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Moderating effects of Walk Score® on the association between neighbourhood disadvantage and body mass index among mid-to-older aged Australian adults

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ABSTRACT

Introduction: This study examined whether the association between neighbourhood disadvantage and body mass index (BMI) was moderated by neighbourhood walkability among mid-to-older aged adults.

Methods: Data were from the 2016 wave of the How Areas in Brisbane Influence Health and Activity (HABITAT) study, including 3249 mid-to-older aged adults residing in 200 neighbourhoods. Self-reported height and weight were used to calculate BMI; neighbourhood disadvantage was assessed using a census-derived index, analysed in quintiles; and walkability was determined using Walk Score®.

Results: BMI was associated with neighbourhood disadvantage with those residing in the most disadvantaged neighbourhoods (Q4 and Q5) having higher BMI compared to those in the least disadvantaged neighbourhoods (Q1). There was evidence of moderation by Walk Score in the most disadvantaged neighbourhoods (Q5). For every 10-unit increase in Walk Score, BMI differences between the most disadvantage neighbourhoods (Q5) and the least disadvantaged (Q1) reduced ($\beta = -0.40$, 95 % CI: -0.75, -0.05).

Conclusion: These findings suggest that greater walkability in disadvantaged neighbourhoods may present an opportunity to narrow the health inequities observed across neighbourhoods. Improving walking infrastructure in disadvantaged neighbourhoods could promote physical activity and support healthier weight outcomes to reduce health disparities.

1. Introduction

Body mass index (BMI) is widely used to classify the body weight of individuals and to evaluate weight related health risks. The World Health Organisation (WHO) defines overweight as a BMI of 25 kg/m^2 or greater and obesity as a BMI of 30 kg/m^2 or greater (World Health Organisation, 2024). Having a BMI categorised as overweight or obese has long been associated with a range of noncommunicable diseases, including cardiovascular disease, diabetes, cancers, neurological disorders, chronic respiratory diseases

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and digestive disorders (Zhou et al., 2024). In 2022, 43 % of adults worldwide were classified as overweight, with an additional 16 % meeting the criteria for obesity, presenting a significant global public health challenge (World Health Organisation, 2024). Furthermore, the prevalence of overweight and obesity is rising. The 2021 Global Burden of Disease Study found that deaths and disability-adjusted life years attributable to high BMI more than doubled since 1990, placing an immense strain on healthcare systems worldwide (Zhou et al., 2024).

In line with the global trends, more than 65 % of Australian adults are considered overweight or obese (Australian Bureau of Statistics, 2023). According to the 2022 National Health Survey, the proportion of Australian adults classified as overweight and obese increased with age, reaching its highest prevalence among men aged 65–74 years and women aged 55 to 64. Furthermore, over the past decade, the proportion of overweight or obese adults has risen by 3 %, largely due to an increase in obesity rates from 27.5 % to 31.7 % (Australian Bureau of Statistics, 2023). In the context of an ageing population, these trends highlight the need to address obesity in older adults. Obesity has been shown to impact mobility, chronic disease and overall health, which can strain healthcare systems and reduce quality of life in later years (Kerr et al., 2012).

Obesity typically follows a socioeconomic gradient, with higher prevalence among more disadvantaged populations (Peeters and Backholer, 2015). Prior research globally (McCormack et al., 2017, 2018; Pearson et al., 2014) and in Australia (Carroll et al., 2023; Nkemdilim et al., 2025; Rachele et al., 2017, 2019; Zhang et al., 2024) has consistently found that those residing in more disadvantaged neighbourhoods are more likely to have higher BMI. The built environment characteristics of disadvantaged neighbourhoods, such as inadequate greenspace and recreational facilities, compared to more advantaged areas may be a contributing factor (Lovasi et al., 2009a). As a result, residents of disadvantaged neighbourhoods typically engage in less leisure-time physical activity, however, they are more likely to rely on walking for transport due to lower car ownership (Turrell et al., 2013). Physical inactivity is a key risk factor for obesity (World Health Organisation, 2024) and features of the neighbourhood built environment (e.g., green spaces, parks, land use mix and transportation systems) are likely to affect BMI by supporting or discouraging physical activity (World Health Organisation, 2022). Furthermore, the neighbourhood environment is particularly important for physical activity in older adults as they are often retired and tend to spend more time in their local community (Kerr et al., 2012).

Walkability, a feature of the neighbourhood built environment, is typically defined as the combination of residential density, mix of land uses and destinations, pedestrian-friendly streets and street connectivity (Cerin et al., 2017). Numerous studies have linked neighbourhood walkability with active transport (Cerin et al., 2017; Cole et al., 2015; Hirsch et al., 2014; Knuiman et al., 2014; Smith et al., 2017), total physical activity (Barnett et al., 2017) and lower BMI or waist circumference (Chandrabose et al., 2019; Creatore et al., 2016; Hirsch et al., 2014; McCormack et al., 2018; Müller-Riemenschneider et al., 2013; Paulo dos Anjos Souza Barbosa et al., 2019). While there is substantial evidence supporting a relationship between walkability and BMI, not all studies have identified this association. A study in Brisbane, Australia did not find a link between walkability and BMI (Rachele et al., 2024).

In recent years, there has been an increased emphasis on the role of walkability as a key mechanism underlying the relationship between neighbourhood disadvantage and health (Loh et al., 2019; Turrell et al., 2013). It is plausible that neighbourhood walkability may act as a moderator, that may alter the strength of the association between neighbourhood disadvantage and BMI, presenting an opportunity to narrow neighbourhood socioeconomic inequalities in BMI. However, studies examining moderating effects of walkability are inconclusive (Selvakumaran et al., 2023). McCormack et al. (2017) found that lower walkability, determined by curvilinear street patterns, in disadvantaged neighbourhoods was associated with higher waist circumference. Conversely, a US study found that walkability, determined by population density, land use mix, transit use, and transit stops within 1 km circular buffer, was more strongly and consistently associated with BMI in advantaged neighbourhoods, while there was little evidence to support similar associations for disadvantaged neighbourhoods. The findings are potentially due to overriding factors such as safety concerns or the food environment (Lovasi et al., 2009b). Fast-food outlet density is typically higher in more disadvantaged neighbourhoods (Macdonald et al., 2018; van Erpecum et al., 2022) and greater exposure to these outlets may outweigh the potential benefits of walkability (Lovasi et al., 2009b). In an Australian study, walkability, determined by number of amenities within 1 km road network buffer, did not moderate the association between BMI or waist circumference and neighbourhood disadvantaged (Carroll et al., 2023).

The mixed findings in previous research may partially be attributed to variations in the measurement of walkability. These measurements encompass both objective and perceived characteristics of the neighbourhood environment, such as those assessed through questionnaire using Neighbourhood Environment Walkability Scale (NEWS) (Cerin et al., 2017).

One measure of walkability is Walk Score®. Walk Score is a validated, objective composite index of walkability, combining the shortest distance to key destinations (e.g., public transport, shops, parks, schools), block length, and intersection density using a network buffer (Carr et al., 2011). It has been used widely in public health research (Cole et al., 2015; Hall and Ram, 2018) and higher Walk Scores have been associated with increased physical activity and lower BMI (Hirsch et al., 2014; McCormack et al., 2018). The objectivity of Walk Score reduces the potential for subjective biases that are common in self-reported measures. Furthermore, using a network buffer, as opposed to Euclidean, can provide a more accurate measure of walkability as it reflects travel routes following the road network (Mavoa et al., 2019). These attributes make Walk Score a valuable tool for examining the relationship between the neighbourhood environment and health outcomes.

Greater walkability in disadvantaged neighbourhoods has potential to promote healthy behaviours such as physical activity and walking for transportation (Turrell et al., 2013), which may reduce neighbourhood-based inequalities in BMI. This is particularly relevant for older adults, for whom walking represents the most common form of physical activity in their daily routines (Kerr et al., 2012). Therefore, the aim of this study is to examine whether the association between neighbourhood disadvantage and BMI differs according to Walk Score in a cohort of mid-to-older-aged Australian adults, using multilevel linear regression models to assess both the main association and the inclusion of an interaction term to examine effect modification by Walk Score.

2. Methods

Data from the HABITAT (**H**ow **A**reas in **B**risbane **I**nfluence Heal**T**h and **A**c**T**ivity) study were used for this investigation. HABITAT is a multilevel longitudinal study of mid-older aged men and women living in the Brisbane Local Government Area from 2007 to 2016. The objective of the study was to examine the relative contributions of environmental, social, psychological and sociodemographic factors on physical activity change (Turrell et al., 2021). The HABITAT study received ethical clearance from the RMIT University Human Research Ethics Committee (CHEAN B 20577-01/17), in alignment with the principles outlined in the Declaration of Helsinki. All participants in this study were informed about the study's objectives, procedures, potential risks, and benefits, and their rights to withdraw at any time without any consequences and provided informed consent prior to their inclusion.

2.1. Sample

Details about HABITAT's baseline sampling have been described elsewhere (Burton et al., 2009). Briefly, a multi-stage probability sampling design was used to select a stratified random sample of adults aged 40–65 years from Brisbane, Australia. Census Collection Districts (CCDs) (n = 1625) were ranked by their Index of Relative Socioeconomic Disadvantage (IRSD), categorised into deciles, and 20 CCDs from each decile were selected to provide 200 CCDs. In 2006 CCDs were the smallest administrative units used by the Australian Bureau of Statistics (ABS) for the collection of census data. An average of 85 people were recruited from within each CCD. CCDs are embedded within a larger suburb, hence the area corresponding to, and immediately surrounding, a CCD is likely to have meaningful influence on the residents. For this reason, we use the term 'neighbourhood' to refer to each CCD. The baseline HABITAT sample in 2007 was broadly representative of the wider Brisbane population of adults aged 40–65 years (Turrell et al., 2013).

2.2. Data collection and response rates

Individual data were collected through a structured self-administered questionnaire sent during May–July in 2007, 2009, 2011, 2013 and 2016 using the Dillman (2011) mail survey method. After excluding out-of-scope respondents (i.e. deceased, no longer at the address, unable to participate for health-related reasons), the total number of useable surveys returned in each survey wave was 11,035 (68.3 %), 7866 (72.3 %), 6900 (66.7 %), 6520 (69.3 %) and 5187 (58.8 %) respectively. This present study used data from the fifth wave (2016) of data collection, comprising a sample size of 5187 participants.

2.3. Measures

2.3.1. Neighbourhood socioeconomic disadvantage

The baseline sample was derived from CCDs, the smallest geographic unit used by ABS to collect census data, which contained an average of 200 dwellings. However, changes were made to the standards and geographical classifications from the Australian Standard Geographical Classification to the Australian Statistical Geography Standard in 2011 and consequently, there were changes to geographical units and boundaries used for generating socioeconomic indexes (Australian Bureau of Statistics, 2016). To account for this, neighbourhood disadvantage was derived using a weighted linear regression, using Index of Relative Socioeconomic Disadvantage (IRSD) scores from each of the previous censuses from 1986 to 2016. A neighbourhood's IRSD score reflects the overall level of socioeconomic disadvantage within an area, derived from 17 census-based indicators describing the characteristics of its residents. These indicators include the proportion of individuals aged 15 years and over whose highest level of education is Year 11 or below, those who are unemployed, employed as labourers, or working in low-skill community and personal service occupations. Additional indicators capture the proportion of one-parent families, individuals aged under 70 years with a disability, divorced or separated residents, machine operators and drivers, households paying low rent, dwellings without a motor vehicle, overcrowded dwellings, and individuals aged 15 years and over with no educational attainment or who have limited English proficiency. Each variable included in the index has a loading that represents its correlation with the overall index, where a negative loading denotes a disadvantaging variable. All variables included in the IRSD are indicators of socioeconomic disadvantage. Further details on the loadings and variable derivations are available in the Census of Population and Housing: Socio-Economic Indexes for Areas (SEIFA), Australia, 2011 (Australian Bureau of Statistics, 2013). The HABITAT neighbourhoods were grouped into quintiles based on their IRSD scores, with Q1 denoting the 20 % least disadvantaged areas relative to the whole of Brisbane, and Q5 the most disadvantaged 20 %.

2.3.2. Walkability

Neighbourhood walkability was measured using Walk Score. Each household address in the HABITAT study was assigned a Walk Score. Walk Score measures walkability on a scale of 0–100 (100 most walkable) by allocating points based on the distance to various amenities and destinations such as grocery stores, schools, parks, restaurants, and retail within a 1.6 km network buffer. A lower Walk Score indicates greater car dependence, with few or no destinations within walking distance. As Walk Score increases more destinations are accessible, with scores at the highest end of the scale indicating that nearly all daily errands can be accomplished on foot, making it possible to live without a car (Walk Score, 2024). The score is derived using a distance decay function to score each destination based on its distance from the address. The score is then adjusted for two street network measures: intersection density and block length around each location (Nykiforuk et al., 2016; Walk Score, 2024). It has been demonstrated to be a valid and reliable tool for estimating walkable access (Carr et al., 2011). For analysis, Walk Score was rescaled by 10 to improve interpretability in the regression models.

2.3.3. Self-reported BMI

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 and analysed as a continuous variable.

2.3.4. Education

Respondents were asked to report the highest education qualification they had attained. Consistent with other studies using HABITAT data, education attainment was grouped into four mutually exclusive categories: (i) Bachelor degree or higher (the latter included postgraduate diploma, master's degree, or doctorate), (ii) Diploma (associate or undergraduate), (iii) Certificate (trade or business certificate or apprenticeship), and (iv) No post-secondary school qualification.

2.3.5. Occupation

Respondents who were employed at the time of completing the survey were asked to indicate their job title and then to describe the main tasks or duties they performed. For this study, the original Australian and New Zealand Standard Classification of Occupations

Table 1
Sociodemographic characteristics, mean (SD) BMI and mean (SD) Walk Score for HABITAT Wave 5 analytic sample.

	Total sample (n = 3249)	BMI	Walk Score [a]
	%	Mean (SD)	Mean (SD)
Neighbourhood			
Q1 (least disadvantaged)	29.64	26.58 (5.26)	42.12 (22.23)
Q2	22.50	27.22 (5.16)	51.65 (20.86)
Q3	19.67	27.49 (5.49)	56.41 (19.41)
Q4	14.74	28.42 (6.53)	53.07 (20.13)
Q5 (most disadvantaged)	13.45	28.51 (7.07)	55.01 (17.13)
Sex			
Male	42.75	27.70 (4.96)	50.73 (21.31)
Female	57.25	27.24 (6.35)	50.19 (21.09)
Age			
44–49 years	2.46	27.66 (5.81)	53.16 (21.55)
50–54 years	20.22	27.56 (5.99)	49.76 (21.71)
55–59 years	21.95	27.62 (5.74)	50.73 (20.81)
60–64 years	20.74	27.33 (5.48)	49.04 (22.18)
65–69 years	19.70	27.35 (5.81)	51.47 (20.21)
70+ years	14.93	27.18 (6.05)	50.96 (20.75)
Education			
Bachelors+	38.75	26.68 (5.19)	50.82 (22.57)
Diploma/Associate degree	11.79	26.91 (5.18)	49.72 (22.25)
Certificate (trade/business)	16.50	28.09 (5.91)	51.07 (19.36)
None beyond school	32.75	28.19 (6.47)	49.88 (19.94)
Occupation			
Manager/professional	31.02	27.20 (5.28)	50.32 (22.38)
White collar	15.48	27.73 (6.04)	51.05 (20.56)
Blue collar	8.49	27.45 (5.51)	49.96 (19.54)
Home duties	4.03	27.76 (7.55)	48.12 (22.38)
Retired	33.09	27.13 (5.53)	50.39 (20.90)
Not easily classifiable	7.88	28.85 (7.26)	51.41 (19.86)
Household Income			
$130000+	20.99	26.95 (4.98)	48.97 (22.86)
$72800-129999	24.32	27.48 (5.94)	49.02 (21.57)
$52000-72799	12.87	27.43 (5.70)	51.68 (20.50)
$26000-51599	18.53	27.71 (5.98)	52.03 (19.91)
Less than $25999	11.33	28.20 (6.96)	53.23 (19.79)
Don't know	2.37	27.33 (5.69)	51.34 (21.36)
Don't want to answer	9.60	26.95 (5.30)	48.84 (20.71)

SD: standard deviation.
[a] Walk Score reported in original 0–100 scale.

(ANZSCO) classification was recoded into six categories: (i) managers/professionals (managers and administrators, professionals, and paraprofessionals), (ii) white-collar employees (clerks, salespersons, and personal service workers), (iii) blue-collar employees (tradespersons, plant and machine operators and drivers, and labourers and related workers), (iv) home duties, (v) retired, and (vi) Not easily classifiable (examples include participants who were unemployed but seeking work, permanently unable to work, students, participants on leave, and if an occupation could not be recoded using the ANZSCO classification).

2.3.6. Household income

Respondents were asked to indicate their total annual household income (including pensions, allowance and investments) using a 14-category measure that was subsequently recoded into seven groups: (i) ≥ AU$130,000, (ii) AU$78,800-129,999, (iii) AU $52,000–78,799, (iv) AU$26,000–51,999, (v) ≤ AU$25,999, (vi) Don't know, and (vii) Don't want to answer this.

2.3.7. Neighbourhood self-selection

To assess residential preferences for living in a particular neighbourhood, participants were asked to respond on a five-item Likert scale (ranging from 'not at all important' to 'very important') to 17 statements asking, 'How important were the following reasons for choosing your current address?' Examples of items included: 'Ease of walking to places', 'Closeness to open spaces' and 'Closeness to public transport'. Principal Component Analysis with varimax rotation showed that six of 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, $\alpha = 0.62$).

2.3.8. Age and sex

Respondents self-reported their date of birth and sex. For descriptive purposes, the age variable was categorised into six groups: (i) 44–49 years, (ii) 50–54 years, (iii) 55–59 years, (iv) 60–64 years, (v) 65–69 years, (vi) 70 years and older.

2.4. Statistical analysis

Our analysis only included participants who remained at their original residence since baseline (2007) (n = 3640). Participants who had missing data on education (n = 8), household income (n = 107), neighbourhood self-selection (n = 158) and BMI (n = 118), were excluded leaving a final sample of 3249 participants (89.3 % of the in-scope participants). The analytic sample was broadly representative of the baseline HABITAT cohort. The proportion of participants in the most disadvantaged neighbourhoods (Q5) was comparable to baseline (13.5 % vs 14.8 %), although slightly more participants resided in the least disadvantaged (Q1) (29.6 % vs 23.7 %) and fewer in Q2 (22.5 % vs 24.2 %) and Q4 (14.7 % vs 16.4 %) than the baseline cohort. We evaluated our findings against bias from sample attrition and determined that data were missing at random (MAR). If the missing is related only to covariates and not to the outcome variable (BMI), regression estimates are minimally biased under MAR (Fitzmaurice et al., 2012). The final analytic sample is presented in Table 1.

Multilevel linear regression models were undertaken with a random effect specified at the neighbourhood level. The analysis was conducted in two stages. Model 1 examined the association between neighbourhood disadvantage and BMI. Model 2 examined effect measure modification by including an interaction term between neighbourhood disadvantage and Walk Score. Both models were adjusted for potential confounders: age, sex, socioeconomic indicators (education, occupation, household income), and residential self-selection. Q1 (the least disadvantaged neighbourhoods) were used as the reference group in both models. Moderation effects were presented graphically using the 'margins' command in Stata, with predicted BMI plotted against Walk Score (0–100) for each neighbourhood disadvantage quintile. All analysis was undertaken using Stata MP version 18 (StataCorp, 2023).

3. Results

Mean BMI and Walk Score for neighbourhood disadvantage, age, sex, education, occupation and household income are presented in Table 1. Mean BMI was highest in the more disadvantaged neighbourhoods (Q4 and Q5), those in the 44–49 year age category, those with no qualifications beyond school and those in the 'not easily classifiable' occupation category.

The distribution of Walk Scores varied across neighbourhood quintiles (Table 2). Fig. 1 displays the full 0–100 scale for interpretability, however, observed Walk Scores differed between quintiles, ranging from 1 to 94 in the least disadvantaged neighbourhoods (Q1) and from 9 to 98 in the most disadvantaged neighbourhoods (Q5). Descriptive statistics for Walk Score by neighbourhood disadvantage are presented in Table 2.

Table 2
Descriptive statistics for Walk Score by neighbourhood disadvantage quintile.

n = 3249	%	Mean	SD	Min	Max
Neighbourhood Quintile					
Q1 (least disadvantaged)	29.64	42.12	22.22	1	94
Q2	22.5	51.65	20.86	0	97
Q3	19.67	56.41	19.41	0	91
Q4	14.74	53.06	20.13	4	95
Q5 (most disadvantaged)	13.45	55.01	17.13	9	98

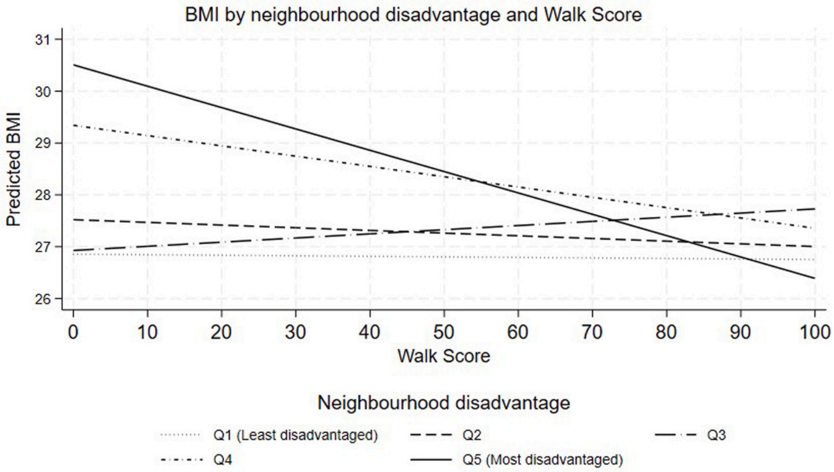

Fig. 1. Predicted BMI across levels of neighbourhood disadvantage and Walk Score (0–100), based on Model 2 regression coefficients presented in Table 3.

Results of the multilevel linear regression are presented in Table 3. BMI increased with neighbourhood disadvantage, with participants in moderately (Q3) and more disadvantaged neighbourhoods (Q4 and Q5) having higher BMI than participants in the least disadvantaged neighbourhoods (Q1) (β = 0.66 95 %CI 0.06, 1.26; β = 1.54 95 %CI 0.89, 2.20; and β = 1.51 95 %CI 0.82, 2.19 respectively).

There was evidence of moderation by Walk Score in the most disadvantaged neighbourhood (Q5) only. For every 10-unit increase in Walk Score the differences in BMI between categories of neighbourhood disadvantage reduced for participants in Q5 (β = −0.40 95 %CI -0.75, −0.05) compared to participants residing in the least disadvantaged neighbourhoods (Q1).

The interaction between neighbourhood disadvantage and Walk Score is shown in Fig. 1. As illustrated, predicted BMI decreased with higher Walk Score among residents of disadvantaged neighbourhoods. A decrease in predicted BMI can also be observed for Q4 however this was not significant. Predicted BMI remained stable across Walk Scores in other neighbourhoods.

4. Discussion

Consistent with previous research (Carroll et al., 2023; McCormack et al., 2017, 2018; Nkemdilim et al., 2025; Pearson et al., 2014; Rachele et al., 2017, 2019; Zhang et al., 2024) our study found inequalities in BMI across neighbourhoods with varying levels of socioeconomic disadvantage. Participants residing in the moderate (Q3) and most disadvantaged neighbourhoods (Q4 and Q5) exhibited higher BMI compared to those in the least disadvantaged neighbourhoods (Q1). These findings give provide further evidence that social and environmental determinants influence obesity. Residents of disadvantaged neighbourhoods are more likely to be exposed to built environment conditions, such as fewer greenspaces and a greater concentration of fast food outlets, that create an obesogenic neighbourhood and reinforce health inequalities (Lovasi et al., 2009a; Macdonald et al., 2018; van Erpecum et al., 2022).

Our findings also suggest that Walk Score has potential to reduce neighbourhood-level socioeconomic BMI inequalities. However, the moderating effect of walkability is not uniform across all neighbourhoods, evidence of moderation was observed only in the most disadvantaged neighbourhoods (Q5). This suggests that as walkability increases, BMI inequalities between the most and the least disadvantaged neighbourhoods narrow, highlighting the potential for local walkability to help reduce the influence of socioeconomic

Table 3
Association between BMI and Walk Score by level of neighbourhood disadvantage.

Neighbourhood Disadvantage	Model 1: Association between neighbourhood socioeconomic disadvantage and BMI [a]	Model 2: Interaction between neighbourhood disadvantage and Walk Score [b, c]
	β (95 %CI)	β (95 %CI)
Q1 (least disadvantaged)	Ref	Ref
Q2	0.50 (−0.06, 1.06, p = 0.080)	−0.04 (−0.30, 0.21, p = 0.751)
Q3	0.66 (0.06, 1.26, p = 0.031) *	0.09 (−0.19, 0.37, p = 0.526)
Q4	1.54 (0.89, 2.20, p < 0.001) *	−0.19 (−0.49, 0.11, p = 0.221)
Q5 (most disadvantaged)	1.51 (0.82, 2.19, p < 0.001) *	−0.40 (−0.75, −0.05, p = 0.025) *

CI: confidential interval.
*$p < 0.05$.
[a] adjusted for age, sex, education, occupation, household income and neighbourhood self-selection.
[b] Model 1 plus neighbourhood disadvantage * Walk Score.
[c] Walk Score rescaled from 0 to 100 to 0–10.

disadvantage on BMI. There are several possible mechanisms that could explain this relationship. Residents of more advantaged neighbourhoods may have greater access to health-related resources and a wider range of recreational opportunities, and therefore the BMI of these residents may be less dependent on neighbourhood walkability. In contrast, those in disadvantaged neighbourhoods often face constraints and may rely more heavily on their immediate environment for physical activity (McCormack et al., 2017, 2018). Walking for transport in these neighbourhoods is the most common form of physical activity among women, older adults and those of low socioeconomic status (Grant et al., 2010). In these contexts, greater walkability can provide a cost-effective, accessible opportunity to engage in physical activity and consequently reduce BMI (World Health Organisation, 2022). Furthermore, a study in Brisbane found that residents of disadvantaged neighbourhoods are less likely to own a vehicle and more likely to walk for transport (Turrell et al., 2013). Therefore, greater access to a variety of destinations and services with shorter distances between them can encourage active transport in these neighbourhoods (Turrell et al., 2013). A higher Walk Score, reflecting proximity to essential amenities such as grocery stores, schools, parks, restaurants, and retail outlets, is associated with increased walking for transportation (Hirsch et al., 2014, 2017). For example, a study among Australian adults, found that residents in highly walkable neighbourhoods and somewhat walkable neighbourhoods were twice and 1.4 times more likely, respectively, to accumulate 30 min of walking per day compared to those in car-dependent neighbourhoods (Cole et al., 2015). Therefore, greater walkability in disadvantaged neighbourhoods, where the moderation effect was evident, may present an opportunity to narrow the health inequities observed between advantaged and disadvantaged neighbourhoods.

The results of this study highlight the potential for walkability to reduce neighbourhood socioeconomic inequalities in BMI. The findings indicate that interventions aimed at improving neighbourhood walkability could be particularly effective in disadvantaged neighbourhoods, where residents are more reliant on their local environment for daily movement. Addressing the quality of the built environment could therefore present an opportunity for reducing socioeconomic disparities. These findings have important policy implications for urban planning, transport, and public health. The WHO calls for governments to prioritise walking (and cycling) in urban planning policy and to ensure integration of infrastructure and networks to facilitate active transport (World Health Organisation, 2022). However, Australian cities face significant challenges in achieving walkable urban environments. Many Australian cities, including Melbourne, Sydney, and Adelaide, are built around cars, with low population density, poor street connectivity, and inadequate access to frequent public transport, particularly in the urban fringe (Lowe et al., 2022). In Australia, car-centric urban design hinders the WHO's target of a 15 % reduction in physical inactivity by 2030 and exacerbates health inequalities (World Health Organisation, 2022). These neighbourhood designs create barriers to active lifestyles, disproportionately affecting lower socioeconomic groups who may have fewer opportunities for physical activity. Integrating walkability metrics such as Walk Score and prioritising pedestrian infrastructure, public transport access, and mixed-use developments in housing policy and urban planning could help reduce inequalities in physical activity and BMI. Although urban planning policies in Australia frequently include objectives and strategies to enhance active and public transport, there is little evidence that these are prioritised over infrastructure supporting private vehicle use (McGreevy et al., 2020). Therefore, policies should prioritise greater residential density, improving pedestrian infrastructure, and setting targets for street connectivity and active transport networks (Lowe et al., 2022).

This study has several strengths. First, the representativeness of the HABITAT study is ensured by its sampling design, which included a large population-based sample drawn from areas spanning low, mid, and high levels of socioeconomic disadvantage, thereby capturing a broad range of socioeconomic and built environment factors. Second, the study accounts for residential self-selection. Previous studies revealed that the examination between neighbourhood attributes and health behaviours without adjustment for self-selection may not account for individual preferences (McCormack and Shiell, 2011; Van Dyck et al., 2011). Last, Walk Score was calculated based on the distance to various amenities and destinations within a 1.6 km network buffer of each household address. This measure has been validated as a reliable tool (Carr et al., 2011) and provides a standardised and novel approach to assessing neighbourhood walkability, offering a more comprehensive understanding of its role in influencing health outcomes.

This study also has limitations. First, the cross-sectional design of our study limits casual assertions. Second, BMI was assessed from self-report surveys, which may introduce bias. Furthermore, BMI does not differentiate fat from muscle mass and fails to capture fat distribution, which is an important determinant of health risks linked to obesity (Gurunathan and Myles, 2016). However, self-reported measure is commonly used in large observational studies and strong correlations have been demonstrated between self-reported and objectively measured height and weight (Vuksanović et al., 2014). Third, while Walk Score is a useful tool for evaluating certain aspects of the built environment, it has notable limitations in fully capturing the complexity of the relationship between walkability and physical activity. Specifically, its applicability to walking for certain purposes and other pedestrian-focused environments may be overlooked (Hall and Ram, 2018). Fourth, as our sample only included mid-to-older aged adults, the findings may not be generalisable to younger populations. Furthermore, differential attrition may have led to slight overrepresentation of higher socioeconomic groups (Turrell et al., 2021), potentially underestimating socioeconomic differences in BMI.

Building on these limitations, several areas for future research emerge. First, longitudinal study designs are critical for capturing the dynamic nature of neighbourhood changes and their long-term effects on BMI (Smart, 2018). For instance, longitudinal research has shown that changes in urban infrastructure, such as improved walkability, can have sustained effects on physical activity and weight status over time, providing evidence for the benefits of targeted urban planning interventions (Smart, 2018). Second, future studies could examine whether Walk Score also moderates the association between individual level disadvantage and BMI. In addition, research could explore factors that contribute to moderation effects observed in the most disadvantaged neighbourhoods (Q5) but not Q4. Third, incorporating alternative adiposity measures such as waist circumference, or objective measures of BMI, such as advanced body composition analyses, could offer a more nuanced understanding of obesity-related risks. Fourth, both the neighbourhood disadvantage measure and Walk Score measure were only available as composite indices. Future research examining the individual attributes that make up these indices may provide a more nuanced understanding of the nature their relationship with BMI. Finally, integrating other metrics, such as sidewalk quality, traffic safety, and access to green spaces, could provide a more holistic assessment of the built environment (Carr et al., 2011), which can guide policies promoting equitable, health-supportive urban spaces.

CRediT authorship contribution statement

Rebecca A. Reid: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Venurs Loh:** Writing – review & editing, Writing – original draft, Validation, Methodology. **Ruirui Xing:** Writing – review & editing, Writing – original draft, Conceptualization. **Beiou Zhang:** Writing – review & editing, Writing – original draft, Conceptualization. **Sarah Bates:** Writing – review & editing, Writing – original draft, Conceptualization. **Jerome N. Rachele:** Writing – review & editing, Writing – original draft, Validation, Methodology.

Data statement

The data that support the findings of this study are available from the HABITAT study, but restrictions apply to the availability of these data, which were used under licence for the current study and so are not publicly available. The data are, however, available from the authors upon reasonable request and with the permission of the HABITAT Study.

Walk Score: Data provided by RedfinRealEstate.

Ethics approval and consent to participate

The HABITAT study received ethical clearance from the RMIT University Human Research Ethics Committee (CHEAN B 20577-01/17), in alignment with the principles outlined in the Declaration of Helsinki. All participants in this study were informed about the study's objectives, procedures, potential risks, and benefits, and their rights to withdraw at any time without any consequences and provided informed consent prior to their inclusion.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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