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Changes in neighbourhood walkability and body mass index: An analysis of residential mobility from a longitudinal multilevel study in Brisbane, Australia

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ABSTRACT

This study examined associations between changes in neighbourhood walkability and body mass index (BMI) among 1041 residents who relocated within Brisbane, Australia between 2007 and 2016 over five waves of the HABITAT study. Measures included spatially-derived neighbourhood walkability (dwelling density, street connectivity, and land use mix) and self-reported height and weight. No associations were found between any neighbourhood walkability characteristics and BMI. Examining these associations over the life course, and the impact of residential relocation in the younger years, remains a priority for future research.

1. Background

Obesity is strongly linked to poor health and all-cause mortality (Di Angelantonio, 2016). Individuals with a high body mass index (BMI) are more likely to present with non-communicable diseases, including type 2 diabetes, coronary heart disease and stroke (World Health Organization, 2015). High BMI can also have adverse social impacts, including discrimination, social exclusion, reduced earnings and unemployment (Spahlholz et al., 2016; World Health Organization, 2015). There is an increasing body of evidence on the causes of obesity, with the neighbourhood physical environment identified as a potential important determinant (Mackenbach et al., 2014; Mayne et al., 2015), given its association with physical activity (Reiner et al., 2013).

Neighbourhood built environment features, such as walkability, can influence key factors that determine BMI: one such factor being physical activity (Chandrabose et al., 2019). Walkability is typically defined using combinations of residential density, land use mix, and street connectivity (Bentley et al., 2018). Residential density is typically measured using the ratio of residential units per area of land, therefore with dwelling density acting as a proxy for population density (Frank et al., 2009). Research on land use mix emerged following adverse health impacts of land use separation policies and resultant sprawled, single-use, auto-dependent development (Ewing et al., 2003). Land use mix is typically measured using an "entropy", which ranges from 0 to 1, with 0 denoting a single land use within an area, and 1 an equal distribution of different land uses (Song et al., 2013). Street connectivity is typically measured via intersection density (Frank et al., 2009), where greater amounts improve access to destinations by increasing the number of possible routes available and reducing the distance and time required to walk to destinations (Handy et al., 2002). To date, several

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systematic reviews have documented associations between neighbourhood walkability characteristics and several physical activity behaviours including active travel (Cerin et al., 2017), recreational walking (Haselwandter et al., 2015), and overall physical activity (Haselwandter et al., 2015). Among epidemiological (observational) studies, from which causation can be inferred, is the examination of how change in an exposure is related to change in an outcome. One example of this study design which has been used in epidemiological studies is those that examine residential relocation. Environmental studies that follow participants as they move residences (therefore exposing them to different environmental conditions after relocation) provide a strong basis to infer causation, as they capture changes in neighbourhood built environment exposure, along with changes in health (Benton et al., 2016; Firebaugh et al., 2013; McCormack and Shiell, 2011). This is because studies with large changes in exposures are able to make within-individual comparisons (as shown in fixed effects regression models). Such comparisons, by their design, automatically control for unobserved confounding for individual-level covariates that do not change over time (Firebaugh et al., 2013).

Originating in health economics (Crane et al., 2020), residential relocation is becoming increasingly popular in epidemiological research as a unique opportunity to investigate causal relationships between environmental exposures, and health behaviours and outcomes (Saucy et al., 2023). Cohort studies that follow participants as they change residences require additional strategies to optimise cohort maintenance. Examples of these strategies include the collection of contact details about a family member or friend who did not live with the participant in case the participant moved or contact was lost, and change-of-address cards with participant correspondence (Turrell et al., 2021). The causes of residential relocation often reflect differences in socioeconomic position, such as in residential instability among people from lower socioeconomic backgrounds (Cotton and Schwartz-Barcott, 2016), and individual preferences with regards to selecting their new residence. This ‘residential self-selection’ can form substantial bias in epidemiological research (Heinen et al., 2018; Lamb et al., 2020). A lack of adjustment for residential self-selection is problematic for analyses of causal inference between neighbourhood walkability characteristics and obesity, due to the risk of confounding. That is, relocating residents may select their new neighbourhood according to their lifestyle and personal preferences, and those seeking to improve their health (e.g., through increases in physical activity or changes to diet) may seek neighbourhoods that facilitate that objective (McCormack and Shiell, 2011; Van Dyck et al., 2011). Adjustment for residential self-selection was among the poorest scoring of all study quality attributes in a recent systematic review and meta-analysis of the built environment and cardio-metabolic health (including obesity) (Chandrabose et al., 2019).

There have been several longitudinal studies of objectively-measured neighbourhood walkability (e.g. residential density, street connectivity, land use mix, or related indices) and BMI in which participants have changed residences, with mixed results. Among studies that have used walkability indices, Hirsch et al. (2014a) found that an increase in Street Smart Walk Score was significantly negatively associated with BMI and Wasfi et al. (2016) found that, among men, moving to a high-walkable neighbourhood improved BMI trajectories over 12 years, while moving to a low-walkable neighbourhood worsened BMI trajectories. However, neither Berry et al. (2010), Michael et al. (2014) or Braun et al. (2016) found associations between walkability and BMI after 6-year, 18-year and 5-year follow-ups respectively. Among studies that have examined mix of land uses (such as destinations), Hirsch et al. (2014b) found significant associations between intensity of development (density of walking destinations, population density, and percent residential) and BMI, but no associations for connected retail centres or public transportation. Boone-Heinonen et al. (2013) found associations between density of commercial physical activity facilities and BMI, but no associations for density of public physical activity facilities or neighbourhood development intensity, after 5-year follow-up. Among studies of sprawl and urbanicity, Plantinga and Bernell (2007) and Coogan et al. (2011) found significant associations between a sprawl index and BMI, and urbanicity and body weight and obesity among women, respectively. Lee et al. (2009) found associations between urban sprawl and BMI, but only among those who moved to less sprawling areas, not those who moved to more sprawling areas. Finally, Arcaya et al. (2014) found that relocation to areas with greater urban sprawl, which was defined as having lower residential density and poorer street connectivity, were significantly positively associated with BMI among 280 displaced Hurricane Katrina survivors, however, they found no detectable influence of neighbourhood walkability on body weight for women.

While there may appear to be a plethora of studies of objectively-measured neighbourhood walkability and BMI, clear gaps in the literature remain. Of the aforementioned studies, only Arcaya et al. (2014) and Berry et al. (2010) directly adjusted for residential self-selection. There is a clear need for high quality longitudinal studies that can examine within-individual associations where there is change in neighbourhood walkability attributes, such as in residential relocation, and body mass index, with adjustment for potential confounding by residential self-selection. This study therefore aimed to examine associations between neighbourhood walkability attributes (residential density, street connectivity, and land use mix) and BMI among a sample of mid-to-older aged adults who relocated within Brisbane, Australia between 2007 and 2016.

2. Methods

This study used data from the How Areas in Brisbane Influence healTh And acTivity (HABITAT) project. HABITAT is a multilevel longitudinal (2007–2018) study of mid-aged adults (40–65 years in 2007) living in Brisbane, Australia (Turrell et al., 2021). The primary aim of HABITAT is to examine patterns of change in physical activity, sedentary behaviour and health over the period 2007–2018 and to assess the relative contributions of environmental, social, psychological and socio-demographic factors to these changes. Details about HABITAT's sampling design have been published elsewhere (Burton et al., 2009). Briefly, a multi-stage probability sampling design was used to select a stratified random sample (n = 200) of Census Collector's Districts (CCD) (from a total of n = 1625) from the Australian Bureau of Statistics (ABS), and from within each CCD, a random sample of people aged 40–65 years (n = 16,127). Over the duration of the study, participants moved residences, such that the derived HABITAT neighborhoods for each of the wave were n = 200 in 2007, n = 415 in 2009, n = 576 in 2011, n = 724 in 2013 and n = 799 in 2016.

A questionnaire was sent during May–September in 2007, 2009, 2011, 2013 and 2016 using the mail survey method developed by Dillman (2000). After excluding out-of-scope respondents (i.e., deceased, no longer at the address, unable to participate), the total number of useable surveys returned at baseline was 11,035 (68.3% response): this sample was broadly representative of the Brisbane Population (Turrell et al., 2010). Responses for subsequent waves were 7866 (72.3%) for wave 2, 6900 (66.7%) for wave 3, 6520 (69.3%) for wave 4, and 5180 (46.9%) for wave 5. The HABITAT study was approved by the Human Research Ethics Committee of Queensland University of Technology (Ref no. 3967H).

2.1. Main exposure measures

Neighbourhood built environment characteristics were sourced from 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 Land Use Activity Database and StreetPro were obtained under data access agreements restricting public release (Pitney Bowes Software). Proxy measures of three neighbourhood walkability characteristics were calculated: dwelling density, street connectivity and land use mix. Each measure was sourced in 2007, 2009, 2011, 2013 and 2016. Each of these characteristics were defined within a 1 km road network buffer. That is, the area within a 1 km distance on local roads from each participant's dwelling. A 1 km distance was chosen as it has been shown to be a reasonable distance to walk to destinations among middle-aged cohorts (Villanueva et al., 2014). Density comprises the number of units (e.g., people, dwellings, employees) that exist in a unit of land area (Giles-Corti et al., 2012). It is usually defined as population density, represented as a proxy in this study by the number of dwellings in an area, but has also been measured as employment or building square footage (Handy et al., 2002). Dwelling density in this study was measured as the number of dwellings per hectare of residential land (Adams et al., 2014). For analysis, this was divided by 10 so that the coefficient is interpreted as a 10-dwelling increase in dwelling density. Street connectivity has been shown to promote walkability by improving access to 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). In this study, street connectivity was measured as the number of three-way or more intersections, and for analysis, was divided by five so that the coefficient is interpreted as a 5-intersection increase in intersection density. Land use mix was measured as a ratio of the balance of five land use categories (retail, office/business, leisure/recreation, residential, and health/community services) and calculated using an entropy equation (Leslie et al., 2007). A land use mix of 0 indicates all land being used for a single land use category, and 1 indicates an even balance of each of the categories. For analysis, the land use variable was multiplied by 10 so that the coefficient is interpreted as a 0.1 (or 10%) increase in land use mix.

2.2. Main outcome measure

Body mass index: for each survey, participants were asked "how tall are you without shoes?" and were able to respond in either centimetres or feet and inches; and "how much do you weigh without your clothes and shoes?" and were able to respond in either kilograms or stones and pounds. BMI was calculated as weight in kilograms, divided by height in metres squared.

2.3. Covariates included in analysis

Neighbourhood self-selection: To assess residential attitudes, participants were asked to respond on a five-item Likert scale, ranging from 'strongly disagree' to 'strongly agree' on a number of statements regarding "How important were the following reasons for choosing your current address?". Principal components analysis (PCA) with varimax rotation showed that the items loaded onto three factors, subsequently described as 'destinations' (three items, $\alpha = 0.81$) 'nature' (three items, $\alpha = 0.78$) and 'family' (two items, $\alpha = 0.62$).

Neighbourhood socioeconomic disadvantage: derived using scores from the ABS' Index of Relative Socioeconomic Disadvantage (Australia Bureau of Statistics, 2006) (IRSD). A neighbourhood's IRSD score reflects each area's overall level of disadvantage measured on the basis of 17 variables that capture a wide range of socioeconomic attributes, including: education, occupation, income, unemployment, household structure and household tenure. Neighbourhood socioeconomic disadvantage was time-varying, with different scores derived for each wave (i.e. 2007, 2009, 2011, 2013 and 2016). The derived socioeconomic scores from each of the HABITAT neighbourhoods were quantised as percentiles, relative to all of Brisbane. Neighbourhoods were grouped into quintiles based on their disadvantage scores with Q1 denoting the 20% most advantaged areas relative to the whole of Brisbane and Q5 the most disadvantaged 20% for each wave.

Occupation: participants who were employed at the time of completing each survey were asked to indicate their job title and then to describe the main tasks or duties they performed. This information was subsequently coded to the Australian Standard Classification of Occupations (ASCO) (Austalian Bureau of Statistics, 1997). The original 9-level ASCO classification was recoded into five categories: (1) managers/professionals (managers and administrators, professionals, and paraprofessionals), (2) white-collar employees (clerks, salespersons, and personal service workers), (3) blue-collar employees (tradespersons, plant and machine operators and drivers, and labourers and related workers), (4) home duties, (5) retired, and (6) not easily classifiable (not employed, students, permanently unable to work, or other).

Household income: participants were asked to estimate the total pretax annual household income using a single question with 13 categorical responses at each survey. For analysis, these were re-coded into six categories: (1) $\geq$ AU$130,000, (2) AU$129,999–72,800, (3) AU $72,799–52,000, (4) AU$51,999–26,000, (5) $\leq$ AU$25,999, (6) 'Don't know' and (7) 'Don't want to answer this'.

Age: participants reported their date of birth, which was subsequently converted to years of age.

Living arrangements: Participants were also asked to choose from the following options with regard to living arrangements (1) living alone with no children, (2) single parent living with one or more children, (3) single and living with friends or relatives, (4) couple (married or defacto) living with no children, (5) couple (married or defacto) living with one of more children, and (6) other.

2.4. Covariates not included in analysis

Participants were asked to provide information about their highest education qualification attained in the baseline survey. Responses were coded as: (1) bachelor degree or higher (including postgraduate diploma, master's degree, or doctorate), (2) diploma (associate or undergraduate), (3) vocational (trade or business certificate or apprenticeship), or (4) no post-school qualifications. Participants also recorded their sex. As the fixed effects modelling approach (detailed below) does not include time-invariant covariates, and no participants reported a change of sex during the study, education and sex are included in descriptive statistics, but not in the analysis.

2.5. Statistical analysis

We first present baseline sociodemographic statistics to compare 'movers' and 'stayers'. Data were excluded from this baseline comparative analysis if participants were only in the study for a single wave (n = 2176). Data were also excluded if participants did not provide baseline data on education (n = 19), household income (n = 105) and living arrangements (n = 55). This left 6480 'stayers' and 1085 'movers'.

The analytic sample included participants who changed address at some point during the study. Participants who returned to the study after a non-response, and had moved, were included in the sample. Overall, 1100 participants were considered in-scope after participants who were not the same participants at follow-up (n = 34) were excluded (e.g., the survey was completed by another member of the household), with a total of 4688 observations. From those participants, observations were further excluded due to missing data on neighbourhood self-selection (n = 90), household income (n = 83), occupation (n = 103), living arrangements (n = 153) and BMI (n = 110), leaving a total of n = 4149 observations across 1088 participants. A further 47 participants were excluded as they only had data for one wave. The final analytic sample therefore comprised n = 4102 observations across 1041 participants.

An analysis of factors related to participant drop-out revealed that drop-out was associated with demographic variables (e.g. neighbourhood disadvantage) but was not related to prior values of BMI (the outcome variable), as has been shown in other studies using the HABITAT data (Turrell et al., 2018). When drop-out is related to covariates only, and not to prior or missing values of the outcome variable, the drop-out pattern is called (conditionally on the covariates) 'missing at random' (Fitzmaurice et al., 2012; Knuiman et al., 2014).

We postulated that the relationship between neighbourhood walkability and BMI would likely be confounded by self-selection into neighbourhoods, neighbourhood disadvantage, and individual-level socioeconomic indicators education, occupation, and household income. With the exception of education (measured at baseline only), age, occupation, household income, living arrangements and neighbourhood disadvantage were measured at each wave and were included as covariates in the analysis. The association between changes in neighbourhood walkability and BMI over time was examined using fixed effects linear regression with cluster-robust standard errors. The model fixed effects are interpreted as the mean difference in BMI for every 1 unit increase in the exposure. Data were analysed using Stata SE version 18 (StataCorp, 2020).

3. Results

A comparison of stayers and movers is presented in Table 1. Participants who were most likely to relocate were single parents living with one or more children (21.2% of this group relocated during the study period) followed by those with household incomes greater than AU $130,000 (19.2%), while participants who were least likely to relocate were those who were retired (8.9%), followed by those on household incomes less than AU$25,000 and those aged 60–64 (both 9.8%).

The mean changes in dwelling density, street connectivity and land use mix are presented in Table 2. On average, more participants resided in areas with higher dwelling density, street connectivity and lower land use mix in 2016 compared to 2007. Mean changes in BMI by change in neighbourhood environment attribute are also presented in Table 2. Participants who resided in areas with higher dwelling density and higher street connectivity in 2016 compared to 2007 had the highest mean increase in BMI, followed by those who had an increase in land use mix respectively.

The results of the fixed effects regression are presented in Table 3. No associations were found between any of the neighbourhood walkability characteristics and BMI. The coefficients represent the average changes in BMI for every 10-dwelling increase in dwelling density ($\beta = 0.06$, 95% CI = −0.06, 0.18), five-intersection increase in street connectivity ($\beta = -0.00$, 95%CI = −0.02, 0.02), and 0.10 increase in land use mix, respectively, after adjustment for confounders ($\beta = 0.02$, 95%CI = −0.07, 0.11).

4. Discussion

This study examined associations between neighbourhood walkability attributes (residential density, street connectivity, and land use mix) and BMI among a sample of mid-to-older aged adults who relocated within Brisbane, Australia between 2007 and 2016. The majority of participants experienced increases in each of the neighbourhood walkability characteristics. However, no associations were found between any of these characteristics and BMI in this cohort.

Our findings add to what is a somewhat inconsistent field of longitudinal studies, with studies examining various walkability attributes including indices, sprawl, and individual attributes of dwelling density, street connectivity, and land use mix. This is further complicated by the lack of studies that adjust for residential self-selection. Our study findings are somewhat in agreement with Hirsch et al. (2014b) and Boone-Heinonen et al. (2013) both of which found significant and null associations between various destination attributes and BMI. They are also in agreement with those of Berry et al. (2010), Michael et al. (2014) and Braun et al. (2016), all of whom found no associations between walkability and Arcaya et al. (2014) who did not find associations among women. Of the two studies that adjusted for residential self-section, only one found a significant association, which was only among men (Arcaya et al., 2014; Berry et al., 2010). Outside neighbourhood environment attributes used, there were also vast differences in the age of participants. The current study was designed to understand the influence of the neighbourhood environment on the health of participants during transitions from middle to older age (i.e. 40-65 years at baseline), with a mean age of 49.9 years. Mean baseline ages for other studies included 25.1 years (Arcaya et al., 2014), 61.8 years (Hirsch et al., 2014a), and 38 years (Wasfi et al., 2016).

Several strengths and limitations should be considered when interpreting this study's findings. A major strength of this study was that we sourced walkability and neighbourhood disadvantage at all fives waves. We did not assume that key neighbourhood characteristics remained constant over the study period (i.e. 2007 to 2016), which is a limitation of previous work (e.g. Hirsch et al. (2014b). Another strength is that we conducted within-individual analysis. This accounts for all

Table 1
Baseline characteristics of the movers and stayers in the HABITAT study: 2007–2016 in Brisbane, Australia[a].

	Stayer		Mover	
	n	%	n	%
Neighbourhood disadvantage				
Q1 (least disadvantaged)	1965	84.9	348	15.1
Q2	1260	86.3	200	13.7
Q3	1210	86.1	196	13.9
Q4	1214	85.6	205	14.5
Q5 (most disadvantaged)	831	85.9	136	14.1
Age (years)				
40-44	1175	81.2	273	18.9
45-49	1433	84.8	256	15.2
50-54	1329	85.2	231	14.8
55-59	1249	87.2	184	12.8
60-64	1294	90.2	141	9.8
Sex				
Male	2777	84.9	493	15.1
Female	3703	86.2	592	13.8
Living arrangements				
Living alone with no children	935	84.9	166	15.1
Single parent living with one or more children	497	78.8	134	21.2
Single and living with friends or relatives	394	83.3	79	16.7
Couple (married/defacto) living with no children	1786	87.5	255	12.5
Couple (married/defacto) living with one or more children	2868	86.4	451	13.6
Education				
Bachelor+	2103	84.7	379	15.3
Diploma/Assoc Deg	731	83.7	142	16.3
Certificate (trade/Business)	1137	86.1	184	13.9
None beyond school	2509	86.9	380	13.2
Occupation				
Mgr/prof	2202	82.8	458	17.2
White collar	1402	85.5	238	14.5
Blue collar	928	87.1	138	13
Home duties	395	88.6	51	11.4
Retired	621	91.1	61	8.9
Not easily classifiable	932	87	139	13
Household income				
$130000+	1108	80.8	264	19.2
$72800–129,999	1724	84.8	308	15.2
$52000–72799	973	83.7	189	16.3
$26000–51599	1191	88.4	156	11.6
Less than $25999	645	90.2	70	9.8
Don't know	163	89.1	20	10.9
Don't want to answer	676	89.7	78	10.3
Total	6480	85.7	1085	14.3

[a] Participants must be in the study for at least two waves.

Table 2
Descriptive statistics for participants that had an increase or decrease in their built environment characteristics between 2007 and 2016 and body mass index: participants aged 40–65 years at baseline in the HABITAT analytic sample.

	Change in built environment characteristic						Mean BMI change (SD)
	N	Mean	Standard Deviation	Median	Interquartile range	Range	
Residential density							
Increase	384	11.85	18.80	4.87	0.04, 100.04	0.01, 158.96	0.75 (3.19)
Decrease	215	−5.95	8.21	−3.51	−27.47, −0.06	−70.31, −0.02	0.04 (4.94)
Overall	599	1.49	17.99	1.49	−27.47, 100.04	−70.31, 158.96	
Street connectivity							
Increase	328	30.97	25.70	25	1, 108	1, 162	0.44 (4.20)
Decrease	261	−28.71	23.11	−23	−90, −1	−142, −1	0.53 (3.61)
Overall	599	4.45	38.19	4	−90, 108	−142, 162	
Land use mix							
Increase	323	0.11	0.09	0.09	0.00, 0.40	0.00, 0.51	0.85 (2.65)
Decrease	276	−0.09	0.08	−0.07	−0.33, −0.00	−0.39, −0.00	0.08 (4.99)
Overall	599	0.02	0.13	0.01	−0.33, 0.40	−0.39, 0.51	

Table 3
Associations between the built environment and body mass index following residential relocation in the HABITAT study in Brisbane, Australia, 2007–2016: Fixed effects models*.

	β (95%CI)
Dwelling density[a]	0.06 (−0.06, 0.18)
Street connectivity[b]	−0.00 (−0.02, 0.02)
Land use mix[c]	0.02 (−0.07, 0.11)

[*] Adjusted for age, education, neighbourhood self-selection, and changes in occupation, income, and neighbourhood disadvantage.
[a] Dwelling density is divided by 10, such that the coefficient is interpreted as the mean change in BMI for every 10 additional dwellings.
[b] Street connectivity is divided by 5, such that the coefficient is interpreted as the mean change in BMI for every 5 additional intersections.
[c] Land use mix is divided by 10, such that the coefficient is interpreted as the mean change in BMI for every 0.10 increase in land use mix.

time-invariant confounding; we also accounted for further time-varying confounding by individual-level occupation and household income. We also adjusted for self-selection into neighbourhoods, which has been identified as a major confounder in epidemiological studies of neighbourhoods and health (McCormack and Shiell, 2011; Van Dyck et al., 2011). Further, despite the large number of covariates in our model, a power analysis using a r-squared of 0.0207 and 26 model parameters indicated a required sample size of at least 1,118, which is exceeded by the 4102 observations in our study. Among the limitations, survey non-response in the HABITAT baseline study was 31.5%, and slightly higher among residents from lower individual socioeconomic profiles, and those living in more disadvantaged neighbourhoods. The findings of this study may also be confounded by unobserved time-varying individual and neighbourhood-level socioeconomic factors, or bias from the misclassification of self-reported responses. However, this study employed commonly-used indicators of individual-level socioeconomic position (occupation and household income (Dutton et al., 2005)), while the neighbourhood-level IRSD measure (which forms the basis of our neighbourhood disadvantage measure) provides a comprehensive assessment of neighbourhood-level disadvantage (Australia Bureau of Statistics, 2006). The use of self-reported height and weight to calculate BMI is subject to measurement error that may result in the underestimation of BMI. This underestimation appears to be higher as measured BMI increases, may differ in women and men (Dhaliwal et al., 2010), and may also vary by age and socioeconomic background. However, the within-individual comparisons mean that if this measurement error is constant over time within individuals, bias from measurement error is mitigated. It should also be noted however, that self-reported BMI is often used in large population studies due to its ease of recording (Gorber et al., 2007; Hattori and Sturm, 2013), and that studies have found strong correlations between self-reported and objectively measured height and weight (Vuksanović et al., 2014). Last, given that this was a study of residential relocation, the findings (i.e., examining associations of neighbourhood walkability and BMI) may have limited generalisability to those who remain at the same residence.

There are a number of relevant future research priorities. Our measure of land use mix only captured the mix of land uses for five land use codes. While greater land use diversity suggests more destinations in the neighbourhood that may encourage physical activity, the extent to which those destinations affect BMI remains unknown. For example, the destinations within the neighbourhood may have represented those which were supportive (e.g., a green grocer), or detrimental (e.g. fast food outlet) to healthy BMI (Rundle et al., 2009). Further, it is possible that sensitivity to the built environment may differ by age. Reproducing this study with a wider age range of participants would help to progress the field. This study adds to the limited literature examining whether changes in the neighbourhood built environment are associated with differences in BMI during residential relocation.

While the current study did not find evidence of an association between neighbourhood walkability and BMI among residents who relocated, policy-makers should nevertheless be encouraged to design neighbourhoods that are supportive of physical activity, in order to improve health outcomes. For example, a large body of evidence demonstrates an association between the neighbourhood built environment and other health behaviours and outcomes, including active travel (Cerin et al., 2017), diet (Mayne et al., 2015), and cognition (Besser et al., 2017). Examples of policies that facilitate walking include the Subdivision and Neighbourhood Design section of the Auckland Design Manual (Auckland Council), The New York City Department of City Planning's Active Design Guidelines (New York City Department of Planning, 2010), and the NSW Guide to Walkable Public Space by the New South Wales Government.

This study examined associations between changes in neighbourhood walkability characteristics and BMI among a sample of mid-to-older aged adults who relocated within Brisbane, Australia between 2007 and 2016. In conclusion, using a methodically rigorous epidemiological study design that made within-individual comparisons, accounting for all time-invariant confounding, and time-varying confounding, notably residential self-selection, we investigated whether the change in walkability attributed due to relocation affected BMI. While no associations were found, policymakers should not be discouraged from pursuing walkable neighbourhood strategies considering the numerous health benefits found in the existing evidence base.

CRediT authorship contribution statement

Jerome N. Rachele: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Suzanne Mavoa:** Writing – review & editing, Methodology, Formal analysis. **Takemi Sugiyama:** Writing – review & editing, Methodology. **Anne Kavanagh:** Writing – review & editing, Methodology. **Billie Giles-Corti:** Writing – review & editing, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Wendy J. Brown:** Writing – review & editing, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization. **Shigeru Inoue:** Writing – review & editing, Conceptualization. **Shiho Amagasa:** Writing – review & editing, Conceptualization. **Gavin Turrell:** Writing – review & editing, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of competing interest

None declared.

Data availability

Data will be made available on request.

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