within 30 min by public transport	Estimates the total number of jobs accessible from home area in a 30-min morning peak hour public transport commute	Contour	Absolute, potential, place based (home)	• Simple measure • 30-min contour reflects both average travel behavior and policy threshold • Potential accessibility measure identifying the accessibility of *possible* opportunities that the individual may need to access in future, in general, or outside of the survey day • VITM uses sophisticated algorithms to determine average travel time on public transport, including system characteristics such as congestion
Commute time by car compared with public transport	Estimates the differential in commute time by car and public transport from home to place of work or education	Relative travel time	Relative, realized, individual	• Simple measure • Captures the relative dimension of accessibility (i.e., travel time by car and public transport over the same absolute distance) • Assesses the "modal accessibility gap" (Kwok and Yeh 2004) for the commute • Captures the individual's ability to reach an essential destination • Uses sophisticated algorithms to determine average travel time on public transport and car, including transport system characteristics such as congestion
Level of Public Transport Service Indicator: Home Level of Public Transport Service Indicator: Work/ Education	Analyses integral characteristics of public transport networks to determine their levels of service and the regional accessibility they provide	Network analysis	Integral, potential, place based (home and work)	• Complex accessibility measure • Measures integral access to the entire public transport system using network analysis • Takes into account both spatial/structural characteristics of the network, such as the connectedness of the system, and temporal/functional dimension, such as travel times between modes • Measures accessibility from both origin (home) and commute destination (place of work/education)

Note: VITM, Victorian Integrated Transport Model.

SNAMUTS indicators: network coverage describing whether or not the Mesh Block of the home or place of work/education is within walking distance of a public transport service meeting a minimum standard (as detailed below), closeness/contour catchment as a proxy for the combined effect of public transport speed, service frequency, and land use intensity, and nodal connectivity indicating the capacity of activity nodes to be a hub for the network [for more detail on each indicator, see Curtis and Scheurer (2016)]. Each of these characteristics are given a score of 1 if the Mesh Block meets an acceptability threshold, with a maximum score of 3. Mesh Blocks without a stop with a minimum service frequency ($\leq$20 mins during weekday interpeak and $\leq$30 mins on weekends for bus and tram, and $\leq$30 min for rail) within walking distance (400 m for bus/tram, 800 m for train/ferry) from the centroid were used as a reference category. This index measures the potential and integral accessibility offered by the public transport system to all the land uses within the metropolitan region accessible by public transport from the vantage point of the Mesh Block of the individuals' home and place of work/education (Figure 1). This differentiation is critical, as the endowment of residential and employment areas with public transport varies greatly in Metropolitan Melbourne. For example, in 2014 in Melbourne, only 40% of residents but nearly 70% of jobs were located within walking distance of public transport using the minimum standards detailed above (Scheurer and Curtis 2015). Commuters' motivations for mode choice are thus subject to separate accessibility-related influences at home and work/education locations. Due to small numbers of people with high accessibility, the top two categories of this index were collapsed such that three categories remained, 0 (reference), 1, and >2, and the index renamed as the Level of Public Transport Service: Home and Work/Education to delineate it from the original and prevent confusion with the local accessibility measure, which was also based on home and work/education locations.

For ease of interpretation, measures were derived so that accessibility increases with increases in the measure.

Covariates

As well as being related to urban spatial structure and form, walking and travel behavior have been associated with a range of individual socioeconomic characteristics (e.g., age, sex, ethnicity, driver licensing) and household-level characteristics (e.g., household income, family structure, vehicle ownership) (Heinen and Chatterjee 2015; Plaut 2005; Targa and Clifton 2005). Covariates were selected by means of their probable association with both the exposures and outcomes as identified in existing literature and derived from VISTA survey data. Individual-level covariates included sex (male or female), age (18–24, 25–44, and $\geq$45 y), occupational skill level (high, medium, low, not in work/not a student), driver's license status (yes or no), and street network distance of the journey to work or education (in kilometers) measured continuously. Household-level characteristics included household income in Australian dollars (0–799; 800–1,249; 1,250–1999; 2,000–2,999; and $\geq$3,000) and vehicle availability (one car, two cars, or more). Area-level covariates consisted of the Index of Relative Socio-economic Disadvantage score (categorized into quintiles), a measure of area-level disadvantage in the individual's neighborhood (ABS 2013). The Statistical Area 1 (SA1) geographic unit was used as the neighborhood proxy and has $\sim$400 persons/area (ABS 2016).

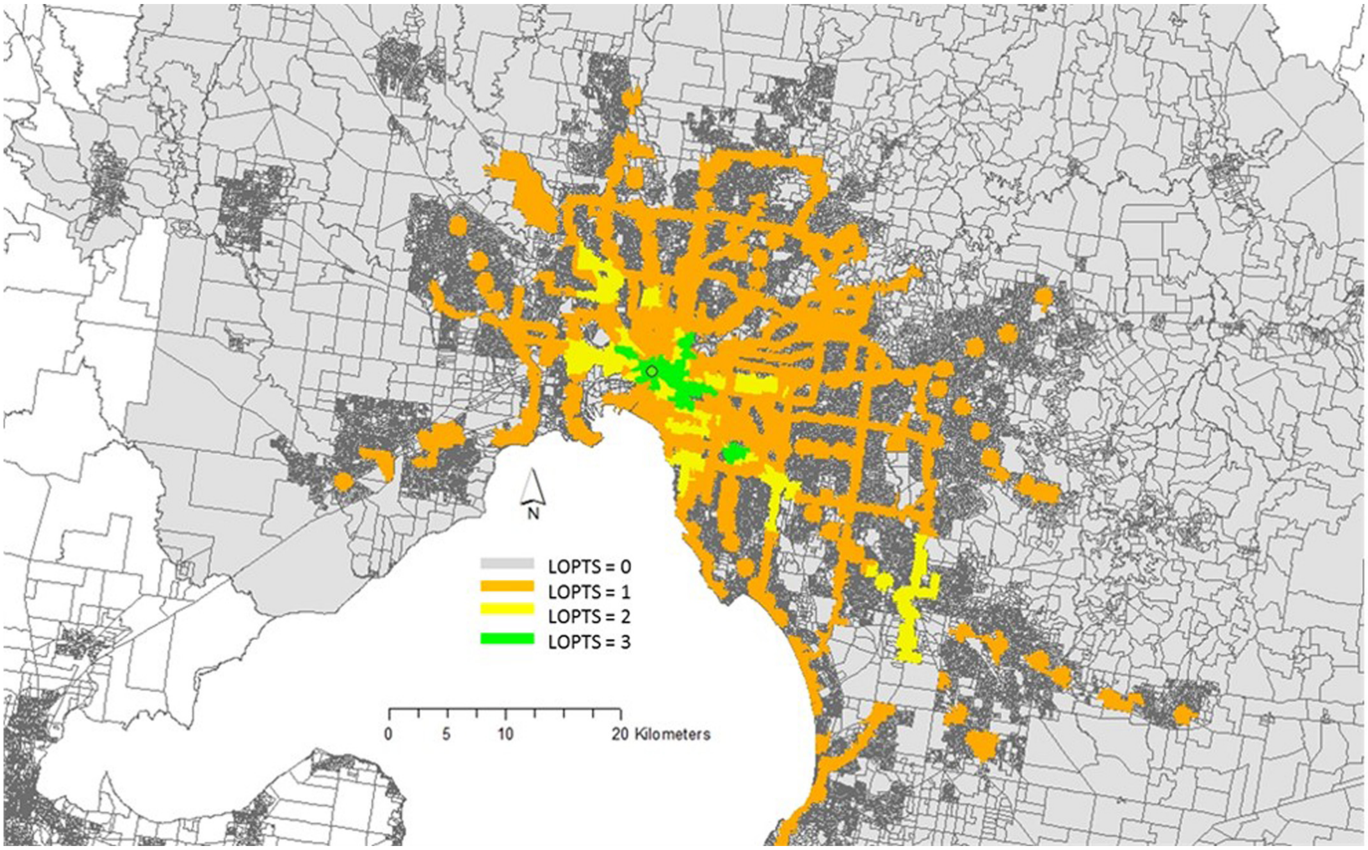

Figure 1. Distribution of the Spatial Network Analysis for Multimodal Urban Transport Systems (SNAMUTS) Level of Public Transport Service Indicator across Mesh Blocks in the Metropolitan Melbourne Area, 2011. Gray shaded areas are Mesh Blocks in Metropolitan Melbourne in 2011 that have no minimum level of public transport service. (Darker grey areas display Mesh Blocks in areas of higher population density that are therefore smaller in area and clustered, making them appear darker in color). The orange, yellow, and green shaded areas represent the distribution of Mesh Blocks in Metropolitan Melbourne in 2011 that have a Level of Public Transport Service Indicator (LOPTS) score of 1, 2, and 3, respectively. Due to low numbers of participants with a LOPTS of 3, the top two levels of this index (LOPTS 2 and 3) were collapsed for regression analysis. LOPTS categories 2 and 3 were combined and treated as the highest category in analyses. The comparison group was LOPTS 0.

Outcomes

The duration of all trip legs by walking, including incidental walking associated with car trips, were summed to derive a continuous variable of minutes walked throughout the day.

We chose to use total walking throughout the day as the basis of the outcome measure, rather than commute-only walking, which is only one aspect of walking that is associated with high local accessibility at home and work and high regional accessibility by public transport. For example, we might expect that commuters who live and work in more walkable environments accumulate more daily walking outside of the work commute. Similarly, commuters who respond to high regional accessibility of public transport by using public transport may walk more than just the walking legs to access and egress public transport, as argued above. Therefore, it was essential to capture differences in walking across the day associated with the accessibility exposures, not only the commute.

Analysis

Stata (version 14.2; StataCorp) was used for descriptive and statistical analysis.

The association of local and regional accessibility with walking was investigated using linear regression (regress command in Stata) with robust standard errors. Regression models were estimated in Stata and adjusted for covariates thought to be confounders of the relationship under consideration (as above). Models were adjusted for clustering at the SA1 level. We did not cluster by household because on average, there were only 1.4 people per household in the analytic sample. Complete case analysis was undertaken.

Visual inspection of residuals for the normality of their distribution [using Quantile Quantile (QQ) plots] was used to screen a range of potential transformations of our outcome, minutes walking, including (overdispersed) Poisson, negative binomial and lognormal, and a range of Box-Cox transformations [linear, loglinear, square root (power 1/2), cube root (power 1/3), power 1/2.1, power 1/2.2, etc.)]. On this basis, we transformed minutes of walking by a power of 1/2.6 (through a manual application of the Box-Cox transformation procedure). The residuals obtained provided the lowest deviation from the normal distribution. Diagnostics of the model fit in the form of a QQ plot are provided in Figure S1. We bootstrapped the models 10,000 times to protect against model misspecification.

Three sets of models were estimated. First, local and regional accessibility measures were entered separately into models and adjusted for individual-, household- and, area-level covariates thought to be potential confounders as described above, and for clustering at the SA1 level. Second, models were mutually adjusted for local accessibility at home and work/education location and then one of each of the regional measures, again adjusted for covariates and clustering. For the regional accessibility measures, each was adjusted for local living at home and work/education in a single model. We did not adjust the regional accessibility measures for each other, given their conceptual overlap. The third set of models included interaction terms between each regional accessibility measure and one of either LLI at home or work/education. We fitted models with interaction terms treating the exposure variables as continuous, nominal, and binary variables to assess the sensitivity of the models (see Table S1). Results presented in the main tables are from models where regional and local measures were treated continuously, generating two main effect terms and one interaction term.

With models including interaction terms and using a transformed outcome, we were able to predict each individual's outcome for any (combination) of the two local living and four regional accessibility exposures, assuming our models had achieved exchangeability or an absence of confounding. To estimate the average marginal effect, we averaged the counterfactual minutes of walking from models adjusted for covariates for the highest and lowest level of exposure ("contrasts") for each measure (for both local and regional levels) and calculated the differences. Confidence intervals (CIs) were obtained from 5,000 bootstrap replications of the full procedure (estimate model, predict counterfactuals). This is also known as g-computation (Snowden et al. 2011).

To describe interactions using this approach, the first contrast estimated was the mean walking time for the highest accessibility in both local living at home and regional levels compared with the mean walking time for the lowest accessibility in both home and regional levels. The second was between the mean walking time for the highest accessibility home and lowest regional compared with the mean walking time for the highest accessibility in home and the highest in regional levels. The third was between the mean walking time for the lowest home accessibility and the highest regional compared with the mean walking time for the lowest home accessibility and the lowest regional. These three contrasts were generated similarly for local work/education and regional accessibility interactions. The selected contrasts indicate the estimated effect of high local home or work/education and regional accessibility on walking time, as well as how the estimated effect of regional accessibility changes for those in high home and work/education local accessibility compared with low home and work/education local accessibility.

To describe the heterogeneity, we report the absolute minutes walked for key comparison groups. To describe and explore the nature of the potential effect of an interaction between local living and regional accessibility on walking, we report the difference in minutes walked between a reference category of low exposure to both measures and: *a*) high exposure at regional, low exposure at local living; *b*) low exposure at regional, high exposure at local living; and *c*) high exposure at both regional and local living. In addition, we calculated the relative excess risk due to interaction (RERI), which estimates any additional minutes greater than the independent effect of exposure to either high regional or high local living.

Results

The VISTA commuter sample had a similar distribution of age and sex to commuters in Greater Melbourne, with more males than female commuters and the highest proportion of commuters between 25 and 44 years of age (Table 2). Commuters in this sample were employed in more highly skilled occupations compared with the broader VISTA sample and commuters in Greater Melbourne. Compared with households in Greater Melbourne, a larger proportion of the VISTA commuters' households were in higher household income categories and had two or more cars.

The distribution of local exposures by covariates and outcome in the sample of commuters is available in Table S2. Proportionately more commuters with high LLIs (or walkability) (10 or more destination types within an 800-m walk) at home included younger people (59% in the 25- to 44-y age group compared with 41% of those with low accessibility with 0–3 destinations), people in high-skill occupations, (59% compared with 44% of those with low accessibility) and those without a driver's license (7% compared with 2% of those with low accessibility). A lower proportion of commuters with high LLIs at home had two or more vehicles in the household (46% compared with 84% of those with low accessibility).

Proportionately more commuters with high LLIs at work/education (10 or more destination types within an 800-m walk) included females (51% compared with 35% of those with low accessibility) and people in high-skill occupations (50% compared with 40% of those with low accessibility). A lower proportion of commuters with high LLIs at work had two or more vehicles in the household (66% compared with 81% of those with low LLIs) (see Table S2).

Compared to people with low regional accessibility, people with high regional accessibility tended to be commuters 25–44-y-old, in higher-skill occupations, with less than two motor vehicles in the household (Tables S3 and S4).

RQ1. Is Walkability Around Home and Place of Work/Education Associated with Walking?

Marginal mean walking times for strata of the LLI at home and work/education are presented in Table 3. Increased local living scores around home were associated with more minutes of walking on average. The difference in mean walking time between individuals exposed to the highest indices of local living at home (10 or more destination types within an 800-m walk) and the lowest (0–3) was 5.1 min (95% CI: 3.4, 6.8) on average. Likewise, a marginal mean difference of 8.6 min of walking (95% CI: 7.5, 9.5) was estimated for people exposed to the highest LLI at work/education (10 or more destination types within an 800-m walk) compared with the lowest (0–3 destinations) (see Table 3).

RQ2. Is Regional Accessibility of Place of Work/Education Opportunities Associated with Walking?

Marginal mean minutes of walking for regional accessibility exposures are presented in Table 3. Increased accessibility in all four models was associated with more minutes of walking on average, with variation in the minutes predicted according to the measure. For example, in the model with the "Level of Public Transport Service: Home" indicator, marginal mean minutes of additional walking of 6.0 min (95% CI: 4.0, 7.9) was estimated from comparison of the highest compared with the lowest categories of accessibility. In contrast, the model incorporating "Commute time by car compared with public transport" showed more substantial differences of 12.0 min (95% CI: 9.2, 14.6) for highest compared with the lowest categories of exposure (see Table 3).

RQ3. Are Associations between Accessibility (Local and Regional) and Walking Independent of One Another?

For research question 3, we found that even after accounting for accessibility in the other domains, there remained evidence of associations between each domain of accessibility and walking.

In models mutually adjusted for local living scores at home and work/education, increased scores around home and around work/education were associated with increased mean minutes of walking. Adjusting for local living scores at the place of work/education, people high on the LLI at home (i.e., 10 or more destination types within an 800-m walk) had 3.9 min more walking on average (95% CI: 2.3, 5.5) compared with people with a low LLI

Table 2. Summary of the age, sex, occupational, licensing characteristics, household income, vehicles and area disadvantage of VISTA 2012–2014 participants compared with 2011 census data for the Melbourne metropolitan region.

	Melbourne metropolitan region[a]		VISTA 2012–2014 sample ≥18-y-old		VISTA 2012–2014 subsample of commuters ≥18-y-old (analytical sample)	
	Individuals [*n* (%)]	Households[c] (families[d] for SEIFA) [*n* (%)]	Individuals [*n* (%)]	Households [*n* (%)]	Individuals [*n* (%)]	Households [*n* (%)]
Sex						
Male	913,118 (52.0)	—	8,597 (47.7)	—	2,634 (53.6)	—
Female	843,288 (48.0)	—	9,442 (52.3)	—	2,279 (46.4)	—
Age group (y)						
18–24[b]	248,099 (14.1)	—	1,911 (10.6)	—	579 (11.8)	—
25–44	842,602 (48.0)	—	6,338 (35.1)	—	2,273 (46.3)	—
≥45	665,705 (37.9)	—	9,790 (54.3)	—	2,061 (41.9)	—
Occupational skill level						
High skill	679,450 (38.7)	—	5,513 (30.6)	—	2,349 (47.8)	—
Medium skill	649,547 (37.0)	—	3,579 (19.8)	—	1,386 (28.2)	—
Low skill	401,363 (22.9)	—	2,726 (15.1)	—	1,018 (20.7)	—
Not in work/Student	26,047 (1.5)	—	6,221 (34.5)	—	160 (3.3)	—
Licensed to drive						
Yes	—	—	16,692 (92.5)	—	4,656 (94.8)	—
No	—	—	1,347 (7.5)	—	257 (5.2)	—
Weekly household income range (Australian dollars)						
0–799	—	383,512 (26.8)	—	2,429 (27.0)	—	410 (11.9)
800–1,249	—	222,164 (15.5)	—	1,513 (16.8)	—	545 (15.8)
1,250–1,999	—	274,897 (19.2)	—	1,876 (20.9)	—	808 (23.4)
$2,000–2,999	—	244,346 (17.1)	—	1,920 (21.3)	—	958 (27.8)
>3,000	—	157,563 (11.0)	—	1,255 (14.0)	—	727 (21.1)
Missing	—	148,182 (10.4)	—	0 (0.0)	—	0 (0.0)
Number of household vehicles						
One or less vehicles	—	631,691 (44.2)	—	3,987 (44.3)	—	1,096 (31.8)
Two or more vehicles	—	757,337 (52.9)	—	5,006 (55.7)	—	2,352 (68.2)
Missing	—	41,636 (2.9)	—	0 (0.0)	—	0 (0.0)
SEIFA (IRSD) in quintiles						
Q1 (most disadvantaged)	—	233,990 (14.7)	—	1,806 (20.1)	—	581 (16.9)
Q2	—	252,822 (15.8)	—	1,826 (20.3)	—	606 (17.6)
Q3	—	323,696 (20.3)	—	1,792 (19.9)	—	743 (21.5)
Q4	—	390,993 (24.5)	—	1,807 (20.1)	—	773 (22.4)
Q5 (least disadvantaged)	—	391,772 (24.6)	—	1,762 (19.6)	—	745 (21.6)
N/A	—	2,190 (0.1)	—	0 (0.0)	—	0 (0.0)
Total number	1,756,407	1,430,664	18,039	8,993	4,913	3,448

Note: —, no data; IRSD, Index of Relative Socio-Economic Disadvantage; SEIFA, Socio-Economic Indexes for Areas; VISTA, Victorian Integrated Survey of Travel and Activity.
[a]Employed person ≥15 y from the 2011 Australian Census of Population and Housing, based on place of work in Greater Melbourne (ABS 2012b).
[b]Equivalent Australian Bureau of Statistics (ABS) age category: 20–24 y.
[c]Number of households from 2011 Australian Census of Population and Housing, based on place of usual residence in Greater Melbourne (ABS 2012a).
[d]Number of families from the 2011 Australian Census of Population and Housing, based on place of usual residence in Greater Melbourne (household-level table not available) (ABS 2017).

at home (0 to 3 destinations) (see Table 3). Similarly, we estimated a marginal mean walking time of 8.3 min (95% CI: 7.3, 9.3), comparing the highest with the lowest LLI around the place of work/education, adjusting for the score at home.

When regional accessibility indicators were introduced into models and mutually adjusted for LLIs at home and work/education, the relationship of local living at home and work/education and marginal minutes of walking was attenuated but remained significant. The size of the estimates also remained relatively consistent across the four models adjusted for regional accessibility (see Table 3). For example, the marginal difference in minutes of walking between the lowest and highest categories of the LLI at home (i.e., between 0–3 and 10 or more destination types within an 800-m walk) ranged from 2.6 (95% CI: 1.0, 4.3) for the "Jobs within 30 min by public transport" model to 4.7 (95% CI: 3.0, 6.4) for the "Commute time by car compared with public transport" model. Similarly, the marginal difference in minutes of walking between the lowest and highest categories of the LLI at work/education ranged from 5.3 (95% CI: 4.2, 6.5) for the "Level of Public Transport Service: Work/Education" model and 8.2 min (95% CI: 7.2, 9.2) for the "Level of Public Transport Service: Home" model.

The minutes of walking with increased regional accessibility was similarly attenuated, as would be expected, but also remained significant and sizeable relative to the predicted minutes in the other domains. Although all regional accessibility indicators predicted more walking on average with increasing levels of exposure, marginal minutes of walking were more varied across models. Marginal average minutes of walking between the lowest and highest categories of regional accessibility ranged from 2.8 (95% CI: 1.0, 4.6) for the "Level of Public Transport Service: Home" model to 8.3 (95% CI: 7.0, 9.6) for the for the "Level of Public Transport Service: Work/Education" model (see Table 3).

RQ4. Does the Association between Regional Accessibility and Walking Vary by Local Accessibility around Home and Work/Education?

Heterogeneity of the estimated effect of regional accessibility by local living score was observed. People with high scores for local living at work/education were predicted to walk for 17 min on average per day (95% CI: 16, 19) if they also scored highly for "Jobs within 30 min by public transport." This compared with people with the same local living score but low regional

Table 3. Predicted estimates of mean minutes of daily walking [95% confidence interval (CI)] for exposure to high vs. low measures local or regional accessibility with and without additional adjustment for other measures of local or regional accessibility, VISTA 2012–2014.

	Lowest accessibility		Highest accessibility		
Exposure[a]	n^b	Predicted walking[c]	n^b	Predicted walking[c]	Difference in predicted walking[c]
Local accessibility measures					
LLI: Home					
Single-exposure model	2,245	7.04 (6.51, 7.57)	522	12.14 (10.56, 13.71)	5.09 (3.41, 6.78)
+ LLI (work/education)	2,245	7.87 (7.30, 8.44)	522	11.74 (10.23, 13.25)	3.87 (2.26, 5.48)
+ Jobs within 30 min	2,245	8.19 (7.51, 8.86)	522	10.80 (9.33, 12.28)	2.62 (0.96, 4.28)
+ Commute time by car/public transport	2,233	7.70 (7.12, 8.27)	520	12.39 (10.81, 13.97)	4.69 (3.02, 6.37)
+ LOPTS home	2,245	7.58 (6.95, 8.20)	522	11.03 (9.47, 12.59)	3.46 (1.69, 5.23)
+ LOPTS work/education	2,245	8.30 (7.70, 8.89)	522	11.54 (10.09, 12.99)	3.24 (1.69, 4.80)
LLI: Work/Education					
Single-exposure model	1,094	4.79 (4.25, 5.33)	1,793	13.45 (12.59, 14.32)	8.66 (7.67, 9.66)
+ LLI (home)	1,094	5.00 (4.45, 5.55)	1,793	13.27 (12.41, 14.13)	8.27 (7.28, 9.27)
+ Jobs within 30 min	1,094	5.18 (4.61, 5.74)	1,793	13.17 (12.31, 14.03)	7.99 (6.99, 8.99)
+ Commute time by car/public transport	1,080	5.66 (5.02, 6.29)	1,792	12.64 (11.80, 13.48)	6.99 (5.93, 8.04)
+ LOPTS : Home	1,094	5.02 (4.46, 5.58)	1,793	13.25 (12.40, 14.10)	8.24 (7.24, 9.23)
+ LOPTS : Work/education	1,094	6.69 (5.94, 7.45)	1,793	12.03 (11.22, 12.84)	5.34 (4.21, 6.47)
Regional accessibility measures					
Jobs within 30 min by public transport					
Single-exposure model	1,232	6.06 (5.46, 6.65)	1,232	12.58 (11.46, 13.71)	6.53 (5.24, 7.82)
+ LLI (home) and LLI (work/education)	1,231	7.32 (6.57, 8.07)	1,231	11.61 (10.54, 12.67)	4.29 (2.89, 5.68)
Commute time by car vs. public transport					
Single-exposure model	1,332	5.87 (5.26, 6.49)	272	17.79 (15.25, 20.33)	11.92 (9.25, 14.59)
+ LLI (home) and LLI (work/education)	1,332	7.60 (6.84, 8.35)	272	14.81 (12.56, 17.06)	7.21 (4.79, 9.64)
LOPTS: Home					
Single-exposure model	2,909	7.42 (6.92, 7.93)	480	13.38 (11.56, 15.20)	5.95 (4.04, 7.87)
+ LLI (home) and LLI (work/education)	2,909	8.68 (8.04, 9.33)	480	11.56 (9.96, 13.15)	2.87 (1.08, 4.66)
LOPTS: Work/Education					
Single-exposure model	1,447	4.70 (4.23, 5.16)	1,486	16.05 (14.97, 17.14)	11.36 (10.17, 12.55)
+ LLI (home) and LLI (work/education)	1,447	6.21 (5.56 ,6.86)	1,486	14.5 (13.5, 15.53)	8.29 (7.03, 9.56)

Note: +indicates the inclusion of the named variable in the single exposure model specified above it. LLI, local living index; LOPTS, level of public transport service.
[a]Lowest and highest categories for each exposure are defined, respectively, as follows: LLI (home and work/education), 0–3 and 10–12 destinations; jobs within 30 min by public transport, <4,000 and >30,000; commute time by car:public transport ratio, <0.25 and ≥0.75; level of public transport service (home and work/education), 0 and 2–3.
[b]Numbers of observations in each exposure category; does not account for missing covariate data. There were 16 missing values for commute time by car/public transport.
[c]Estimates from linear regression models of minutes of daily walking (transformed by a power of 1/2.6 and back transformed to compare in bootstrapped contrasts) in association with local accessibility measures (LLI: Home and LLI: Work/Education) and regional accessibility measures among 4,913 adults commuting to work or education on the survey day. Single-exposure models were adjusted for age group, sex, household income, occupational skill level, license to drive, number of household vehicles, distance to work/education (km), Socio-Economic Indexes for Areas (SEIFA), and clustering at a Statistical Area 1 (SA1) level. Models of local accessibility measures were additionally adjusted for the alternative LLI and each of the regional accessibility measures; models of each reginal accessibility measure were additionally adjusted for LLI: Home and LLI: Work/Education.

accessibility on this measure who walked 8 min on average per day (95% CI: 7, 9), a differential of 9 min (Table 4). A similar pattern was observed across regional accessibility measures with estimated values of 21 (95% CI: 18, 23) and 8 (95% CI: 7, 9) min, respectively, for "Commute time by car compared with public transport," 17 (95% CI: 15, 20) and 11 (95% CI: 10, 12) minutes for "Level of Public Transport Service: Home" and 18 (95% CI: 17, 19) to 5 (95% CI: 4, 5) min for "Level of Public Transport Service: Work/Education." People with high scores for local living at home also walked more if their scores for "Level of Public Transport Service: Work/Education" were also high: 17 min compared with 6 min. People experiencing both low local living scores at home or work/education and low regional accessibility reported the least time spent walking (ranging from 4 to 8 min per day).

Importantly, we found evidence that the combination of high local living and high regional accessibility is superadditive and greater than the estimated independent effect of having a high score on one measure only (Table 4). For example, people with a high score for both local living at work/education and "Jobs within 30 min by public transport" walked nearly 13 min more than people with low scores on both measures (95% CI: 11, 15) and, importantly, 9.3 min (95% CI: 6.7, 11.8) in excess of the sum of the independent effects of high vs. low regional alone and high vs. low home alone estimated by the RERI. For local living at work/education, RERI estimates were substantial in size and ranged from 7.4 min for "Level of Public Transport Service: Home" to 11.6 min for "Level of Public Transport Service: Work/Education."

While this was consistently observed for local living at work/education, a significant interaction was also observed for the combination of "Level of Public Transport Service: Work/Education" and local living at home (estimated RERI of 4.8 min; 95% CI: 1.7, 7.9).

Discussion

This study advances the current evidence base by simultaneously examining three domains of accessibility (local accessibility at home and around the place of work/education, and regional accessibility of employment/education) with walking in a sample of adult commuters. Accessibility in each domain was independently associated with increased minutes of walking per day, and these associations remained significant when local accessibility at home and work/education and regional accessibility measures were introduced into models together and mutually adjusted. Although there was some attenuation of estimates of differences in minutes walked between low and high accessibility, the association of increased regional accessibility and walking was independent of local accessibility at home or work/education. This finding was robust in that it held regardless of whether the exposures used measured absolute or relative, realized or potential, integral, or travel path (commute)– or place (home or work)-based dimensions of regional accessibility, and supported the results of

Table 4. Estimated mean difference in walking associated with high regional accessibility alone, high local accessibility alone (high local living index at work or at home), and high regional and local accessibility combined, relative to low regional and low local accessibility.

Regional: local contrast[a]	n^b	Predicted walking (minutes)	Mean difference in walking from reference (95% CI) (minutes)[c]	Interaction p-value[d]
Number of jobs within 30 min + LLI (home)	—	—	—	0.29
Low regional + low local	1,038	6.79 (6.14, 7.44)	0 (reference)	—
High regional + low local	113	10.23 (8.99, 11.48)	3.44 (1.95, 4.94)	—
Low regional + high local	12	7.22 (5.18, 9.25)	0.43 (−1.74, 2.59)	—
High regional + high local	312	12.99 (11.39, 14.60)	6.2 (4.48, 7.92)	—
RERI[e]	—	—	2.33 (−1.23, 5.89)	—
Number of jobs within 30 min + LLI (work)	—	—	—	0.01
Low regional + low local	370	4.45 (3.78, 5.13)	0 (reference)	—
High regional + low local	133	4.45 (3.60, 5.29)	−0.01 (−1.21, 1.20)	—
Low regional + high local	314	8.00 (6.94, 9.06)	3.55 (2.30, 4.79)	—
High regional + high local	601	17.25 (15.72, 18.79)	12.80 (11.07, 14.53)	—
RERI	—	—	9.26 (6.72, 11.80)	—
Commute time by car : public transport + LLI (home)	—	—	—	0.46
Low regional + low local	709	5.97 (5.29, 6.65)	0 (reference)	—
High regional + low local	138	12.67 (10.83, 14.50)	6.7 (4.49, 8.9)	—
Low regional + high local	112	8.42 (6.98, 9.86)	2.45 (0.85, 4.06)	—
High regional + high local	22	18.33 (14.67, 22.00)	12.37 (8.64, 16.09)	—
RERI	—	—	3.21 (−2.07, 8.49)	—
Commute time by car : public transport + LLI (work)	—	—	—	—
Low regional + low local	482	4.44 (3.78, 5.11)	0 (reference)	—
High regional + low local	2	5.87 (4.07, 7.67)	1.43 (−0.76, 3.62)	—
Low regional + high local	283	8.22 (7.23, 9.20)	3.77 (2.57, 4.97)	—
High regional + high local	182	20.60 (18.25, 22.95)	16.16 (13.73, 18.58)	—
RERI	—	—	10.95 (7.15, 14.76)	—
Level of public transport service : home + LLI (home)	—	—	—	0.99
Low regional + low local	1960	7.69 (7.12, 8.26)	0 (reference)	—
High regional + low local	24	10.31 (8.13, 12.49)	2.62 (0.29, 4.94)	—
Low regional + high local	35	10.42 (8.67, 12.16)	2.72 (0.83, 4.62)	—
High regional + high local	150	12.76 (10.55, 14.96)	5.06 (2.82, 7.31)	—
RERI	—	—	−0.28 (−4.82, 4.27)	—
Level of public transport service : home + LLI (work)	—	—	—	0.00
Low regional + low local	814	4.75 (4.17, 5.34)	0 (reference)	—
High regional + low local	45	3.62 (2.48, 4.77)	−1.13 (−2.53, 0.27)	—
Low regional + high local	884	10.97 (10.05, 11.90)	6.22 (5.14, 7.29)	—
High regional + high local	268	17.25 (14.97, 19.54)	12.5 (10.05, 14.95)	—
RERI	—	—	7.41 (4.33, 10.50)	—
Level of public transport service : work/education + LLI (home)	—	—	—	0.0
Low regional + low local	850	4.87 (4.28, 5.46)	0 (reference)	—
High regional + low local	513	11.49 (10.39, 12.59)	6.62 (5.27, 7.97)	—
Low regional + high local	80	5.66 (4.39, 6.92)	0.79 (−0.62, 2.19)	—
High regional + high local	229	17.04 (15.04, 19.05)	12.18 (10.03, 14.32)	—
RERI	—	—	4.76 (1.66, 7.87)	—
Level of public transport service : work/education + LLI (work)	—	—	—	0.0
Low regional + low local	759	4.41 (3.89, 4.92)	0 (reference)	—
High regional + low local	79	6.30 (5.05, 7.56)	1.9 (0.48, 3.31)	—
Low regional + high local	95	4.48 (3.61, 5.35)	0.07 (−0.98, 1.13)	—
High regional + high local	895	18.02 (16.72, 19.32)	13.61 (12.23, 14.99)	—
RERI	—	—	11.64 (9.14, 14.14)	—

Note: —, no data; LLI, local living index; LOPTS, level of public transport service; RERI, relative excess risk due to interaction.
[a]Lowest and highest categories for each exposure are defined, respectively, as follows: LLI (home and work/education), 0–3 and 10–12 destinations; Jobs within 30 min by public transport, <4,000 and >30,000; Commute time by car: public transport ratio, <0.25 and ≥0.75; level of public transport service (home and work/education), 0 and 2–3.
[b]Numbers of observations in each combined exposure group, does not account for missing covariate data.
[c]Estimates from linear regression models of minutes of daily walking (transformed by a power of 1/2.6 and back transformed to compare in bootstrapped contrasts) in association with local accessibility measures (LLI: Home and LLI: Work/Education) and regional accessibility measures among 4,913 adults commuting to work or education on the survey day. Models were adjusted for age group, sex, household income, occupational skill level, license to drive, number of household vehicles, distance to work/education (km), Socio-Economic Indexes for Areas (SEIFA) (IRSED), and clustering at a Statistical Area 1 (SA1) level.
[d]p-Value from likelihood ratio test compare models with vs. without an interaction term between local living and regional accessibility with variables treated continuously.
[e]Defining HH as the estimate for High regional and High local, HL as the estimate for High regional and Low local etc., RERI was calculated as: RERI = (HH − LL) − (HL − LL) − (LH − LL), e.g., in the first model reported in the table, the RERI of 2.33 was calculated as $6.2 - (3.44 + 0.43)$.

previous studies that included examination of indicators of regional accessibility, active travel, and physical activity as described above (Ewing and Cervero 2010; Hoehner et al. 2012; Yang et al. 2015; Næss 2005; Frank et al. 2010). Of the three domains of accessibility, local environment around the place of work/education, often ignored in studies of accessibility and active travel or physical activity, was most consistently and strongly associated with differences in predicted marginal minutes walked, comparing low and high accessibility. This finding is also consistent with and extends the findings of studies examining built environment and walking around the workplace and other secondary activity spaces (Yang et al. 2015; Lachapelle and Frank 2009; Howell et al. 2017).

Examination of heterogeneity by levels of regional access indicated that at the highest levels of each access measure, people report walking 13 to 21 min per day on average compared with 4 to 7 min for their counterparts with low regional and local accessibility at work or education (Table 4), a differential in daily activity that has potential significance for health. We also found evidence that the combined effect of high regional access and high local living score for work/education was more beneficial than expected based on the estimated independent effects of each alone, suggesting a synergistic relationship between the domains and walking.

In terms of general policy implications, this study highlights the potential of well-designed and integrated transport systems and built environments, both at the local and regional levels, to support physical activity through active travel. Our findings lend weight to the impetus to ensure that cities are sustainable and healthy through delivering integrated regional and local planning interventions in current planning frameworks, including smart growth, walkable urbanism, and transit-orientated development. The independent association of regional accessibility and walking suggests improvements to regional accessibility may be critical to improving population levels of walking and physical activity. This could be achieved through improving cycling infrastructure and public transport systems and strengthening economic activity and employment in metropolitan regional activity centers accessible by short commutes from homes (Giles-Corti et al. 2016; Department of Environment, Land, Water and Planning 2017). The relative size of the difference in predicted marginal minutes between low and high local accessibility around the place of work/education compared with residential local accessibility reinforces that employment clusters also need to be pedestrian friendly. Indeed, transit-orientated and walkable employment clusters may potentially be more influential for working adults in supporting active mode choice than interventions delivered around the home, which represent the "best-designed, compact, mixed-use development in a remote location" (Ewing and Cervero 2010).

There are a number of research implications of the findings. First, local environments around work/education settings appear to be equally important predictors of walking for commuters as those around the home, and more research must be done on the walkability of these secondary activity spaces. Second, for commuters, the local and regional accessibility of places of work and education have independent associations with walking. Future research on built environment and transport system determinants of active travel and walking needs to investigate the phenomena of local accessibility in different activity spaces and regional accessibility simultaneously. Third, more sophisticated measures of regional accessibility need to be developed and monitored, taking advantage of transport planning data and modeling expertise. There is currently no consensus on definitions or measures of regional accessibility. Developing better exposure measures, and applying them consistently in well-designed research, will further develop the evidence base for the relationships between regional accessibility, mode choice, walking, and physical activity. Finally, household travel surveys provide unparalleled opportunity to investigate relationships between individual, household, and built environment influences on travel behaviors at a range of scales, and these publicly funded surveys could be better utilized by health researchers.

Limitations and Strengths

There were several limitations to this research. The research used secondary transport survey data adapted for the purposes of the study, which had a number of shortcomings. Significantly, as this research design was cross sectional, and as no information on self-selection was available in the survey, causality could not be inferred from the associations observed. The survey did not include all covariates of interest, such as country of birth or time spent in physical activity outside of transport-related walking. In addition, single day travel surveys provide limited snapshots of individuals' longer-term travel patterns, and there is likely a degree of measurement error, especially in the outcome of minutes of walking. Findings from this sample of adult commuters cannot be generalized to other populations, as their demographics and travel patterns are distinct from other groups.

Residual confounding was a potential problem, as it is for all other observational spatial studies of this type. For this reason, we adjusted for important individual-, household, and area-level confounders, which previous research suggests are important correlates of walking. The complexity of the built environment is nearly impossible to reduce to measurable objective exposures, so we were also careful to define our local accessibility exposure variable to combine two of the most consistent built environment correlates of walking: land use (via presence of destination types) and street connectivity (via network distance). Nonetheless, because we needed a single local accessibility variable to preserve some parsimony in what already complex models were, we were not able to include some characteristics of the built environment associated with walking, such as presence and quality of footpaths. We acknowledge that these characteristics are likely to be correlated with our local accessibility measures, thereby potentially generating some residual confounding of our results. It is unlikely, however, that the amount of residual confounding would be significant enough to explain the findings.

Similarly, there were limitations associated with secondary data used for the accessibility exposures. The zone-to-zone nature of VITM-based measures reduced their spatial specificity in comparison to door-to-door travel times (Benenson et al. 2011). In addition, short trips that were intrazonal in the VITM measures were excluded from the analysis. However, this affected only a small number of people ($n = 63$), and summary statistics indicated that they did not substantially differ from interzonal travelers in the outcome, so this exclusion was unlikely to have a major impact on estimates.

Patterns of significance may also be related to other differences in the measures themselves. For example, the commute travel time by public transport compared with car measure captured the relative accessibility of the two modes but did not capture absolute commute time: two commutes where the car travel time was half that of public transport would both score a ratio of 0.5, even if the car travel time of one commute was 15 mins and the other car travel time commute was 1 h. All three regional accessibility measures were calculated for either travel zones or Mesh Blocks, and a single measure was applied to all residents within an area, ignoring individual differences in accessibility within areas (Iacono et al. 2010; Niedzielski and Eric Boschmann 2014). Regardless of these measurement faults, the three measures used in this study arguably still met a key condition of sound accessibility measures: the capacity to differentiate large disparities in accessibility between individuals, groups, or areas (Benenson et al. 2011).

Despite these limitations, this research had significant strengths in relation to design, sample, outcomes, and exposures. In terms of study design, this research examined three domains of accessibility simultaneously, which has previously been identified as an important gap in the literature. These built environment characteristics were investigated while concurrently adjusting for individual- and household-level factors known to be associated with travel mode choice and walking. The study examined the relationships of accessibility opportunities and walking activity across different spatial scales in depth. We used a relatively large data set of individuals from randomly selected households across an entire metropolitan area. The data set provided a detailed outcome measure of walking time, which is arguably superior to data typically used in other health and built environment research. Household travel surveys, such as VISTA, are a valuable but underutilized source of active travel data. Compared with health surveys that often rely on self-reported estimates of total walking recalled over the past week or month, VISTA sources an individual's walking trips from a travel diary of a single day, potentially improving accuracy of recall (Merom et al. 2010). In terms of exposures, we developed and applied novel measures of regional accessibility. The study developed and applied two local and four regional exposure measures from various data sources, which assessed different aspects of accessibility and varied in terms of their strengths and limitations. This allowed us to cross-reference and look for trends in findings across the exposures.

Conclusion

This study showed local and regional accessibility are independently associated with walking. We observed consistent increases in minutes of walking with increasing local (home and work/education) and regional accessibility. This expands the evidence base and supports the importance of walkable urbanism and transit-orientated development around home and work and education settings.

Acknowledgments

The authors acknowledge Professor T. Blakely (University of Melbourne), Dr. A Singh (University of Melbourne), and Ms. Zoe Aitkin (University of Melbourne) for the provision of epidemiological advice; the Victorian Department of Economic Development, Jobs, Transport and Resources (DEDJTR) for the provision of the VISTA data, partnership support; and expert advice; the Victorian Roads Corporation (VicRoads) for the provision of VITM data, partnership support, and expert advice; the Victorian Health Promotion Foundation (VicHealth) for project funding, partnership support and expert advice; and the Australian Research Council (ARC) for project funding (LP140100680).

S.M. is supported by an NHMRC Early Career Fellowship (#11201035). B.G.C. is supported by an NHMRC Senior Principal Research Fellowship (#1107672). H.B. is supported by an RMIT University Vice Chancellor's Senior Research Fellowship and is the 2018 Australian Health Promotion Association Thinker in Residence. R.B. is supported by an Australian Research Council Future Fellowship (150100131).

References

ABS (Australian Bureau of Statistics). 2012a. Census of Population and Housing: Basic Community Profile, 2011 First Release (ABS cat. no. 2001.0). Tables based on place of usual residence in Greater Melbourne. http://www.censusdata.abs.gov.au/census_services/getproduct/census/2011/communityprofile/2GMEL?opendocument&navpos=220 [accessed 28 December 2017].

ABS. 2012b. Census of Population and Housing: Working Population Profile, 2011 First Release (ABS cat. No.2001.0). Tables based on place of work in Greater Melbourne. http://www.censusdata.abs.gov.au/census_services/getproduct/census/2011/communityprofile/2GMEL?opendocument&navpos=220 [accessed 28 December 2017].

ABS. 2013. 2033.0.55.001—Census of Population and Housing: Socio-Economic Indexes for Areas (SEIFA), Australia, 2011. IRSD. http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/2033.0.55.001∼2011∼Main%20Features∼IRSD∼10005 [accessed 21 June 2017].

ABS. 2016. 1270.0.55.001—Australian Statistical Geography Standard (ASGS): Volume 1—Main Structure and Greater Capital City Statistical Areas, July 2016. http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/1270.0.55.001∼July%202016∼Main%20Features∼Mesh%20Blocks%20(MB)∼10012 [accessed 28 December 2017].

ABS. 2017. 2011 Census—Counting Families, Place of Usual Residence. Socio-Economic Indexes for Areas (SEIFA) Index of Relative Socio-Economic Disadvantage (IRSD) Deciles at SA1 level (area) by greater capital city statistical areas. http://www.abs.gov.au/websitedbs/censushome.nsf/home/tablebuilder?opendocument&navpos=240 [accessed 30 May 2017].

Badland H, Hickey S, Bull F, Giles-Corti B. 2014. Public transport access and availability in the RESIDE study: is it taking us where we want to go? J Transp Health 1(1):45–49, https://doi.org/10.1016/j.jth.2013.10.001.

Badland H, Mavoa S, Boulangé C, Eagleson S, Gunn L, Stewart J, et al. 2017. Identifying, creating, and testing urban planning measures for transport walking: findings from the Australian national liveability study. J Transp Health 5:151–162, https://doi.org/10.1016/j.jth.2016.08.010.

Badland H, Schofield GM. 2005. Transport, urban design, and physical activity: an evidence-based update. Transp Res D Transp Environ 10(3):177–196, https://doi.org/10.1016/j.trd.2004.12.001.

Barrington WE, Beresford SAA, Koepsell TD, Duncan GE, Moudon AV. 2015. Worksite neighborhood and obesogenic behaviors: findings among employees in the promoting activity and changes in eating (PACE) trial. Am J Prev Med 48(1):31–41, PMID: 25442234, https://doi.org/10.1016/j.amepre.2014.08.025.

Bauman AE, Bull FC. 2007. *Environmental Correlates of Physical Activity and Walking in Adults and Children: A Review of Reviews*. London, UK: National Institute of Health and Clinical Excellence.

Beavis MJ, Moodie M. 2014. Incidental physical activity in Melbourne, Australia: health and economic impacts of mode of transport and suburban location. Health Promot J Austr 25(3):174–181, PMID: 25435098, https://doi.org/10.1071/HE14057.

Benenson I, Martens K, Rofé Y, Kwartler A. 2011. Public transport versus private car GIS-based estimation of accessibility applied to the Tel Aviv metropolitan area. Ann Reg Sci 47(3):499–515, https://doi.org/10.1007/s00168-010-0392-6.

Chaix B, Duncan D, Vallée J, Vernez-Moudon A, Benmarhnia T, Kestens Y. 2017. The "residential" effect fallacy in neighborhood and health studies: formal definition, empirical identification, and correction. Epidemiology 28(6):789–797, PMID: 28767516, https://doi.org/10.1097/EDE.0000000000000726.

Curtis C, Scheurer J. 2016. *Planning for Public Transport Accessibility: An International Sourcebook*. Abingdon, UK: Routledge.

Department of Environment, Land, Water and Planning. 2017. *Plan Melbourne 2017–2050: Metropolitan Planning Strategy*. Melbourne, Australia: Victoria State Government.

Department of Infrastructure, Transport, Cities and Regional Development. 2016. Smart Cities Plan. https://cities.infrastructure.gov.au/18190/documents/48080 [accessed 7 September 2018].

Ewing R, Cervero R. 2001. Travel and the built environment: a synthesis. Transp Res Rec 1780(1):87–114, https://doi.org/10.3141/1780-10.

Ewing R, Cervero R. 2010. Travel and the built environment: a meta-analysis. J Am Plann Assoc 76(3):265–294, https://doi.org/10.1080/01944361003766766.

Frank L, Bradley M, Kavage S, Chapman J, Lawton TK. 2008. Urban form, travel time, and cost relationships with tour complexity and mode choice. Transp Res D Transp Environ 35(1):37–54, https://doi.org/10.1007/s11116-007-9136-6.

Frank LD, Greenwald MJ, Winkelman S, Chapman J, Kavage S. 2010. Carbonless footprints: promoting health and climate stabilization through active transportation. Prev Med 50(suppl 1):S99–S105, PMID: 19850071, https://doi.org/10.1016/j.ypmed.2009.09.025.

Giles-Corti B, Knuiman M, Timperio A, Van Niel K, Pikora TJ, Bull FCL, et al. 2008. Evaluation of the implementation of a state government community design policy aimed at increasing local walking: design issues and baseline results from RESIDE, Perth, Western Australia. Prev Med 46(1):46–54, PMID: 17881044, https://doi.org/10.1016/j.ypmed.2007.08.002.

Giles-Corti B, Vernez-Moudon A, Reis R, Turrell G, Dannenberg AL, Badland H, et al. 2016. City planning and population health: a global challenge. Lancet 388(10062):2912–2924, PMID: 27671668, https://doi.org/10.1016/S0140-6736(16)30066-6.

Heinen E, Chatterjee K. 2015. The same mode again? An exploration of mode choice variability in Great Britain using the National Travel Survey. Transp Res Part A Policy Pract 78:266–282, https://doi.org/10.1016/j.tra.2015.05.015.

Hillsdon M, Coombes E, Griew P, Jones A. 2015. An assessment of the relevance of the home neighbourhood for understanding environmental influences on physical activity: how far from home do people roam? Int J Behav Nutr Phys Act 12:100, PMID: 26277369, https://doi.org/10.1186/s12966-015-0260-y.

Hoehner CM, Allen P, Barlow CE, Marx CM, Brownson RC, Schootman M. 2013. Understanding the independent and joint associations of the home and workplace built environments on cardiorespiratory fitness and body mass index. Am J Epidemiol 178(7):1094–1105, PMID: 23942215, https://doi.org/10.1093/aje/kwt111.

Hoehner CM, Barlow CE, Allen P, Schootman M. 2012. Commuting distance, cardiorespiratory fitness, and metabolic risk. Am J Prev Med 42(6):571–578, PMID: 22608372, https://doi.org/10.1016/j.amepre.2012.02.020.

Howell NA, Farber S, Widener MJ, Booth GL. 2017. Residential or activity space walkability: what drives transportation physical activity? J Transp Health 7(Part B):160–171, https://doi.org/10.1016/j.jth.2017.08.011.

Hurvitz PM, Moudon AV, Kang B, Fesinmeyer MD, Saelens BE. 2014. How far from home? The locations of physical activity in an urban U.S. Setting. Prev Med 69:181–186, PMID: 25285750, https://doi.org/10.1016/j.ypmed.2014.08.034.

Iacono M, Krizek KJ, El-Geneidy A. 2010. Measuring non-motorized accessibility: issues, alternatives, and execution. J Transp Geogr 18(1):133–140, https://doi.org/10.1016/j.jtrangeo.2009.02.002.

Ipsos. 2016. *VISTA 2013 – 2014 Technical Report*. Melbourne, Australia: Ipsos.

Kawabata M. 2009. Spatiotemporal dimensions of modal accessibility disparity in Boston and San Francisco. Environ Plan A 41(1):183–198, https://doi.org/10.1068/a4068.

Kwok RCW, Yeh AGO. 2004. The use of modal accessibility gap as an indicator for sustainable transport development. Environ Plan A 36(5):921–936, https://doi.org/10.1068/a3673.

Lachapelle U, Frank LD. 2009. Transit and health: mode of transport, employer-sponsored public transit pass programs, and physical activity. J Public Health Pol 30(suppl 1):S73–S94, PMID: 19190584, https://doi.org/10.1057/jphp.2008.52.

Lachapelle U, Frank L, Saelens BE, Sallis JF, Conway TL. 2011. Commuting by public transit and physical activity: where you live, where you work, and how you get there. J Phys Act Health 8(suppl 1):S72–S82, PMID: 21350265, https://doi.org/10.1123/jpah.8.s1.s72.

Lee C, Moudon AV. 2006. The 3ds+ R: quantifying land use and urban form correlates of walking. Transp Res D Transp Environ 11(3):204–215, https://doi.org/10.1016/j.trd.2006.02.003.

Lei TL, Church RL. 2010. Mapping transit-based access: Integrating GIS, routes and schedules. Int J Geogr Inf Sci 24(2):283–304, https://doi.org/10.1080/13658810902835404.

Litman T. 2017. Land use impacts on transport: how land use patterns affect travel behavior. http://www.vtpi.org/tdm/tdm20.htm [accessed 31 July 2017].

Lovelace R, Ballas D, Watson M. 2014. A spatial microsimulation approach for the analysis of commuter patterns: from individual to regional levels. J Transp Geogr 34:282–296, https://doi.org/10.1016/j.jtrangeo.2013.07.008.

Mavoa S, Eagleson S, Badland HM, Gunn L, Boulange C, Stewart J, Giles-Corti B. 2018. Identifying appropriate land use mix measures for use in a national walkability index. J Transp Land Use 11(1):681–700, https://doi.org/10.5198/jtlu.2018.1132.

Merom D, van der Ploeg HP, Corpuz G, Bauman AE. 2010. Public health perspectives on household travel surveys: active travel between 1997 and 2007. Am J Prev Med 39(2):113–121, PMID: 20621258, https://doi.org/10.1016/j.amepre.2010.04.007.

Næss P. 2005. Residential location affects travel behavior—but how and why? The case of Copenhagen metropolitan area. Prog Plann 63(2):167–257, https://doi.org/10.1016/j.progress.2004.07.004.

Niedzielski MA, Eric Boschmann E. 2014. Travel time and distance as relative accessibility in the journey to work. Ann Am Assoc Geogr 104(6):1156–1182, https://doi.org/10.1080/00045608.2014.958398.

Owen N, Humpel N, Leslie E, Bauman A, Sallis JF. 2004. Understanding environmental influences on walking: review and research agenda. Am J Prev Med 27(1):67–76, PMID: 15212778, https://doi.org/10.1016/j.amepre.2004.03.006.

Plaut PO. 2005. Non-motorized commuting in the US. Transp Res D Transp Environ 10(5):347–356, https://doi.org/10.1016/j.trd.2005.04.002.

Rissel C, Curac N, Greenaway M, Bauman A. 2012. Physical activity associated with public transport use - a review and modelling of potential benefits. Int J Environ Res Public Health 9(7):2454–2478, PMID: 22851954, https://doi.org/10.3390/ijerph9072454.

Saelens BE, Handy SL. 2008. Built environment correlates of walking: a review. Med Sci Sports Exerc 40(7 suppl):S550–S566, PMID: 18562973, https://doi.org/10.1249/MSS.0b013e31817c67a4.

Saelens BE, Sallis JF, Frank LD. 2003. Environmental correlates of walking and cycling: findings from the transportation, urban design, and planning literatures. Ann Behav Med 25(2):80–91, PMID: 12704009, https://doi.org/10.1207/S15324796ABM2502_03.

Saelens BE, Vernez Moudon A, Kang B, Hurvitz PM, Zhou C. 2014. Relation between higher physical activity and public transit use. Am J Public Health 104(5):854–859, PMID: 24625142, https://doi.org/10.2105/AJPH.2013.301696.

Salonen M, Toivonen T. 2013. Modelling travel time in urban networks: comparable measures for private car and public transport. J Transp Geogr 31:143–153, https://doi.org/10.1016/j.jtrangeo.2013.06.011.

Scheurer J, Curtis C. 2015. The impact of political changes on public transport accessibility in Melbourne, 2008–2014. In: Proceedings of the 7th State of Australian Cities Conference. 9–11 December 2015, Gold Coast, Queensland, Australia: 7th State of Australian Cities Congress (SOAC).

Sener IN, Lee RJ, Elgart Z. 2016. Potential health implications and health cost reductions of transit-induced physical activity. J Transp Health 3(2):133–140, PMID: 27347481, https://doi.org/10.1016/j.jth.2016.02.002.

Sinclair Knight Merz and AECOM. 2010. *Recalibration and Revalidation of the Melbourne Integrated Transport Model. Vol. 1: Summary Report*. Melbourne, Australia: SKM and AECOM.

Snowden JM, Rose S, Mortimer KM. 2011. Implementation of G-computation on a simulated data set: demonstration of a causal inference technique. Am J Epidemiol 173(7):731–738, PMID: 21415029, https://doi.org/10.1093/aje/kwq472.

Sugiyama T, Neuhaus M, Cole R, Giles-Corti B, Owen N. 2012. Destination and route attributes associated with adults' walking: a review. Med Sci Sports Exerc 44(7):1275–1286, PMID: 22217568, https://doi.org/10.1249/MSS.0b013e318247d286.

Targa F, Clifton KJ. 2005. Built environment and nonmotorized travel: evidence from Baltimore city using the NHTS. J Transp Stat 8:55–70, https://doi.org/10.1016/j.tra.2009.02.001.

Te Brömmelstroet M, Silva C, Bertolini L. 2014. *Assessing Useability of Accessibility Instruments*. Brussels, Belgium: European Cooperation in Science and Technology (COST).

Troped PJ, Wilson JS, Matthews CE, Cromley EK, Melly SJ. 2010. The built environment and location-based physical activity. Am J Prev Med 38(4):429–438, PMID: 20307812, https://doi.org/10.1016/j.amepre.2009.12.032.

van Heeswijck T, Paquet C, Kestens Y, Thierry B, Morency C, Daniel M. 2015. Differences in associations between active transportation and built environmental exposures when expressed using different components of individual activity spaces. Health Place 33:195–202, PMID: 25862996, https://doi.org/10.1016/j.healthplace.2015.03.003.

Witten K, Blakely T, Bagheri N, Badland HM, Ivory V, Pearce J, et al. 2012. Neighborhood built environment and transport and leisure physical activity: findings using objective exposure and outcome measures in New Zealand. Environ Health Perspect 120(7):971–977, PMID: 22456536, https://doi.org/10.1289/ehp.1104584.

Yang L, Hipp JA, Adlakha D, Marx CM, Tabak RG, Brownson RC. 2015. Choice of commuting mode among employees: do home neighborhood environment, worksite neighborhood environment, and worksite policy and supports matter? J Transp Health 2(2):212–218, PMID: 26085979, https://doi.org/10.1016/j.jth.2015.02.003.