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Associations of local-area walkability with disparities in residents' walking and car use

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ABSTRACT

Research has examined spatial distribution of physical activity, mostly focusing on *between-area* differences by examining associations of area-level walkability measures with physical activity. *Within-area* distribution is also relevant, since larger disparities in physical activity within an area can contribute to greater inequalities in health. However, associations of within-area disparity in walking and walkability have been examined only at a large geographical scale (city level). This cross-sectional study examined associations of local-area walkability measures with within-area disparities in residents' walking and car use, using data collected in the 2009 South-East Queensland Travel Survey in Australia. For each Statistical Area 2 (SA2), we calculated disparity indices of the duration of walking and car use among participants aged 18–84 years, using Gini coefficients. Linear regression examined associations of the disparity measures with population density, street connectivity, and Walk Score. Analyses were conducted for 196 SA2s, which contained 15,895 participants. Higher walkability was associated with lower levels of disparity in walking and higher levels of disparity in car use, regardless of the measures used. Each one-SD increment in Walk Score was associated with a 0.64 lower SD in walking disparity and a 0.50 higher SD in car-use disparity, after adjusting for covariates. The associations remained significant after further adjusting for car ownership. Higher walkability is known to be associated with more walking and less car use. This study extends previous knowledge by showing that higher local-area walkability can be associated with less inequality in residents' walking and higher diversity in their car use.

1. Introduction

Lack of physical activity is a major health risk and a leading cause of chronic diseases and premature death (Lee et al., 2012). Environmental attributes related to walkability (population density, street connectivity, and availability of utilitarian and recreational destinations), which differ between areas, are associated with residents' overall physical activity and with their walking (Christiansen et al., 2016; Cole et al., 2015; Koohsari et al., 2018; Thielman et al., 2015). A recent study using data from 14 cities worldwide found several built-environment attributes including higher residential density, well-connected streets, better access to public transport, and higher number of parks to be associated with higher levels of adults' physical activity (Sallis et al., 2016).

There are complex patterns in the distribution of physical activity. Disparities in physical activity can contribute to widening socio-economic inequalities in health (Petrovic et al., 2018). Socio-demographic disparities have been documented for self-reported leisure-time physical activity (Blackwell et al., 2014), self-reported walking for transportation (Paul et al., 2015), and accelerometer-measured physical activity (Troiano et al., 2008). However, geographic disparities in physical activity are less understood. There is a need to better understand spatial disparities in physical activity to help develop the place-based interventions that address contextual factors contributing to health problems and inequalities based on understanding of local socioeconomic and environmental characteristics (Smedley and Amaro, 2016).

There are studies examining how physical activity is spatially

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distributed, but they typically focus on *between-area* differences in physical activity. For instance, an Australian study found that a measure of walkability (consisting of dwelling density, intersection density, and land use diversity) constructed at a postal-area level accounted for between-area variation in those engaging in walking and moderate-to-vigorous physical activity sufficient for health benefits (Mayne et al., 2017). Similarly, a study conducted in the US showed that a measure of urban sprawl constructed at the level of county (a large administrative unit, which can include an entire metropolitan area) partially explained spatial variations in physical inactivity (Congdon, 2016). Investigating between-area differences in physical activity is an important step to understand its spatial distribution. However, such studies can assume that each unit area is homogeneous in environmental characteristics and activity levels, which is unlikely to be a tenable assumption across large areas, such as counties or cities. Investigating the *within-area* distribution of physical activity is therefore relevant, since physical activity can vary within an area, and greater within-area disparities may contribute to greater inequalities in health (Petrovic et al., 2018).

A recent study in the US examined within-city disparities of walking steps using the Gini coefficient, and found that cities with higher walkability (measured by Walk Score®) were more likely to have lower disparities in walking (Althoff et al., 2017). Higher city-level walkability was associated not only with higher levels of "mean" walking among residents but also with lower "dispersion" in walking within the city. These findings suggest that improving walkability may contribute to increasing community-level physical activity as well as reducing disparities in physical activity, which may mitigate health inequalities.

In this context, it will be informative to understand to what extent local-area walkability may be associated with within-area disparities in physical activity. Examining such associations at the level of local area, where destinations providing goods and services necessary for everyday life exist, is relevant, as urban design/planning decisions that can affect residents' travel mode choice (e.g., residential density, land use, public open space, sidewalk) are usually made at the local level. In addition to the adverse health consequences of lack of physical activity, there are also detrimental associations of prolonged car use with health outcomes (McCormack and Virk, 2014; Sugiyama et al., 2016). It can be postulated that car use is likely to be more common (less dispersion) in low-walkable areas, while it may be more variable in high-walkable local areas.

We examined the associations of local-area walkability measures with within-area disparities in residents' walking and car use, using household travel survey data collected in a socially and geographically heterogeneous region around an Australian capital city.

2. Methods

2.1. Data source

Data were drawn from the 2009 South-East Queensland Travel Survey (SEQTS), a cross-sectional household travel survey administered by the Queensland (Australia) State Government in Brisbane (the state capital city), and the adjacent Sunshine Coast and Gold Coast Statistical Divisions. This region covers a mix of urban, suburban, and regional areas, with a geographic size of 10,946 km^2. Its population was approximately 2.9 million in 2009. The SEQTS used a multi-stage random sampling in which Census Collection Districts (CCDs), the smallest geographic units for census data collection at the time of the survey (Australian Bureau of Statistics, 2006), were selected first, followed by households within each CCD. Data were collected from 10,335 households (4.4% of households from the selected CCDs; 60% response rate). The total number of participants in the 2009 SEQTS was 27,213. We used data from adult participants aged between 18 and 84 years old (N = 20,527). Older adults over 85 years were excluded, as they tend to be low in mobility and can require support for daily activities (Jacobs et al., 2012). The SEQTS was administered in accordance with ethical guidelines under government statutes and regulations. Informed consent was obtained from participants.

2.2. Area unit

The geographic unit of a Statistical Area 2 (SA2) was selected as the unit of analysis in the study. They generally have a population range of 3000 to 25,000 residents (Australian Bureau of Statistics, 2011). SA2s were chosen as the area unit for the study, as they typically align with the boundary of officially-recognized "suburbs" (e.g., neighborhoods) in Australia (Australian Bureau of Statistics, 2011), and include a commercial service area where residents come to access stores and services. A smaller area unit, Statistical Area 1 (population range: 200–800), was considered too small to assess within-area disparity due to its small geographic size (median = 0.23 km^2). A larger area unit, Statistical Area 3 (population range: 30,000–130,000), was almost at the city scale, which did not fit the purpose of the study. There were 211 SA2s in the SEQTS study area. Their median size was 7.9 km^2 (25th–75th percentile: 4.4–19.7 km^2), and the median population was 9000 (25th–75th percentile: 6756–13,292).

3. Measures

3.1. Outcome measures

All members in the selected households on the night before the specified "survey day" were asked to complete a 24-hour travel diary. A short-span activity diary has been found to be more valid and reliable in measuring physical activity and sedentary behavior than conventional self-report questionnaires (van der Ploeg et al., 2010). They reported details of their instances of travel on the survey day, including origin, destination, start time, end time, mode, and purpose. The variables employed were disparities in the duration of walking and car trips (minutes/day). To ensure the instances of travel took place within a participant's local area, we used "home-based" walking and car trips, which commenced or ended at home, to measure the trip duration. Disparity was measured using Gini coefficients, a common measure of inequality or dispersion (Allison, 1978), and used frequently in public health studies to measure income inequality. In this study, Gini coefficients measured the dispersion in the duration of walking and car use. The coefficient ranges from 0 (perfect equality, e.g., everyone walks the same amount) to 1 (perfect inequality, e.g., one person does all the walking).

3.2. Exposure measures

We examined two walkability-related constructs and one composite measure of walkability: population density, street connectivity, and Walk Score (mainly an indicator of access to destinations such as stores and services). Population density (the number of residents divided by area size) was extracted for each SA2 from the demographic data provided by the Australian Bureau of Statistics.

For street connectivity, we used a space syntax measure of street integration, which is known to be associated with walking for transport (Koohsari et al., 2016). Street integration shows how topologically close a street is to all other streets within a specified street network: A more integrated street segment requires fewer turns to reach a destination from other streets within the network, compared with less-integrated street segments (Baran et al., 2008). Street integration was calculated for each street segment within a 1 km buffer from its center, using Axwoman and DepthMap software (Jiang, 2012; Turner, 2004). This buffer size was chosen as 1 km is considered to be a reasonable cut-point within which residents would walk to destinations (Millward et al., 2013). Higher integration denotes greater street connectivity. The mean integration value of all street segments was computed for each Statistical Area 1 (SA), which is the smallest geographic unit for

Australian Census data since 2011 (median size: 0.23 km^2). The street integration for an SA2 was the mean integration score of SA1s that belonged to the SA2, using SA1 size as a weight. SA1s rather than CCDs were used as a base unit for calculation because the ABS switched their geographic units from CCD to SA1 in 2011 to have units that are more homogeneous and consistent in population size (Australian Bureau of Statistics, 2011).

Walk Score, which has been shown to be associated with residents' walking (Cole et al., 2015; Koohsari et al., 2018), is a free publicly-available web-based tool that gives a score to any given address based on the availability of various destinations and street connectivity around the address (Front Seat Management, 2017). It ranges from 0 to 100, where higher scores denote better access to destinations. We first obtained Walk Score for each SA1 using its centroid. We then calculated a mean Walk Score for each SA2, using member SA1's size as a weight. The two-step method was used for Walk Score, since its scores depend on destinations within 1.6 km from a specified location (Front Seat Management, 2017), which can be smaller than SA2s.

3.3. Covariates

The SEQTS asked participants' age, gender, and employment status. For households, income and car ownership were collected. Since the unit of analysis was SA2, we used the proportion of women, older adults (65 years and older), and those not working, and the proportion of households with a low income (< $1400 per week) and those with no and one car within each SA2 as covariates. Analyses also adjusted for SA2's geographic size and its level of socio-economic disadvantage. For the latter, the Index of Relative Socio-Economic Disadvantage (IRSD), which was based on area-level income, education, and employment status, was used (Australian Bureau of Statistics, 2008).

3.4. Statistical analyses

Linear regression models were used to examine at the SA2 level the associations of the Gini coefficients of daily duration of walking and car use with population density, street integration, and Walk Score. The Gini coefficients of walking duration were negatively skewed. A "reflect and inverse" transformation [= 1 / (1 + largest Gini coefficient value – Gini coefficient)] was used to produce normally distributed data. After the conversion, a higher coefficient still indicated greater disparity. The Gini coefficient of car use duration was normally distributed, and thus not transformed. Three models were fitted for each outcome measure. Model 1 adjusted for SA2 geographic area size. Model 2 further adjusted for SA2's socio-demographic characteristics (the proportion of women, 65 years old and older, participants not working, households with low income, and IRSD). Model 3 further adjusted for car ownership (the proportion of households with no and 1 car). Each walkability measure was examined separately in all models. Model parameters were estimated using SPSS Version 25 (IBM, Armonk, NY). Statistical significance was set at $p < .05$.

4. Results

Participants who reported no trip (by any mode) on the survey day were excluded from analysis ($n = 4204$). In addition, 15 SA2s where none of the participants reported home-based walking were excluded, as the study was designed to examine disparity in walking. After the exclusions, 15,895 participants living in 196 SA2s were retained for analysis. Tables 1 and 2 show the characteristics of participants and SA2s, respectively. The median number of participants in SA2s was 51. The lowest number of participants in SA2s was 14, which was larger than the minimum sample size for calculation of Gini coefficients ($n = 10$) without introducing severe small-sample bias (Deltas, 2003). On average, the mean walking duration for all participants was about 4 min/day (35 min/day among 2056 participants who reported walking), and the mean car use duration for all participants was 50 min/day (64 min/day among 12,431 participants who reported car use). The mean Gini coefficient for walking was 0.91 (0.92 after conversion) and that of car use was 0.53. Three exposure measures were correlated. Correlation coefficients were 0.62 between population density and street integration, 0.69 between population density and Walk Score, and 0.65 between street integration and Walk Score (all $p < .001$).

Table 3 shows the results of regression analyses for the disparity in walking duration (transformed Gini coefficients) as the outcome. All environmental measures were significantly negatively associated with the disparity in walking: higher walkability measures were related to lower levels of disparity (that is, higher levels of homogeneity) in walking duration. For instance, each one-SD increment in Walk Score was associated with 0.64 lower SD in walking disparity (Model 2). Adjusting for car ownership in Model 3 attenuated the associations, but the regression coefficients remained highly significant: larger Walk Score was associated with a lower disparity in walking to a lesser degree. R^2 ranged from 0.17 to 0.52, with the full model (Model 3) accounting for about half of the variance of the disparity in walking duration. Walk Score was more closely associated with the disparity in walking than the other two measures.

Table 4 shows the results of regression analyses for disparity in car

Table 1
Characteristics of participants and households (the 2009 South-East Queensland Travel Survey).

	Mean (SD) or %
Participants	N = 15,895
Age, years	46.5 (15.9)
Gender, % women	52.5%
Employment status, % employed	71.2%
Walking duration, min/day	3.5 (12.5)
Car use duration, min/day	49.6 (53.7)
Households	N = 8949
Income (AU$)	
< $1400 pw	45.3%
≥ $1400 to < $2500 pw	32.8%
≥ $2500 pw	21.9%
Car ownership	
0 car	3.4%
1 car	33.7%
2 or more cars	62.9%

Table 2
Characteristics of study areas (the 2009 South-East Queensland Travel Survey).

	Mean (SD)
Study areas (SA2s)	N = 196
Demographic characteristics	
Median number of participants [25th–75th percentile]	51 [36–105]
Proportion of women, %	52.3 (5.4)
Proportion of older adults 65+ years, %	13.9 (8.2)
Proportion of non-working participants, %	27.6 (10.5)
Proportion of low income households (< $1400 pw), %	43.9 (15.2)
Proportion of households with no car, %	3.9 (5.3)
Proportion of households with 1 car, %	35.0 (12.9)
Index of Relative Socio-economic Disadvantage	1012.8 (85.3)
Geographic characteristics	
Median size [25th–75th percentile], km^2	7.9 [4.4–18.8]
Population density, #/ha	14.2 (10.2)
Street integration[a]	76.6 (38.4)
Walk Score[a]	49.5 (19.7)
Gini coefficients	
Coefficient for walking	0.91 (0.06)
Transformed coefficient for walking[b]	0.92 (0.05)
Coefficient for car use	0.53 (0.07)

[a] Mean score of SA1s (constituting the SA2), using the SA1 size as weight.
[b] Transformed by the "reflect and inverse" method.

Table 3
SA2-level associations of disparity in walking[a] and walkability measures (the 2009 South-East Queensland Travel Survey).

Walkability measures	Standardized regression coefficient (95% CI), model R^2		
	Model 1	Model 2	Model 3
Population density	−0.56 (−0.65, −0.46)*** R^2 = 0.27	−0.58 (−0.66, −0.47)*** R^2 = 0.27	−0.31 (−0.43, −0.18)*** R^2 = 0.50
Street integration	−0.44 (−0.55, −0.32)*** R^2 = 0.18	−0.45 (−0.55, −0.33)*** R^2 = 0.17	−0.26 (−0.38, −0.12)*** R^2 = 0.49
Walk Score	−0.63 (−0.71, −0.54)*** R^2 = 0.35	−0.64 (−0.72, −0.55)*** R^2 = 0.34	−0.37 (−0.48, −0.24)*** R^2 = 0.52

Model 1: adjusted for area size.
Model 2: further adjusted for the proportion of women, of 65+ years, of those not working, of household with low income, and IRSD.
Model 3: further adjusted for the proportion of households with no car and those with 1 car.
Each walkability measure was examined separately in all models.
[a] Transformed Gini coefficient (higher values denote higher disparity).
*** $p < .001$.

Table 4
SA2-level associations of disparity in car use[a] and walkability measures (the 2009 South-East Queensland Travel Survey).

Walkability measures	Standardized regression coefficient (95% CI), model R^2		
	Model 1	Model 2	Model 3
Population density	0.35 (0.22, 0.47)*** R^2 = 0.10	0.40 (0.28, 0.52)*** R^2 = 0.19	0.18 (0.05, 0.32)* R^2 = 0.35
Street integration	0.29 (0.16, 0.41)*** R^2 = 0.07	0.29 (0.16, 0.42)*** R^2 = 0.13	0.14 (0.00, 0.28)* R^2 = 0.34
Walk Score	0.51 (0.40, 0.61)*** R^2 = 0.21	0.50 (0.38, 0.59)*** R^2 = 0.26	0.28 (0.15, 0.40)*** R^2 = 0.37

Model 1: adjusted for area size.
Model 2: further adjusted for the proportion of women, of 65+ years, of those not working, of household with low income, and IRSD.
Model 3: further adjusted for the proportion of households with no car and those with 1 car.
Each walkability measure was examined separately in all models.
[a] Gini coefficient (higher values denote higher disparity).
* $p < .05$.
*** $p < .001$.

use as the outcome. All environmental measures were significantly positively associated with the disparity in car use: higher walkability measures were related to higher levels of disparity (lower levels of homogeneity) in the duration of car use. For instance, each one-SD increment in Walk Score was associated with a 0.50 higher SD in car use disparity (Model 2). Adjusting for car ownership attenuated the associations, but the regression coefficients remained significant: larger Walk Score was associated with a higher disparity in car use to a lesser degree. The regression coefficients remained significant, but decreased, particularly for population density and street integration. R^2 ranged from 0.07 to 0.37, with the full model (Model 3) accounting for about one third of the variance of the disparity in car use. Walk Score was more closely associated with the disparity in car use than the other two measures.

5. Discussion

We examined the associations of disparities in the duration of walking and car use within a local area was explained by walkability-related measures, using household travel survey data collected in Australia. We found the mean disparity in walking duration to be high, due to a large proportion of participants reporting 0 min of walking on the survey day. The disparity in car use was lower, indicating that residents were relatively more homogeneous in the duration of their car use.

Higher walkability (regardless of the measures used) was associated with lower disparity in walking. In prior studies, higher walkability was related to higher levels of walking for transportation (Christiansen et al., 2016; Cole et al., 2015; Koohsari et al., 2018; Thielman et al., 2015). Current analyses extend prior work by showing that walkability was also related to disparities of walking within the area where walkability was measured. High-walkable neighborhoods had not only a higher level of walking on average but also less inequality in the amount of walking. Walk Score appeared to have the strongest association. Each one-SD increment in Walk Score was associated with almost two-thirds lower SD in walking disparity (in Model 2, which adjusted for socio-demographic covariates but not for car ownership).

The proportion of participants who walked was low in most SA2s in the study area. It can be argued from the findings that low mean levels of walking in low-walkable areas were likely due to a greater number of non-walkers, with a few walkers (rather than due to many walkers who walked for a short period). In contrast, lower Gini coefficients in high-walkable areas suggest that high mean levels of walking in such areas were achieved by a greater number of walkers (rather than by a smaller number of long walkers, which would produce a high Gini coefficient). An implication of these findings is that enhancing walkability may facilitate non-walkers to initiate walking. This is significant considering that the greatest health benefits of physical activity can be seen when those who are least active become regularly active (Warburton et al., 2006), and the difficulty of engaging such inactive people through physical activity interventions or campaigns (Foster et al., 2011). Improving walkability may help reduce inequalities in health within the neighborhood.

For the disparity in car use, lower walkability was associated with lower levels of disparity. It can be argued that those living in low-walkable areas were consistently relying on cars for their daily travels, while those living in high-walkable areas were varied in their car use. The decision to own car(s) depends to some extent on where people live, as well as their income and access to alternative means of transportation (Rachele et al., 2018). The number of cars in the household attenuated the associations of the disparity in car use with walkability measures. Car ownership appears to be a major factor explaining the link between walkability and the disparity of car use, i.e., more households in low walkable areas tend to have 1 or 2+ cars, which may make them equally car dependent. However, the significant associations after adjusting for car ownership suggest that car use was more likely to be common in low-walkable areas independent of the number of cars in the household. Greater disparity in car use in high-walkable areas suggests that some residents living in high-walkable areas may spend a large amount of time sedentary in cars, while most spend relatively little time in cars. Better walkability may allow some residents to rely less on cars. Since prolonged car use appears to be particularly detrimental to health (Sugiyama et al., 2016), car use may be a source of health inequalities in high-walkable neighborhoods.

Limitations of the study included that travel behavior data were collected only for one day, similar to other household travel surveys. Although working adults tend to be consistent in their daily walking and car use, this may not be the case for those who are not working. Their travel patterns may differ between days, and 1 day may not be long enough to capture different patterns. We chose SA2 as the area unit to calculate within-area disparity measures. Different findings may be observed if a different boundary was used for analysis. The findings that we report are based on a 2009 survey conducted in Queensland, Australia, where population density and the prevalence of walking were low. Internationally, new transportation modes, such as bike share programs and rideshare services, are transforming urban mobility. Such changes will influence the generalizability of our findings to other contexts. It was not possible for us to adjust for all potential confounders, including residential self-selection, which has been shown to partially explain the association of built environment attributes with travel behaviors (Cao et al., 2009). The strengths of the study included using data collected from a large sample residing in diverse areas (urban, suburban, and regional). The travel diary asked participants to report the origin, destination, and mode of each trip throughout the day, which may be less susceptible to measurement bias and recall errors than typical self-report measures (Merom et al., 2010). Walking and car trips that did not start or end at home were excluded, which could improve the correspondence between where behaviors occurred and where walkability measures were calculated. Furthermore, we used diverse measures related to walkability. The stronger findings obtained for Walk Score are promising as this tool can be used by practitioners without the need of any geographic information systems software and expertise. For instance, local governments may use Walk Score to identify areas where effort is needed to rectify inequality in walking.

6. Conclusion

Our study found there was more equity in walking in high-walkable areas. By contrast, low-walkable areas, where people tend to rely on cars for daily travels, showed a greater disparity in walking. Thus, neighborhoods designed to be walkable have the potential to reduce inequities in health-promoting physical activity, while reducing exposure to harmful effects of prolonged car use. Improving walkability of existing neighborhoods is not an easy process. However, planning initiatives such as mixed-use infill development can increase both population density and access to retail destinations. For newly planned neighborhoods, a transit-oriented development, where residential and commercial areas gather within walking distance of a transit stop, is now implemented as a sustainable form of development (Cervero and Sullivan, 2011). Such development may help mitigate disparity in walking by reducing the number of non-walkers. Future research can explore how walkability measures may be related to inequalities in health outcomes.

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Conflict of interest statement

None of the authors has any financial interest in walkscore.com.

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