

A Longitudinal Study Examining Changes in Street Connectivity, Land Use, and Density of Dwellings and Walking for Transport in Brisbane, Australia

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BACKGROUND: Societies face the challenge of keeping people active as they age. Walkable neighborhoods have been associated with physical activity, but more rigorous analytical approaches are needed.

OBJECTIVES: We used longitudinal data from adult residents of Brisbane, Australia (40–65 years of age at baseline) to estimate effects of changes in neighborhood characteristics over a 6-y period on the likelihood of walking for transport.

METHODS: Analyses included 2,789–9,747 How Areas Influence Health and Activity (HABITAT) cohort participants from 200 neighborhoods at baseline (2007) who completed up to three follow-up questionnaires (through 2013). Principal components analysis was used to derive a proxy measure of walkability preference. Environmental predictors were changes in street connectivity, residential density, and land use mix within a one-kilometer network buffer. Associations with any walking and minutes of walking were estimated using logistic and linear regression, including random effects models adjusted for time-varying confounders and a measure of walkability preference, and fixed effects models of changes in individuals to eliminate confounding by time-invariant characteristics.

RESULTS: Any walking for transport (vs. none) was increased in association with an increase in street connectivity (+10 intersections, fixed effects OR = 1.19; 95% confidence interval (CI): 1.07, 1.32), residential density (+5 dwellings/hectare, OR = 1.10; 95% CI: 1.05, 1.15), and land-use mix (10% increase, OR = 1.12; 95% CI: 1.00, 1.26). Associations with minutes of walking were positive based on random effects models, but null for fixed effects models. The association between land-use mix and any walking appeared to be limited to participants in the highest tertile of increased street connectivity (fixed effects OR = 1.17; 95% CI: 0.99, 1.35 for a 1-unit increase in land-use mix; interaction *p*-value = 0.05).

CONCLUSIONS: Increases in street connectivity, residential density, and land-use heterogeneity were associated with walking for transport among middle-age residents of Brisbane, Australia. <https://doi.org/10.1289/EHP2080>

Introduction

Walking is the most common form of physical activity (Australian Bureau of Statistics 2011; Rosenberg et al. 2010) and is associated with mental and physical health benefits, including reduced obesity, cardio-vascular disease, and diabetes (Physical Activity Guidelines Advisory Committee 2008; Warburton et al. 2010). Neighborhoods that support walking may be an effective means of increasing population physical activity (Giles-Corti et al. 2013; Stevenson et al. 2016), and evidence from multiple international studies suggests that built environment characteristics may influence the amount of walking people undertake in local areas (Owen et al. 2007). However, many studies have relied on cross-sectional data that may be biased by self-selection, such that associations between walkable neighborhoods and walking may occur not because of an effect of walkable areas on walking, but because people who like to walk choose to live in walkable areas. The extent to which confounding from self-selection may inflate associations is unclear (Martin et al. 2014), but various methods have been used to account for selection (De Vos et al. 2012; Kaczynski and Mowen 2011), including adjustment for proxy indicators of

preferences, and instrumental variables (Greenwald and Boarnet 2001), and associations between neighborhood characteristics and physical activity have been reported to be attenuated by adjustment for selection (Ewing and Cervero 2010) (McCormack and Shiell 2011; Owen et al. 2007). Self-selection bias can affect longitudinal studies as well as cross-sectional studies, and adjustment will not eliminate bias given that self-selection is likely to be classified with some degree of error. In addition, unmeasured confounders that influence both built environment characteristics and physical activity may bias studies. Fixed effect models that estimate effects based on within-person comparisons over time eliminate bias due to confounding by time-invariant characteristics, including personal preferences (assuming they are stable over time), in contrast with commonly used random effects models. However, to our knowledge, these models have not been used in previous studies of built environment and physical activity.

Three recent studies based on natural experiments, whereby individuals who changed residences were followed over time, have reported that changes in street connectivity, land-use mix, and walkability indices are associated with changes in walking for transport (Hirsch et al. 2014; Kamruzzaman et al. 2016; Knuiman et al. 2014). Investigators using data from the U.S.-based Multi-Ethnic Study of Atherosclerosis examined the relationship between area walkability (measured using the Street Smart Walk Score), walking (for transport and recreation), and BMI among 701 participants who relocated during follow-up (2004–2012, 6.3 y on average) (Hirsch et al. 2014). The authors estimated that a 10-point increase in the walkability score (one-third of the baseline standard deviation) following relocation was associated with a 16-min/wk increase in walking for transport, and a 0.06 kg/m² (95% CI = –0.12, –0.01) reduction in BMI. An Australian study of Perth residents who relocated to new housing developments reported that increases in street connectivity and land-use mix predicted an increase in the number of times people walked for transport (Knuiman et al. 2014). Similarly, increases in street connectivity and residential density

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were associated with an increased likelihood of walking for transport in a previous analysis of the first two waves of data from the Brisbane-based cohort used in the present analysis (Kamruzzaman et al. 2016).

The present analysis is based on four waves of data (collected in 2007, 2009, 2011, and 2013) from adults enrolled in How Areas in Brisbane Influence Health and Activity (HABITAT) – a longitudinal study of Brisbane, Australia, residents age 40 to 65 y old at baseline. We used fixed and random effects longitudinal regression models to estimate associations within and between people over time to determine whether changes in neighborhood characteristics (street connectivity, residential density, and land-use mix) were associated with changes in the amount of walking for transport, after accounting for neighborhood walkability preference and time-invariant confounders. In addition, we examined whether neighborhood characteristics appear to interact with each other to affect the amount of walking people do for transport.

Methods

Data

The data used in this analysis come from the HABITAT study: a longitudinal, multilevel study of 11,035 40- to 65-y-old residents in Brisbane, Australia, at four time points approximately two years apart (2007, 2009, 2011, and 2013) (Burton et al. 2009; Turrell et al. 2010).

The primary aim of HABITAT was to identify factors that promote and inhibit aging adults from maintaining healthy levels of physical activity as they age. Accordingly, the parent study comprised a middle-age cohort for whom the prevalence of physical inactivity and overweight/obesity is higher than in younger adults, consistent with a decline in physical activity from young adulthood to middle age.

The survey was conducted using a structured self-administered questionnaire that was sent to 17,000 eligible participants from 200 Census Collector Districts (CCD) (out of a total of 1,680) in Brisbane's Central Business District, and its outskirts, in May 2007, as per Dillman (Dillman 1991). Participants were sent the survey instrument with a cover letter noting their participation in the survey was voluntary. Return of a completed survey instrument by a respondent indicated consent to participate. After excluding 873 out-of-scope contacts (i.e., deceased, no longer at the address, unable to participate for health-related reasons), 11,035 usable surveys were returned, yielding a baseline response rate of 68.3%. The corresponding response rates from in-scope and contactable participants in 2009, 2011, and 2013 were 72.6% ($n=7,866$), 67.3% ($n=6,900$), and 67.1% ($n=6,520$), respectively (Burton et al. 2009).

Participants who changed their address between any two data collection points were followed (unless they moved outside of Australia). Several strategies were implemented to track people, including recording of alternative contact details, provision of a replied paid change-of-address card, and access to a website and toll-free telephone number to register a change of address. Participants who failed to respond at a particular wave were still included in subsequent waves. Address information was geocoded with automated geocoding followed by manual geocoding for any addresses that could not be matched.

This study was awarded ethical clearance by the Queensland University of Technology Human Research Ethics Committee (Ref. no. 3967H & 130000161).

Study setting. Brisbane is the capital city of Queensland, a state in the northeast of Australia. The city of Brisbane has an estimated population of 1.13 million people. It has a humid subtropical climate (with hot, humid summers and dry moderately warm

winters). Average temperatures range from 16.6°C (62°F) to 26.6°C (80°F). Although Brisbane is hilly, much of the city is on low-lying flood plains, with several suburban creeks throughout the suburbs joining the Brisbane River. Public transport in Brisbane consists of buses, trains, and ferries. Cycling is a growing but not common mode of active travel, especially among middle- and older-age residents (and particularly so among older women); hence, this analysis focuses on walking (Heesch et al. 2014; Heesch and Turrell 2014; Heesch et al. 2015).

Predictor Variables

Neighborhood-level data on built environments' characteristics came from two sources: the Brisbane City Council (the local government authority responsible for the jurisdiction covered by the HABITAT study) and MapInfo (Pitney Bowes Software). The Brisbane City Council's Cadastre and their Land Use Activity Database (LUAD) and StreetPro were obtained under data access agreements restricting public (Pitney Bowes Software) release. Neighborhood predictors were derived for June 2007, 2009, 2011, and 2013. These time periods correspond to the individual-level data collections, ensuring temporal correspondence between the neighborhood measures and individual-level survey data.

A large amount of spatial variability in Brisbane exists in the three main components of walkability considered in this paper: residential density, land-use mix, and street connectivity. Closer to the city, neighborhoods are more residentially dense and connected with a greater diversity of land uses (unpublished data) than in the outskirts of Brisbane. People are more likely to walk and cycle for transport in these areas of Brisbane (Turrell et al. 2013). Access to public transport is highly variable across the city.

Changes in neighborhood characteristics (and individual survey data) were defined as differences between waves. This included both participants who changed their address *within* Brisbane between any two data collection waves and people who experienced change in their residential environment without moving.

We derived proxy measures of three neighborhood characteristics that have been used in previous studies as indicators of neighborhood walkability: street connectivity, density, and land-use mix (Frank et al. 2006; Saelens et al. 2003). Each characteristic was defined within a 1-km buffer surrounding the residence address of each participant using a road network buffer, which is an area corresponding to a 1-km distance on local roads from each respondent's dwelling (Oliver et al. 2007). A 1-km distance was chosen because it is a reasonable distance for people in a middle-age cohort to walk for transport or catch public transport (Villanueva et al. 2014). Street connectivity is believed to promote walkability by making it easier to reach destinations, both by increasing the number of possible routes available within an area, and by reducing the distance and time required to walk to destinations (Handy et al. 2002). For the present study, we used the number of four-way intersections within each 1-km buffer as a measure of street connectivity, which has previously been shown an association with active travel (Turrell et al. 2013).

This study uses the number of dwellings per hectare of residential land in each road network buffer to measure density. Land-use mix refers to the range of different land uses within a neighborhood. Neighborhoods that are "mixed use" contain a variety of infrastructure and activities, and are believed to encourage walking because they include a larger number of destinations (Handy et al. 2002). For the present study, we used a metric adapted for studies of active transport based on five types of land use within each 1-km buffer: residential, commercial, industrial, recreational/leisure, and "other" (Christian et al. 2011). The land-

use mix for each buffer was estimated as the negative sum of the proportion of each land-use type multiplied by the natural log of the its proportion, divided by 5 (the number of land categories used) (Leslie et al. 2007). Individual scores ranged from 0 to 1, with 0 representing complete homogeneity of land use within the buffer, and 1 representing an even distribution of each of the five types of land use.

Outcome Variables

At baseline and each subsequent wave, respondents were asked how many minutes in the past week they walked for transport (i.e., to get to or from any destination) using the following question: “What do you estimate was the total time that you spent walking for transport in the LAST WEEK?” with response options of reporting hours or minutes and the direction “If NONE, please write 0.”

Walking for transport was accordingly modeled as both binary (no walking, any walking) and as a continuous variable (in self-reported minutes walked).

Covariates

All models were adjusted for factors theoretically associated with changes in built environment characteristics and changes in walking for transport. The factors were age group (categorical, between 40–44, 45–49, 50–54, 55–59, 60–64, and 65–69 years of age); occupation (professional requiring a level of specialty or skill commensurate with a bachelor’s degree or higher qualification, white collar characterized as managerial or administrative work, blue collar characterized as manual work or not in labour force); self-rated health (a dichotomous measure of 0 (excellent/very good/good) or 1 (fair/poor)); income group (\$AUD 0–\$25,999, \$26,000–\$41,599, \$41,600–\$72,799, \$72,800–\$129,999 or \$130,000 or more per year), and area disadvantage (using the Australian Bureau of Statistics (ABS) Index of Relative Socio-economic Disadvantage (IRSD), with 1 being the most disadvantaged area and 100 the least; tertile cutoffs in the descriptive table were based on the distribution of the IRSD in the HABITAT survey).

Random effects regression models that estimated associations based on differences between individuals (vs. fixed effects models of changes within individuals over time) were also adjusted for sex and education at enrollment (the highest qualification obtained, classified as bachelor’s degree or higher, diploma, certificate, or high school only).

Respondents’ preferences for living in areas that support walking were derived using principal components analysis (with an orthogonal varimax rotation) on a set of responses (on a 5-point Likert scale) to a question asked at baseline and upon moving (that is, each person was asked once): “How important were each of the following in your decision to move to your current suburb?” The items were: affordability of housing, land or rent, investments potential, closeness to work, cheaper to travel to work, safety from crime, quiet location, familiarity with area, closeness to school, ease of walking to places, closeness to childcare, closeness to the city, near to green-space or ‘bushland’ (native forest), closeness to public transport, closeness to open space (e.g., parks) (overlapping with green-space), closeness to shops, and access to freeways or main roads.

Four factors were identified that had an Eigenvalue (the variance of the principle components) of greater than 1 and that explained (in total) 55% of the variance in the data at baseline. The amount of variance explained and the scoring of each factor were reasonably consistent across waves (Table S1).

Of the factors generated, the factor that explained the most variance (19% at baseline) related to preferences for living in

areas that support walking, including ease of walking to places, closeness to public transport, and wanting to live close to shops, and was used as our measure of preference for walking. The Cronbach’s Alpha for this measure was 0.85, indicating good internal consistency across items. This variable was included as a continuous measure in regression models (and as tertiles in the descriptive summary), with an increasing score representing an increase in preference for these environmental features that support walking for transport.

Analysis

All analyses were performed using Stata 14.0 (StataCorp. 2011). To describe the analytic sample, mean and median walking (in minutes) at enrollment in 2007 was estimated across categories of each covariate. We also estimated the average change in each exposure variable between consecutive waves to gauge how much change people experienced across the HABITAT survey (including change experienced by people who moved location and by changes in the built environments of people who stay *in situ* across the four waves).

To facilitate comparisons with previous studies, we used random effects regression models to compare different individuals at each point in time, while accounting for the nonindependence of repeated observations within the same individuals. We used logistic random effects models to estimate associations between the predictors of interest (connectivity, residential density, and land-use mix) and any walking for transport vs. none (using the ‘xtlogit’ command in Stata), and linear random effects models to estimate associations with minutes of walking for transport as a continuous variable (using the ‘xtreg’ command in Stata). All random effects models were adjusted for sex and education at baseline; and such models were adjusted for age, income, occupation, self-reported health, and area disadvantage as time-varying variables. In addition, we ran a second set of models for each outcome that also included the proxy measure of each participant’s preference for walking (derived using principal components analysis and categorized into tertiles) as a covariate. For linear regression models, we estimated models based on the full sample and models restricted to people who walked for transport.

A simplified linear random effects model equation is as follows:

$$Y_{it} = \beta_0 + \chi_{it}\beta + Z_i\gamma + \alpha_i + \mu_{it}$$

where Y_{it} is the dependent variable representing minutes of walking for transport in individual i at time t , χ_{it} is a vector of the time-varying predictors (age, occupation, self-rated health, income, area disadvantage, connectivity, density, and land use mix), Z_i represents the time invariant covariates sex and education, α_i is the unobserved individual effect (the intercept for each individual), and μ_{it} is the time-varying error term for each individual.

In addition, we compared changes over time within individual participants using logistic (xtlogit with the ‘fe’ option in Stata) and linear (xtreg with the ‘fe’ option in Stata) fixed effects regression models to estimate associations with any walking (vs. none) and minutes of walking (continuous), respectively. In contrast with random effects models, these models are conditioned on each individual, and therefore do not include the time-invariant variables sex or education, or individual-level intercepts.

Both random and fixed effects models were based on complete case analysis, such that observations with missing data for any covariate were excluded from the analysis. For random effects models, this left 9,747 participants with 23,646 observations, in comparison with 10,941 and 30,943 in the entire dataset with information on walking for transport. In addition, linear

fixed effects models only include information from study participants whose exposures varied over the study period, whereas logistic fixed effects models only include participants whose exposures and outcomes both varied over the study period (Gunasekara et al. 2014). Therefore, after accounting for missing covariate data, numbers of participants and observations included in each linear fixed effects analysis were 9,747 and 23,646, whereas logistic random effects models included 2,789 participants and 9,107 observations, for models of street connectivity, residential density, and land-use mix.

Interactions. We evaluated pairwise interactions between street connectivity, land-use mix, and density in relation to any walking for transport (vs. none) using separate fixed effects logistic regression models adjusted for age, occupation, income, area disadvantage, and self-reported health at each time point. Models included interaction terms between one predictor as a continuous variable and a second predictor categorized into tertiles (six models in total). Interaction *p*-values were derived using likelihood ratio

tests comparing the fit of models with and without product-interaction terms for each pair of predictors.

Results

Descriptive Statistics

About one-third of respondents reported any walking for transport at baseline. Men reported spending more time walking for transport than women reported, and men were more likely to report any walking for transport (Table 1). Walking for transport decreased for each age group from 40 to 65 y. The socioeconomic measures give a mixed picture of their association with walking for transport. Some markers of lower socioeconomic status (lower income and area disadvantage) were correlated with more walking for transport (in terms of time and proportion of walkers); however, some markers of higher socioeconomic status (more education and higher occupational status) also were correlated with more walking

Table 1. Description of walking for transport at enrollment into HABITAT (2007) by age group, sex, education, occupation self-rated health, income and neighborhood preference.

Covariates	Total sample (<i>n</i>)	Minutes/week of walking (mean ± SD)	Percentage who reported any walking
Age category			
40–44 years	2,514	37.5 ± 89.5	38.4
45–49 years	2,382	39.1 ± 92.0	35.9
50–54 years	2,312	34.1 ± 84.8	33.5
55–59 years	2,080	32.9 ± 80.4	32.3
Over 60 years	1,731	29.0 ± 81.1	29.8
Missing	16		
Sex			
Male	4,849	37.0 ± 88.0	35.5
Female	6,186	33.3 ± 84.6	33.4
Missing	0		
Education			
High school only	4,311	28.9 ± 79.9	28.9
Certificate	1,952	31.8 ± 84.6	30.0
Diploma	1,268	36.7 ± 89.6	36.3
Bachelor's	3,457	43.7 ± 92.5	43.1
Missing	47		
Occupation			
Manager/Professional	3,640	35.3 ± 77.4	38.2
White	2,385	33.9 ± 73.3	35.3
Blue	1,552	25.6 ± 68.3	25.7
Not in the labour force	2,644	28.6 ± 70.8	31.9
Missing	814		
Household Income			
Australian \$0–\$25,999	1,044	42.3 ± 105.1	37.2
Australian \$26,000–\$41,599	1,188	36.5 ± 98.5	32.2
Australian \$41,600–\$72,799	2,438	34.6 ± 76.7	35.5
Australian \$72,800–\$129,999	2,845	35.4 ± 82.6	36.2
Australian \$130,000.00	1,889	35.4 ± 89.0	34.9
Missing	1631		
Self-rated health			
Excellent/very good/good	8,981	35.1 ± 85.4	34.7
Fair/poor	1,950	34.4 ± 89.8	33.2
Missing	104		
Choice of neighbourhood related to walkability			
Tertile 1 (lowest preference)	3,189	24.3 ± 70.5	26.2
Tertile 2	3,189	35.7 ± 91.6	34.5
Tertile 3 (highest preference)	3,189	45.6 ± 91.7	44.2
Missing	1468		
Area level socio-economic disadvantage ^a			
Tertile 1 (High)	3,917	39.0 ± 90.9	39.0
Tertile 2	3,278	34.5 ± 84.8	35.8
Tertile 3 (Low)	3,840	31.2 ± 82.1	33.3
Missing	0		

^aArea disadvantage was measured using the Australian Bureau of Statistics (ABS) Index of Relative Socio-economic Disadvantage (IRSD). This is widely used measure of disadvantage in Australia. The IRSD is calculated using Principal Component's analyses of 17 variables that capture a wide range of socio-economic attributes including education, occupations, unemployment, household structure, and household tenure. Each Census Collector District was assigned a socioeconomic score based on its ABS derived IRSD for the matching survey year.

for transport. In addition, 13% were missing information on walkability preference at baseline, 15% were missing information on income, and 7% lacked information on occupation.

As the derived indicator of walkability preference increased, so did the time people spent walking, such that those residing in the highest tertile for walkability preference walked on average 45.6 min per week (Table 1).

The three environmental predictors of walkability are summarized in Table 2 in relation to their mean and median at their first measurement at baseline and their mean change and range of change between consecutive, subsequent time points. On average, there were 14 four-way intersections, 19 dwellings per hectare, and 43% land-use heterogeneity within 1 km buffer areas surrounding each participant residence at baseline (Table 2). For each predictor, the average mean change (and interquartile range) across all consecutive waves was small in comparison with the standard deviation at baseline and the overall (minimum–maximum) range of mean change over the study period. Out of the total study population ($n=11,035$), 8,769 (28%), 1 (<0.01%), and 1 (<0.01%) had no change in street connectivity, residential density, and land-use mix, respectively, during the study period.

Regression Analysis

Street connectivity. Odds ratios (ORs) from adjusted random effects models that did not account for walkability preference suggested that participants who experienced a 1-unit increase in street connectivity between study waves (representing 10 additional four-way intersections within 1 km) were 49% more likely than people who experienced no change to report any walking for transport (OR = 1.49; 95% CI: 1.42, 1.56) (Table 3). Estimates from random effects models that were adjusted for walkability preference were similar, though somewhat attenuated (OR = 1.40; 95% CI: 1.30, 1.47). Fixed effects conditional logistic regression models based on changes over time within individual participants, which are not confounded by time-invariant characteristics but are limited to participants who experienced a change in both street connectivity and walking ($n=2,789$ people with 9,107 observations after accounting for missing data on time-varying covariates) indicated a positive, but weaker association with a 1-unit increase in street connectivity (OR = 1.19; 95% CI: 1.07, 1.32).

Random effects models of minutes of walking for transport also indicated positive associations with street connectivity that were somewhat attenuated after adjustment for walkability preference ($\beta = 5.23$; 95% CI: 4.10, 6.36 after adjustment for preference for the full sample and $\beta = 1.50$; 95% CI 0.48, 2.53 for the sample restricted to transport walkers only, consistent with a 5-min or 1.5-min increase in walking for transport, respectively, with every 10 additional four-way intersections within a 1 km buffer) (Table 3). However, there was no significant association between street connectivity and changes in minutes of walking within individuals based on fixed effects linear regression models of participants who experienced a change in connectivity during the study period ($\beta = 0.52$; 95% CI: $-3.47, 2.42$; $n = 9,747$ participants with 23,646 observations.)

Residential density. The odds of any walking for transport (vs. none) was also positively associated with residential density, with slightly attenuated estimates from random effects models after adjustment for walkability preference (OR = 1.16; 95% CI: 1.15, 1.25 for a 5 dwelling/hectare increase in residential density within a 1-km buffer based on 8,547 participants and 20,899 observations) (Table 3). The association also was less pronounced based on within-individual changes over time from the fixed effects logistic model (OR = 1.10; 95% CI: 1.05, 1.15 based on 2,789 participants and 9,107 observations). Increases in residential density also were positively associated with minutes of walking for transport based on random effects models ($\beta = 3.49$; 95% CI: 2.91, 4.07 after adjusting for walkability preference), but, as for street connectivity, there was no clear association based on fixed effects linear regression of changes within individuals (9,747 participants with 23,646 observations.)

Land use mix. As for the other predictors, estimates from random effects models, with and without adjustment for walkability preference, indicated positive associations between any walking for transport and an increase in land-use mix (OR = 1.28; 95% CI: 1.20, 1.35 for a 10% increase in land use heterogeneity within a 1-km buffer, after adjusting for walkability preference) (Table 3). The association also was positive, but less pronounced, based on within-individual changes over time from the fixed effects logistic model (OR = 1.12; 95% CI: 1.00, 1.26). As for the other predictors, increases in residential density also were positively associated with minutes of walking for transport based on random effects models, but there was no clear association based on fixed effects models of changes within individuals.

Table 2. Environmental predictors of walkability at enrolment into the HABITAT cohort, and for mean changes in each predictor between each of the four study waves (2007, 2009, 2011, 2013).

Variable	Street connectivity ^a	Residential density ^b	Land use mix ^c
Value at baseline (2007)			
Mean \pm SD	13.92 \pm 11.87	18.69 \pm 10.33	0.43 \pm 0.10
Minimum	0	0.10	0.11
25 th percentile	4	13.61	0.37
50 th percentile	11	15.64	0.43
75 th percentile	21	21.26	0.49
Maximum	67	93.16	0.76
Mean change between waves			
Mean \pm SD	-0.94 ± 4.37	0.43 \pm 4.64	-0.002 ± 0.042
Minimum	-65	-218	-0.50
25 th percentile	0	-0.09	-0.01
50 th percentile	0	0.08	-0.0009
75 th percentile	1.0	0.51	0.008
Maximum	64	125	0.47
n (%) with no change during study period	8,769 (28%)	1 (<0.1%)	1 (<0.1%)

^aNumber of 4-way intersections within 1 km of each residence.

^bNumber of dwellings/hectare within 1 km of each residence.

^cHeterogeneity of five categories of land-use mix (residential, commercial, industrial, recreation and leisure, other) within a 1-km buffer, with 1 representing an even distribution and 0 indicating only a single type of land use.

Table 3. Changes in connectivity, residential density, and land-use mix as predictors of any walking for transport (vs. none, logistic regression models) and minutes of walking for transport (linear regression models).

Outcome and exposure	Random effects models ^a			Random effects models + walking preference ^b			Fixed effects models ^c		
	Participants (Observations)	OR or beta ^d (95% CI)	p-Value	Participants (Observations)	OR or beta ^d (95% CI)	p-Value	Participants (Observations)	OR or beta ^d (95% CI)	p-Value
Any walking (logistic model)									
Connectivity	9,747 (23,646)	1.49 (1.42, 1.56)	<0.001	8,547 (20,899)	1.40 (1.33, 1.47)	<0.001	2,789 (9,107)	1.19 (1.07, 1.32)	0.002
Residential density	9,747 (23,646)	1.20 (1.16, 1.25)	<0.001	8,547 (20,899)	1.23 (1.20, 1.27)	<0.001	2,789 (9,107)	1.10 (1.05, 1.15)	0.003
Land use mix	9,747 (23,646)	1.39 (1.31, 1.46)	<0.001	8,547 (20,899)	1.28 (1.20, 1.35)	<0.001	2,789 (9,107)	1.12 (1.00, 1.26)	0.058
Minutes of walking (linear model)									
Full sample									
Connectivity	9,747 (23,646)	6.20 (5.13, 7.28)	<0.001	9,107 (20,899)	5.23 (4.10, 6.36)	<0.001	9,747 (23,646)	0.52 (-3.47, 2.42)	0.729
Residential density	9,747 (23,646)	3.90 (3.31, 4.49)	<0.001	9,107 (20,899)	3.49 (2.91, 4.09)	<0.001	9,747 (23,646)	0.60 (-0.73, 1.93)	0.375
Land use mix	9,747 (23,646)	5.59 (4.28, 6.90)	<0.001	9,107 (20,899)	4.01 (2.63, 5.40)	<0.001	9,747 (23,646)	0.32 (-2.89, 3.52)	0.847
Restricted to walkers									
Connectivity	5,022 (8,981)	1.32 (-0.83, 3.46)	0.002	4,752 (8,518)	1.09 (-1.04, 3.22)	0.004	5,022 (8,981)	-4.57 (-11.60, 2.47)	0.203
Residential density	5,022 (8,981)	1.65 (0.61, 2.69)	0.08	4,752 (8,518)	1.50 (0.48, 2.53)	0.21	5,022 (8,981)	0.85 (-1.96, 3.65)	0.555
Land use mix	5,022 (8,981)	1.74 (-0.21, 3.71)	0.23	4,752 (8,518)	1.25 (-0.70, 3.21)	0.32	5,022 (8,981)	1.45 (-4.69, 7.58)	0.644

^aRandom effects model adjusted for age, sex, income, occupation, and area disadvantage.

^bRandom effects model with additional adjustment for preference for walking.

^cFixed effects models adjusted for time invariant confounding. Logistic and linear models are based only on data for participants who experienced a change in the predictor over time; logistic model estimates are additionally limited to participants who experienced a change in walking for transport.

^dORs (95% CI) from logistic regression models for any walking vs. no walking, and beta coefficients (95% CI) from linear regression models representing the difference in mean minutes of walking, in association with an increase over time in connectivity (10 additional four-way intersections within 1 km), residential density (five additional dwellings per hectare within 1 km), and land-use mix (10% increase in heterogeneity within 1 km), respectively.

Test for a Statistical Interaction between Built Environment Characteristics

A 1-unit increase in land-use mix (a 10% increase in land-use heterogeneity within a 1-km buffer) was positively associated with any walking for transport among participants who also experienced an increase in street connectivity from the lowest to highest tertile based on fixed effects logistic models adjusted for time-varying covariates (OR = 1.17; 95% CI: 0.99), but was not associated with any walking for transport among those who experienced only low or moderate change in land-use mix (interaction *p*-value = 0.05) (Table 4).

Discussion

In this study, we estimated associations between changes in environmental factors (street connectivity, residential density, and land-use mix) and walking for transport using random effects regression models (to account for repeated observations within individuals) with and without adjustment for a proxy measure of people's preferences for living in areas that are walkable and fixed effects regression to model changes within individuals over time and control for measured and unmeasured confounders that did not change over the 6-y study period. We found that increases in street connectivity, land-use mix, and residential density were associated with increases in the likelihood of any walking for transport among middle-age residents of Brisbane, Australia. The association between any walking for transport and an increase in street connectivity appeared to be limited to participants who also

experienced larger increases in land-use mix. However, we found little evidence that changes in street connectivity, density, and land-use mix increases *time* spent walking. This finding is plausible as local environmental determinants of active transport likely differ from determinants of amount of walking for transport undertaken by walkers.

Our findings support those of a number of studies that have used advanced forms of analysis or study designs to examine how the built environment shapes physical activity and have found similar measures of the local environment (particularly street connectivity) to be significantly associated with their outcomes of interest (Hirsch et al. 2014; Knuiman et al. 2014). Findings from a previous analysis of the HABITAT study population suggest that the socioeconomic patterning of walking for transport in Brisbane is complex (Turrell et al. 2014). At the individual level, the odds of walking for transport were greater among individuals with more education, higher income, and employment managers or professionals, possibly reflecting the influence of health promotion. However, residents of disadvantaged areas also were more likely to walk for transport, regardless of their individual-level socioeconomic status. Findings from the present analysis suggest that this might be at least partly explained by environmental factors that may increase walkability, specifically, higher residential density, street connectivity, and land-use diversity.

Our study adjusts for time-invariant confounding in its analytical design. The relatively large difference in some of the estimates generated from "between person" comparisons without

Table 4. Odds ratios (OR) (95% CI) for associations between changes in continuous built environment predictors and walking for transport (any vs. none) according to tertiles of changes in a second predictor based on adjusted fixed effects logistic regression models of longitudinal data for individuals over time.

Interaction: Change in continuous predictor x categorical predictor	OR (95% CI) ^a	Continuous predictor x categorical predictor Interaction <i>P</i> -Value ^b	Continuous predictor x continuous predictor Interaction <i>P</i> -Value ^b
Street connectivity x land use mix			
Low land use mix	1.07 (0.77, 1.48)		
Med land use mix	0.87 (0.66, 1.14)		
High land use mix	1.39 (1.10, 1.77)	0.18	0.02
Street connectivity x density			
Low density	0.89 (0.56, 1.43)		
Medium density	1.00 (0.74, 1.32)		
High density	1.20 (0.98, 1.44)	0.37	0.96
Density x land use mix			
Low land use mix	1.01 (0.95, 1.07)		
Med land use mix	0.96 (0.91, 1.02)		
High land use mix	1.01 (0.99, 1.02)	0.77	0.37
Density x street connectivity			
Low street connectivity	0.97 (0.89, 1.06)		
Med street connectivity	0.98 (0.93, 1.04)		
High street connectivity	1.02 (1.00, 1.03)	0.43	0.96
Land use mix x density			
Low density	0.83 (0.70, 1.00)		
Medium density	1.05 (0.87, 1.26)		
High density	1.12 (0.94, 1.35)	0.54	0.37
Land use mix x street connectivity			
Low street connectivity	0.97 (0.89, 1.09)		
Med street connectivity	0.97 (0.85, 1.12)		
High street connectivity	1.17 (0.99, 1.39)	0.05	0.02

Note: All models are adjusted for age, occupation, income, area disadvantage, and self-reported health at each time point. For categorization of the exposure variables, ‘Low’ refers to the first tertile, ‘Med’ to the middle tertile and ‘High’ to the third tertile.

^aORs for street connectivity as a continuous variable represent the relative odds of any walking for transport (vs. none) with 10 additional four-way intersections within 1 km according to strata of changes in density or land-use mix, respectively. ORs for density as a continuous variable represent the association with five additional residential dwellings/hectare within 1 km according to strata of street connectivity or land use mix, and ORs for land-use mix as a continuous variable represent the association with a 10% increase in land-use mix within 1 km according to strata of density or land use mix.

^bInteraction *p*-values based on likelihood ratio tests comparing covariate-adjusted models with interaction terms and lower-order terms for each predictor to adjusted models with lower-order terms for each predictor only.

adjustment for self-selection compared with estimates generated from “within person” comparisons (described in Table 4) support our contention that self-selection is an important consideration in assessing current evidence and designing analyses.

We performed an analysis of longitudinal data to examine how changes in built environments affect changes in people’s walking for transport. Our study, however, has a number of limitations. The most important may be the size of our exposure gradient. Previous studies argue that changes in the built environment need to be of a sufficiently large magnitude to detect their impact on changes in walking behavior (Giles-Corti et al. 2013). Most changes in our environmental variables were relatively small (as described in Table 2), and it is possible that they were inadequate to detect significant effects in conservative fixed effects regression models that measure changes *within* people over time. Although we find significant associations in our logistic regression models (where everyone must have changed on the outcome, and walking is modelled as a binary (yes/no)), the null findings in the linear models with continuous outcome measures of time spent walking should be interpreted with this relatively small exposure gradient in mind.

A second limitation is that although we have objectively measured data on the characteristics of the built environment, our outcome measure of minutes spent walking for transport is self-reported and, therefore, likely prone to bias from measurement error. Estimates from the fixed effects models, however, make comparisons within people, so the extent to which each person might misreport the amount of walking they have done may be consistent in the reference and comparison categories mitigating this potential source of bias. Third, we have used a single measure of street connectivity (number of four-way intersections). Three-way intersections might also have been evaluated. Finally,

we have only evaluated walking for transport and did not assess cycling as another common form of active transport.

It is important to note that our study focuses on people 40 years of age and older. Walkable neighborhoods (i.e., a well-connected street network, a mix of land uses, and residential density) facilitate active living (e.g., walking, cycling, use of public transport, social engagement) for all age groups. However, in the context of an aging society such as Australia, walkable neighborhoods are especially important in terms of supporting and promoting healthy aging, slowing declines in functional capacity (physical and cognitive), and enabling people as they age to age in place and to live independently for longer periods (Balfour and Kaplan 2002; Clarke and George 2005; Clarke et al. 2009; Schootman et al. 2012; Werngren-Elgström et al. 2008).

Overall, our study lends support to calls for interventions to change the built environments of cities and neighborhoods in ways that promote walking and improve population health (Sallis et al. 2016; Stevenson et al. 2016). Furthermore, there are potential economic concomitant benefits from urban designs that support walking in the form of increased retail activity (Tolley 2007). A highly connected street network provides the foundation for the creation of a walkable community. Increasing both residential density and land-use heterogeneity may also benefit local shops and services, in addition to increasing the likelihood of active travel.

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