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Exploring non-linear relationships between neighbourhood walkability and health: a cross-sectional study among US primary care patients with chronic conditions

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ABSTRACT

Background A recent study of licensed drivers found a non-linear relationship between density of non-residential destinations (NRDs), a proxy for walkability and body mass index (BMI) across a wide range of development patterns. It is unclear if this relationship can be replicated in a population with multiple chronic conditions or translated to health outcomes other than BMI.

Methods We obtained health data and home addresses for 2405 adults with multiple chronic conditions from 44 primary care clinics across 13 states using the Integrating Behavioral health and Primary Care Trial. In this cross-sectional study, the relationships between density of NRDs (from a commercial database) within 1 km of the home address and self-reported BMI, and mental and physical health indices were assessed using several non-linear methods, including restricted cubic splines, LOWESS smoothing curves, non-parametric regression with a spline basis and piecewise linear regression.

Results All methods demonstrated similar non-linear relationships. Piecewise linear regression was selected for ease of interpretation. BMI had a positive marginal rate of change below the NRD density inflection point of 15 establishments/hectare (β=+0.09 kg/m^2/non-residential buildings ha-1; 95% CI +0.01 to +0.14), and a negative marginal rate of change above the inflection point (β=−0.02; 95% CI −0.06 to 0.02). Mental health decreased with NRD density below the inflection point (β=−0.24; 95% CI −0.31 to −0.17) and increased above it (β=+0.03; 95% CI −0.00 to +0.07). Results were similar for physical health (β= −0.28; 95% CI −0.35 to −0.20) and (β=+0.06; 95% CI 0.01 to +0.10).

Conclusion Health indicators were the lowest in middle density (typically suburban) areas and got progressively better moving in either direction from the peak. NRDs may affect health differently depending on home-address NRD density.

Trial registration number NCT02868983.

STRENGTHS AND LIMITATIONS OF THIS STUDY

- ⇒ We used a large sample (n=2405) of highly vulnerable primary care patients with multiple chronic conditions who are traditionally understudied in the health geography literature.
- ⇒ This study used large data sets with individual-level street address, health and walkability measures to avoid the ecological fallacy.
- ⇒ This study analysed the relationship between walkability and health across a wide range of development but may not generalise to other populations or settings.
- ⇒ Non-linear relationships were consistent across four independent modelling techniques.
- ⇒ LOWESS smoothing and other non-parametric regression are subject to overfitting when sample sizes are small.

INTRODUCTION

Chronic medical conditions such as heart and lung disease, diabetes, musculoskeletal conditions and obesity are among the most common causes of morbidity, mortality and healthcare costs in the USA. These medical conditions often coincide with mental and behavioural health conditions such as anxiety, depression, chronic pain and substance abuse, increasing the likelihood of poor health outcomes.[1] The US Centers for Disease Control and Prevention recommend regular aerobic exercise such as walking for individuals with chronic conditions and disabilities to increase daily living activities, promote independence, prevent the worsening of disease, decrease anxiety, depression and pain, and increase longevity.[2] Given that only one in four older adults meet the minimum aerobic activity levels and even fewer meet the full physical activity guidelines,[3] it is essential to find population-level approaches to increase physical activity. One solution backed by the US surgeon general's Step It Up initiative[4] is the promotion of neighbourhood walkability to increase physical activity.

A walkable environment is characterised by diverse land uses in proximity, connected and pedestrian-friendly street network design, short distances to transit and destination accessibility.[5–10] These characteristics reduce obesity[11] and enhance mental[12–14] and physical health[15] by promoting walking and other forms of active transport.[16 17] For this study, we focused on destination accessibility, measured as the density of non-residential destinations (NRDs) surrounding the participant's home residence. Living within a walkable distance to retail businesses, employers, public offices, restaurants, schools, commuter rail and bus stops, and places of worship can promote active transport and reduce automobile use.

Four systematic reviews examining nearly 200 studies of older adults found that access to NRDs was positively associated with total physical activity participation, overall walking[16 18 19] and walking for transportation.[17] Residing in areas with a high density of NRDs can also improve health. Two longitudinal studies found that accessibility to NRDs was associated with lower rates of obesity in the USA[20] and Canada.[6] A fifth review of 23 articles about the built environment and physical function found some evidence that NRDs can improve physical function but concluded that more research was necessary.[15] Less is known about this relationship between NRDs and mental health. Living in walkable areas may have benefits for individuals with chronic conditions, but the literature is sparse. Adults living in high-walkability areas had lower 10-year incidences of diabetes[21] and cardiovascular disease[22] than those in low-walkability areas, although not glycaemic control.[23]

While the literature suggests an inverse relationship between NRDs and body mass index (BMI) and a positive relationship between NRDs and physical function in high-density settings, there are few studies that include lower density settings. Data from the rural US found that a perceived lack of NRDs was associated with obesity.[24] Studies from China[25] and Texas[26] that spanned a wide range of development found positive relationships between NRDs and BMI. In Vermont—a low-density area—a positive correlation between NRD density and BMI was found using two independent datasets, suggesting that this relationship may vary non-linearly across the density spectrum.[27]

More recent literature has confirmed a non-linear relationship between NRDs and obesity. Using nearly 17 million driver's licence records from six US states, Bonnell *et al* found a positive relationship between NRDs and self-reported BMI below 15 destinations·ha^{-1}, at which point the relationship became negative, creating an inverted-U shaped curve.[28] Lower density areas were characterised by farmlands and farming communities typical of the rural Midwest, while higher density areas were often cities with multifamily buildings and ground floor destinations, such as downtown Chicago or The Bronx, New York. The middle density areas where the inflection point occurred largely corresponded to suburban areas characterised by automobile-oriented development, or near town centres of small rural towns.

There are two goals of the current study: (1) to confirm the non-linear relationship between NRD densities and self-reported BMI across a wide range of development in a national sample of primary care patients with chronic conditions and (2) to assess if the non-linear relationship applies to other health outcomes, including indices of mental and physical health. We hypothesised that BMI would increase as NRDs increased in the range from low to mid densities (typical of suburban areas), but decrease in the range from mid to high densities, forming an inverted-U curve. Conversely, we expected mental and physical health would decrease as NRDs increased in the range from low to mid densities but increase in the range from mid to high densities, forming a U-shaped curve.

METHODS

Data and setting

The characterisation of NRDs as a proxy for walkability is described elsewhere.[28] Briefly, 13 million potential destinations were geocoded using a 2018 database of commercial establishments (Dun & Bradstree, Milburn, New Jersey, USA). We filtered the dataset for facility types likely to serve as destinations for active transport based on their North American Industry Classification codes. Retail establishments, personal service providers, restaurants, community centres, schools, places of worship, post offices and other government facilities, and commercial recreation and entertainment facilities were included (n=3 749 984). We excluded establishments likely to discourage or at least not initiate walking such as agriculture, forestry, mining, quarrying, utilities, construction, manufacturing and wholesale trade.

A second data set contained survey results from the Integrating Behavioural Health and Primary Care, a multicentre, prospective randomised study of a practice-level intervention among chronically ill primary care patients from 2016 to 2021, described in detail elsewhere.[29] Briefly, we obtained health data and home addresses on 3797 adults with multiple chronic conditions from 44 primary care clinics across 13 US states including Alaska, Hawaii, California, Oregon, Washington, Idaho, Texas, Georgia, Kentucky, Ohio, New York, Massachusetts and Vermont (see online supplemental figure 1). All patients had multiple chronic conditions (arthritis, obstructive lung disease, chronic bronchitis or asthma, non-gestational diabetes, heart failure or hypertension, anxiety or depression, chronic pain (including headache, migraine, neuralgia, fibromyalgia or chronic musculoskeletal pain), insomnia, irritable bowel syndrome, substance use disorder, tobacco use or problem drinking) as determined by review of electronic health record visit data, problem lists, medication lists and laboratory results. Data were collected at three timepoints, baseline, midpoint and follow-up, but for this study, we only used the cross-section of data from the follow-up timepoint. Patients were excluded if they had fewer than two chronic conditions, missing Patient-Reported Outcomes

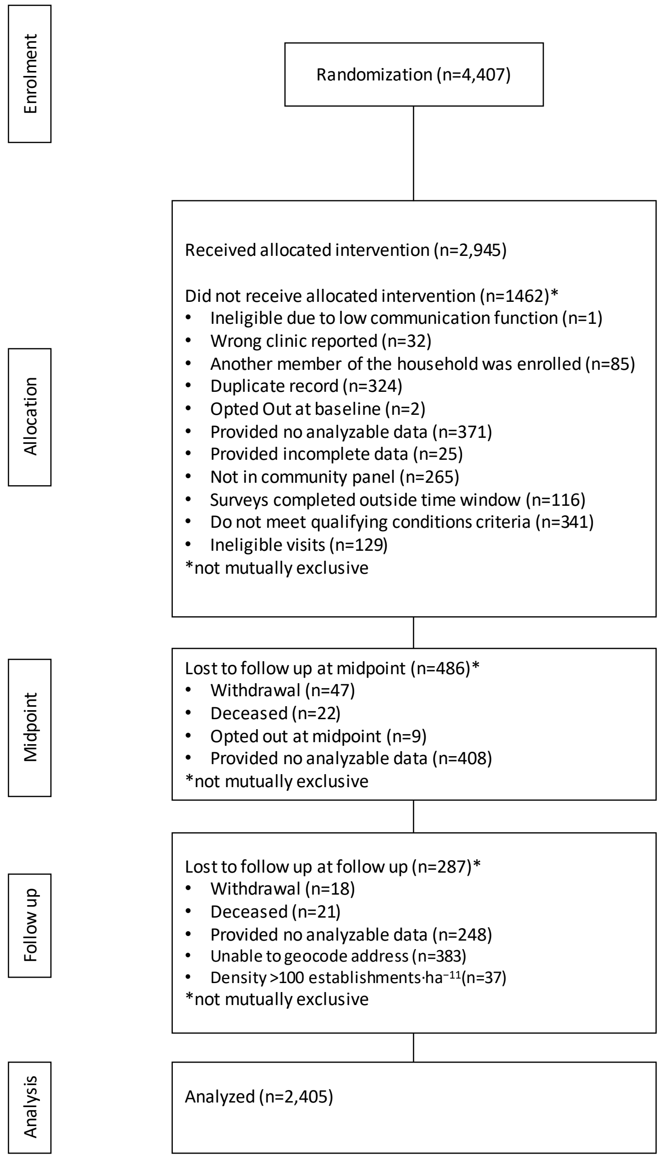

Figure 1 Consort diagram of participants.

Measurement Information System (PROMIS-29) data at follow-up time point, missing address information or density of NRDs >100 establishments/hectare (see figure 1). Our final analytical dataset contained complete information on 2405 adult primary care patients with multiple chronic conditions. After exclusions, there were no missing data. Those with complete data and no address information available tended to be more rural than those with addresses that were geocoded. However, the distribution of demographic variables were statistically similar (age, sex, race, education, marital status and employment status).

The predictor for this analysis was the absolute concentration of NRDs, which was taken as a proxy for destination accessibility or opportunities for active transport and walkability. It was calculated by the ArcGIS Point Density function as the number of establishments/hectare within 1 km of the home address of participants. Each address was assigned the density value of its coinciding 30 m pixel from the point density raster output surface. Each pixel in this surface can be interpreted as giving the density value for an area around it with a Euclidean buffer radius of 1 km. The 1 km spatial scale was chosen based on prior literature that suggests the mean walking trip in the USA is 0.98 km, about a 15 min walk.[30 31] NRDs were spatially joined to the survey results based on the home address of the respondent. Density of NRDs ranged from 0 to 400 establishments/hectare, however, we excluded records with NRD density >100 establishments/hectare because they were statistical outliers and not representative of the majority of places people reside. The statistical techniques used in this study become unstable and tend to overfit the data with very small sample sizes. Only 1% of data (n=37 records) had densities between 100 and 400 establishments/hectare and the resulting findings were unreliable. These participants were statistically similar to the main study participants in terms of age, sex, race, education, marital status and employment status. In this study, 0–100 establishments/hectare represents a wide and representative spectrum of development, ranging from rural south-central Idaho (low density), to the suburbs of Worcester, Massachusetts, USA (middle density), to Bronx, New York, USA (high density).

The outcome variables were BMI, calculated from self-reported height and weight, physical health as measured by PROMIS-29 physical health summary score and mental health as measured by the PROMIS-29 mental health summary score. The PROMIS-29 is a self-reported questionnaire that assesses eight domains of health including pain interference, pain intensity, physical function, depression, anxiety, fatigue, sleep disturbance and social participation. Physical and mental health summary scores are calculated from these eight domains. Scores range from 0 to 100 and are standardised to the US population, where 50 is the mean with an SD of 10. Higher scores indicate better functional health.

Potential mediating variables were considered for inclusion in the multivariable analysis based on prior knowledge. This process was strictly exploratory and used for the purposes of hypothesis generation. Participant-level demographic covariates included age, sex, race, ethnicity, marital status, annual household income, education and number of chronic conditions. Neighbourhood rurality and social deprivation were measured at the census-tract level by The Social Deprivation Index[32] (SDI) and rural urban commuting area (RUCA) codes.[33] The SDI is a composite measure of deprivation based on income, education, employment, housing, single-parent household and access to transportation.

Geocoding

Point locations (latitude and longitude) were assigned for each participant's home address using the ArcGIS address geocoder (ESRI, Redlands, California, USA) with the WGS 1984 coordinate system. Addresses that had less than 100% match to a point location were checked for errors and manually geocoded. A total of 2405 (86%)

were matched to a street address. The others addresses consisted of P.O. Boxes and rural routes that could only be matched to a zip code centroid. These were excluded because NRDs are a granular measure at the street address level. Demographics (age, sex, race, ethnicity, marital status, income, education) and outcomes (BMI, mental and physical health) did not vary systematically by geocoding status. Records that were correctly geocoded were more likely to be urban and have higher NRDs, consistent with previous literature.[34]

Statistical analysis

To allow for the possibility of a non-linear relationship, we used piecewise linear regression to assess BMI and mental and physical health as a function of NRDs. Next, we used restricted cubic splines, LOWESS smoothing curves[35] and non-parametric regression with a spline basis to confirm a similar data fit and make sure the results were not spurious due to the statistical method chosen. After confirmation of similar results with the more complex models using visual assessment and Bayesian information criteria (when possible), we proceeded with the piecewise linear regression only, due to the ease of interpretation of the coefficients. We included covariates in the multivariable model that changed the association between the predictor and outcome by >10%. The main analysis consisted of three separate adjusted models estimating BMI, mental health and physical health as a function of NRDs with 95% CIs. Spatial autocorrelation of the error term was assessed using Lagrange multiplier tests.[36] The Lagrange multiplier test for spatial autocorrelation was significant in the models, suggesting spatial autocorrelation was present and spatial error regression may be warranted. All tests were two tailed and the threshold for statistical significance was $p<0.05$. Stata V.16.1 (StataCorp) was used for data management and statistical analysis. GeoDa was used to assess spatial error regression.[37] We used the Spatial Lifecourse Epidemiology Reporting Standards guidelines.[38]

Patient and public involvement

None.

RESULTS

This study included 2405 participants. The majority were older and female, non-Hispanic, white, married, retired and had low incomes (see table 1). The mean BMI was 31.9 kg/m^2, which is much higher than the US national average (26.5 kg/m^2 men, 26.6 kg/m^2 women),[39] likely because we selected for individuals with multiple chronic conditions that are often related to obesity. Likewise, the average physical health summary score was worse (45.5) than the national average (50). However, the average mental health summary score was slightly higher (51.1) than the national average (50).

Because similar functional forms were found for all non-linear methods, the piecewise linear method was

Table 1 Participant characteristics

	N (%) or mean±SD
N	2405
Age, years	63.8±12.9
Sex	
Female	1544 (64%)
Male	855 (36%)
Other/prefer not to say	6 (0%)
Race	
White	1843 (77%)
Black or African American	298 (12%)
Asian	75 (3%)
Native Hawaiian/other Pacific Islander	25 (1%)
American Indian or Alaskan Native	19 (1%)
Other/prefer not to say	141 (6%)
Ethnicity	
Hispanic	167 (7%)
Non-Hispanic	2197 (92%)
Prefer not to say	23 (1%)
Marital status	
Never married	387 (16 %)
Married	1069 (45%)
Living as married	62 (3%)
Separated	52 (2%)
Divorced	514 (21%)
Widowed	306 (13%)
Employment	
Full time	409 (17%)
Part time	172 (7%)
Retired	1043 (44%)
Disabled	593 (25%)
Home maker	87 (4%)
Student	10 (0%)
Unemployed/looking	80 (3 %)
Other/prefer not to say	3 (0%)
Annual household income	
<US$15 000	652 (27%)
US$15 000–US$29 999	492 (21%)
US$30 000–US$44 999	302 (13%)
US$450 000–US$59 999	229 (10%)
US60 000–US$74 999	189 (8%)
US$75 000–US$99 999	189 (8%)
>US$100 000	305 (13%)
Mean no of chronic conditions	4.1±1.8
Arthritis	1115 (40%)
Asthma	587 (21%)

Continued

Table 1 Continued

	N (%) or mean±SD
Chronic obstructive pulmonary disease	359 (13%)
Chronic pain	2204 (79%)
Non-gestational diabetes	1248 (44%)
Heart failure	222 (8%)
Hypertension	2265 (81%)
Irritable bowel syndrome	117 (4%)
Anxiety	880 (31%)
Depression	1224 (44%)
Insomnia	610 (22%)
Substance use disorder	592 (21%)
Neighbourhood characteristics (home census tract)	
Social Deprivation Index (higher indicates more deprivation)	52.6±28.4
Rural	378 (16%)
Population density, persons per square mile	3917±5998
Primary predictor	
Nonresidential destinations	10.8±14.4
Primary outcomes—PROMIS-29 t-scores	
PROMIS-29 Physical Health Summary t-score*	45.5±9.7
PROMIS-29 Mental Health Summary t-score*	51.1±8.8
BMI kg/m^2	31.9±8.7

*Higher score is better.
BMI, body mass index; PROMIS-29, Patient-Reported Outcomes Measurement Information System .

used for ease of interpretation. Ordinary piecewise linear models and piecewise linear models using spatial error regression were performed. Because the results were statistically similar, we opted to report only the ordinary linear regression results.

We defined the low-to-mid density range from 0 to 15 establishments/hectare and the mid-to-high density range from 15 to 100 establishments/hectare. We found an inverted U-shaped relationship between NRDs and BMI (see figure 2). On average, BMI increased as NRD density increased from low-density (BMI=~31 kg/m^2 at 1 establishments/hectare) to mid-density (BMI=~33 at 15 establishments/hectare) and then decreased from mid-density to high-densities (BMI=~30 at 80 establishments/hectare). Using piecewise linear regression, BMI was positively associated with NRD density below 15 establishments/hectare (β=+0.09 kg·m^{-2}/non-residential buildings ha^{-1}; 95% CI 0.01 to 0.14), and was negatively associated with NRD above 15 establishments/hectare (β=−0.02; 95% CI −0.06 to +0.02). Conversely, we found U-shaped relationships between NRDs and physical and mental health. Mental and physical health was negatively associated with NRD density below 15 establishments/hectare (β=−0.24; 5% CI −0.31 to −0.17) (β=−0.28; 95% CI −0.35 to −0.20), and was positively associated with NRDs above 15 establishments/hectare (β=+0.03; 95% CI −0.00 to +0.07) (β=+0.06; 95% CI 0.01 to +0.10), respectively (see figure 2B,C, table 2). The slopes before and after the inflection point were statistically different (p<0.001) in each model (see figure 2A–C and table 2).

Several variables attenuated the non-linear relationship between NRDs and health outcomes. For the BMI model, age, income and neighbourhood SDI changed the low-to-mid density or the mid-to-high density coefficient more than 10%. Likewise, mental health was attenuated by age, income, marital status and neighbourhood SDI. Finally, the physical health model was attenuated by income, marital status and neighbourhood SDI (table 2).

DISCUSSION

We sought to test the non-linear relationship between NRDs and health outcomes in a highly vulnerable, older population with chronic conditions. Our results are consistent with those from a prior study[28] where BMI peaked in the mid-density range with lower values on either extreme. Mental and physical health were also worse in mid-density areas with better values found in both lower and higher density areas. The largest associations were seen between NRDs and physical and mental health in low-density areas. An increase of 10 establishments/hectare was associated with a decrease of about one-fourth of an SD of physical health. Although the associations are partially attenuated in multivariable models, especially in high-density areas, there is still a significant negative association between NRDs and mental and physical health in low-density areas after covariates variables are added. Further, the differences between the slopes between low and high-density areas remains significant for mental and physical health, suggesting that the association between NRDs and health varies based on the underlying level of development.

The mechanisms by which NRDs are associated with health are unclear, but are likely similar for obesity, mental health and physical health. In higher density areas, previous literature suggests that an increase in accessible destinations promotes walking in the form of active transport, which leads to a reduction in obesity, better physical function, and improved mental health. In mid-density areas, corresponding with many suburbs, we expect fewer opportunities for active transport and more reliance on cars, resulting in higher levels of obesity, and worse mental and physical health, as seen in our results. The mechanism behind lower BMI in lower densities areas is less clear. The lowest density levels of NRDs may be a proxy for more physically intensive rural lifestyles through greater access to outdoor recreation, physical

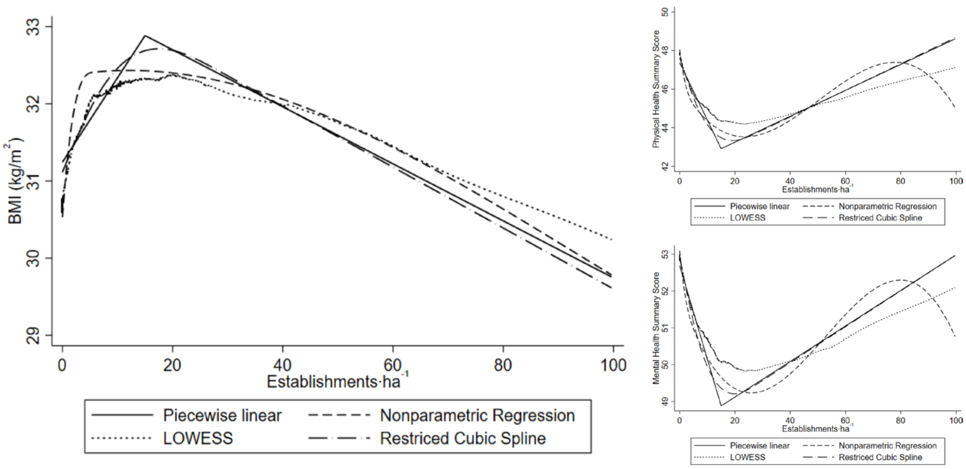

Figure 2 Non-parametric regression with a spline basis, LOWESS smoothing curve, restricted cubic splines and piecewise linear regression used to visualise BMI as a function of NRDs. (B) Non-parametric regression with a spline basis, LOWESS (locally weighted scatterplot smoothing) curve, restricted cubic splines and piecewise linear regression used to visualise mental health summary score as a function of NRDs. (C) Non-parametric regression with a spline basis, LOWESS smoothing curve, restricted cubic splines and piecewise linear regression used to visualise physical health summary score as a function of NRDs. BMI, body mass index; NRDs, non-residential destinations.

employment or home property management as evidenced in the low prevalence among rural Amish community.[40 41]

There is an expansive yet conflicting literature on the benefits of neighbourhood walkability and health benefits for older adults, some of whom may have chronic conditions. However, there is very little information on this relationship among this highly vulnerable population of adults with coexisting medical and behavioural problems. Similar to our results in higher density areas, adults living in more walkable neighbourhoods had lower 10-year cardiovascular risk.[22] In contrast, a recent study found no relationship between neighbourhood walkability and glycaemic markers in people with type 2 diabetes.[23] Another study found no relationship between walkability and mental and physical health among older adults after acute myocardial infarction.[42] However, the two contrasting studies did not consider non-linear relationships. Therefore, it is possible that the conflicting results in the literature are due to linear models missing a non-linear effect, something that future research should consider.

Although our population had similar mental health summary scores to the US population as a whole, their physical health summary scores were much lower. Even after accounting for personal and neighbourhood characteristics, NRDs were significantly associated with lower physical health scores in low-density areas. Perhaps other improvements in the built environment, such as crime safety,[24] are more important in low-density areas than increasing NRDs.

Density is used in this study over alternatives such as the Walk Score (Walk Score, Seattle, Washington D.C., USA) and the National Walkability Index (US EPA, Washington D.C., USA). This is because, although these alternatives

Table 2 Mental and physical health and BMI as a function of NRDs (N=2405)

Radius	Low-density stratum (0–15 establishments/hectare) β Coefficient (CI)	High-density stratum (15–100 establishments/hectare) β Coefficient (CI)	Difference in slopes P value
Unadjusted			
BMI	+0.09 (+0.01 to +0.14)	−0.02 (−0.06 to +0.02)	<0.001
Mental Health	−0.24 (−0.31 to 0.17)	+0.03 (−0.00 to +0.07)	<0.001
Physical Health	−0.28 (-0.35 to 0.20)	+0.06 (+0.01 to +0.10)	<0.001
Adjusted			
BMI*	−0.05 (−0.12 to +0.02)	0.00 (−0.04 to +0.04)	0.55
Mental health†	−0.09 (−0.16 to 0.02)	+0.01 (−0.03 to +0.05)	<0.001
Physical health‡	−0.10 (−0.18 to 0.02)	+0.04 (−0.00 to +0.08)	<0.001

*Adjusted for age, income and neighbourhood SDI.
†Adjusted for age, income, marital status and neighbourhood SDI.
‡Adjusted for income, marital status and neighbourhood SDI.
BMI, body mass index; NRDs, non-residential destinations; SDI, Social Deprivation Index.

take into account several aspects of the built environment including NRDS and intersections, they suffer from the modifiable areal unit problem because their spatial scales are aggregated from points to census tracts or zip codes.[43] NRD density, as measured here, is precise within 30 m of the home address, allowing for granular variability in walkability within zip code or census tracts. This spatial scale may be especially helpful to distinguish the nuances of small rural towns that have town centres.

There are several limitations to consider. First, the health outcomes data are self-reported. Individuals tend to under-report weight and over-report height (used to calculate BMI) and this has been shown to vary by geographical location.[44] However, we have no evidence that the misreporting of height and weight varies systematically with respect to density of NRDs. Second, these findings may only generalise to primary care patients in the USA with multiple chronic conditions. However, this highly vulnerable population is understudied in the health geography literature. Third, the COVID-19 pandemic occurred during data collection and may have affected participants differently at different times based on their home location and density of NRDs. Fourth, LOWESS (locally weighted scatterplot smoothing) curves and non-parametric regression are subject to overfitting when sample sizes are small, but we found an acceptable level of concordance between four different methods.[35] Fifth, participants with multiple chronic conditions may have experienced the pandemic differently (more worried about health), and thus may have answered the questionnaire differently than healthier subjects may have.[45]

We confirmed a non-linear relationship between a measure of neighbourhood walkability and BMI in a highly vulnerable population with multiple chronic conditions. Further, this may be the first study to investigate non-linear relationships between neighbourhood walkability and mental and physical health. Other studies should consider non-linear relationships when studying the built environment and health.

Contributors LNB contributed to the conceptualisation, data curation, formal analysis and writing. ART contributed to the conceptualisation, formal analysis and writing. BL contributed to the conceptualisation, formal analysis, writing and funding acquisition.

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Disclaimer The views, statements and opinions presented are solely the responsibility of the authors and do not necessarily represent the views of PCORI, its Board of Governors or Methodology Committee.

Competing interests None declared.

Patient and public involvement Patients and/or the public were not involved in the design, or conduct, or reporting, or dissemination plans of this research.

Patient consent for publication Not applicable.

Ethics approval This study involves human participants and was approved by University of Vermont IRB, #16-554. Participants gave informed consent to participate in the study before taking part.

Provenance and peer review Not commissioned; externally peer reviewed.

Data availability statement Data are available on reasonable request.

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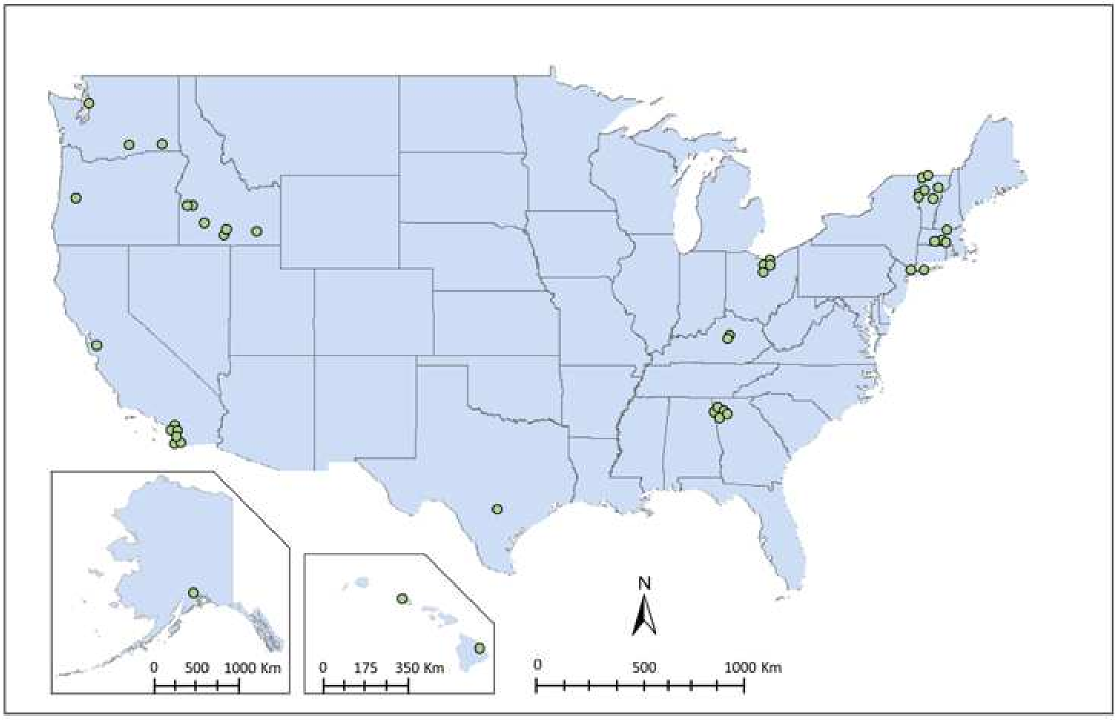
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