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Research article

Exploring the relationship between neighborhood walkability and mental health: A study of urban areas in Texas

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ABSTRACT

Background: While importance of walkable neighborhoods for health is increasingly recognized, the relationship between walkability and mental health remains, especially in urban settings, unclear. This study investigated the link between walkability and mental health in urban Texas. We hypothesized that higher neighborhood walkability would correlate with lower mental health encounters.

Methods: A cross-sectional study using Texas adult outpatient encounters from 2014 to 2019 supplemented by ZIP Code-level US-census socioeconomics data. Neighborhood walkability was assessed using the 2019-WalkScore (0–100) and was categorized into four groups: from completely car-dependent to very walkable/walker's paradise. Outpatient mental health encounters included depression, bipolar disorder, anxiety, and stress disorders. Generalized linear models were used to assess the association between walkability and mental health, while adjusting for demographics and socioeconomics.

Results: We included 55 million encounters from 751 Texas ZIP Codes (median WalkScore 28, 73 % < 65 years, 64 % women, 15 % Blacks, 16 % Hispanics, 15 % live in poverty, and 17 % without health insurance). Anxiety/stress disorders contributed to 68 % of the mental health encounters. The rate of mental health encounters was at least 3 times higher (5543 vs 1827 encounters per 100,000 population) (RR 3.03, 95%CI 1.53–6.03) in urban areas with the highest WalkScores, compared to lowest walkability neighborhoods. A similar pattern was found among depression (RR 4.8, 95%CI 2.45–9.46) and bipolar (RR 10.8, 95%CI 4.17–28.07) encounters. After adjusting for demographic and socioeconomic factors, the positive association remained significant for both depression (aRR 1.94, 95%CI 1.19–3.17) and bipolar (aRR 2.76, 95%CI 1.65–4.65) encounters, but not for total mental health encounters (aRR 1.22, 95%CI 0.76–1.96, P = 0.416).

Conclusion: The study findings challenge our initial hypothesis, revealing a positive association between neighborhood walkability and various mental health encounters, emphasizing the complex intersection between urban environment and mental health. This suggests that walkability does not solely determine mental health outcomes. A deeper understanding of how demographics, socioeconomic factors, and neighborhood characteristics interact is essential to inform policies that create more equitable mentally-healthy cities.

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1. Introduction

Mental health disorders are a major public health concern, with an estimated one in five adults in the United States experiencing mental health problems in any given year [1]. Five percent of global disability was attributed to mental health disorders in 2019 [2]. These disorders can range from mild to severe and can significantly impact an individual's overall health and well-being.

In recent years, there has been a growing interest in understanding the relationship between the built environment, urban planning, and mental health. There is emerging evidence that the physical characteristics of a place can have an impact on the development and prevalence of both mental health disorders and physical health diseases [3–5]. One measurable aspect of the built environment, especially in urban design, is walkability, or the ease with which one can walk to destinations within a community or neighborhood [6]. Walkability describes the capacity of the built environment to promote walking for transportation [6] and the key environmental attributes linked to it are residential density, street connectivity and mixed land use [7,8]. Previous research has demonstrated that more walkable communities are associated with lower rates of obesity and cardiovascular disease [9–11], lower mental health disorders in the elderly, and increased mental well-being [12,13]. On the contrary, other studies have found that living in higher walkability areas may not significantly affect mental health [14], but could contribute to increased exposure to noise, air pollution, and levels of depression in low-income communities [15]. Overall, while walkability and health outcomes studies seem to report consistently favorable results on physical health outcomes, including cardiovascular health, studies of walkability and mental health seem to be rare and contradicting, especially when focusing on urban communities. It is important to keep in mind that walkability can also be experienced very differently in urban, suburban, and rural communities, and other factors such as noise, pollution, and density in urban areas can play a role in influencing mental health [16–18]. For example, highly walkable urban areas are also often characterized by high poverty and low socioeconomic status, adding to the complexity of such studies [19,20]. Therefore, it is important to not only study the effect of walkability on physical health but to explore its effects on mental health as well, especially when focusing on urban communities and walkability measures. Prior studies, including our team's work, have demonstrated a protective effect of urban greenspace and walkability on mental health [21–23]. In this study, we hypothesize that this positive effect might be offset by poverty, noise, crowding, and other urban factors when exploring associations between urban walkability and mental health versus physical health.

To our knowledge, this is the first study to specifically explore the relationship between neighborhood walkability, using Walk-Score, and mental health encounters in the total population of all urban areas in Texas using a multi-year population-level outpatient encounters dataset. Utilizing information from Texas outpatient mental health encounters data, we aimed to not only investigate the correlation between walkability and mental health, but also gain a deeper understanding of the distinct characteristics of urban neighborhoods regarding mental health. His knowledge would prove valuable to the various stakeholders working in urban designing and planning. It would also guide the decisions around pedestrian infrastructure and public spaces, aiming at improving walkability in communities.

2. Methods

2.1. Setting and study design

2.1.1. Texas outpatient encounters data

In this study, we employed a cross-sectional ecological study design using the data obtained from Texas Hospital Outpatient Public Use Data Files. Data from 2014 through mid-2019 was purchased from the Texas Department of State Health Services (DSHS) Center for Health Statistics [24]. These records containing de-identified outpatient encounters (demographics including age, sex, and race, principal diagnoses, other diagnoses, and ZIP Codes of the patients' residence at the time of the encounter) were aggregated at the ZIP Code level.

Due to the de-identified nature of the encounter data, which precludes tracking individual patients across multiple visits, all analyses were conducted at the ZIP Code level. The demographic variables in our models represent the composition of encounters within each ZIP Code area, not individual-level characteristics. For example, the percentage of female encounters in a ZIP Code represents the proportion of all encounters in that area that involved female patients, rather than the underlying population demographics.

2.1.2. U.S. department of agriculture

The outpatient data was also supplemented by the 2010 Rural-Urban Commuting Area (RUCA) codes, ZIP code file, from the US Department of Agriculture Economic Research Service (USDA-ERS) [25]. The RUCA codes do not only categorize geographical areas based on population, but also the commuting patterns "flow" into these areas on regular basis. In this study, we restricted the data analysis to urban areas in Texas only. Therefore, Primary RUCA codes 1, 2, and 3 were used to identify urban areas in Texas [26,27]. Primary RUCA 1–3 codes were defined as follows: 1 corresponded to metropolitan area core (primary/largest flow is within an urbanized area), 2 corresponded to metropolitan area with high commuting (primary/largest flow is 30 % or more to urbanized areas), and 3 corresponded to metropolitan area with low commuting (primary/largest flow is between 10 % and 30 % to urbanized areas) [25].

2.1.3. U.S. census data

U.S. Census Bureau's American Community Survey 5-year estimates (2016–2020) data was used to characterize measures for: total population, adults (18+ years), median household income in US dollars (USD), poverty level, education attainment, health insurance coverage, and employment [28]. Poverty was defined as those living below the poverty level defined by the Census Bureau in that year and based on the number of members per household. Educational attainment was defined as those who are 25 years or older and have a bachelor's degree or higher. Employment was defined as those who are currently employed. All the measures were collected at the ZIP Code level using the 5-Digit ZIP Code Tabulation Area codes (ZCTA5). Finally, these estimates were merged with the Texas outpatient encounters dataset at the ZIP Code level.

2.2. Study population

Residential ZIP Code was used as the unit of observation after aggregating the merged data sets to the ZIP Code level (n = 2596). We excluded 1845 ZIP Codes with no encounters (n = 471), invalid RUCA codes (n = 3), non-urban ZIP Codes (n = 755), and ZIP Codes with no available WalkScore (n = 762). The final analytic sample included 751 ZIP Codes (Fig. 1). In our regression analyses two ZIP Codes with no depression outpatient encounters, due to scarcity of inhabitants, were excluded from the regression analyses (n = 749). Another 17 ZIP Codes were excluded from the relevant analyses as they had no bipolar outpatient encounters (n = 734).

Our original study population comprised 92,681,810 mental health related outpatient encounters from 2014 to mid-2019. We excluded a total of 18,050,949 encounters with invalid or not reported gender, race/ethnicity, ZIP Code, or below the age of 18 (Fig. 1).

2.3. Study variables

2.3.1. Exposure of interest: neighborhood WalkScore

The WalkScore is a rating system (0–100) used to measure the walkability of a particular location [29]. It measures the distance between a certain address and five categories of nearby amenities. These amenities include schools, grocery stores, restaurants, parks and gyms, and movie theaters. The system considers the number and the proximity of amenities in the final assigned score. The higher the score, the more walkable the location is. Maximum points are given if the distance is within 5 min walking (~0.25 miles = 0.4 Kilometers) and zero points are given if the distance is more than 30 min walking (1 mile = 1.6 km). It also measures pedestrian friendliness by analyzing population density and road metrics such as block length and intersection density. The system uses publicly

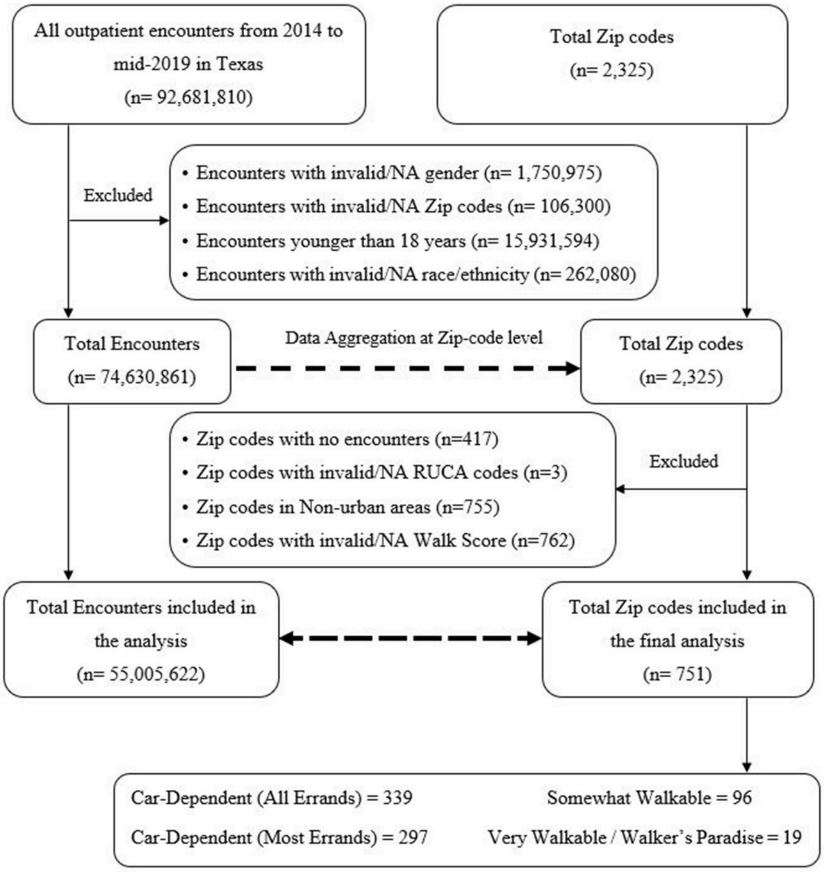

Fig. 1. Flow chart showing the population included in the final analysis.

available sources such as Google Maps to calculate the straight-line distance between that address and each amenity. Geographical information systems (GIS) was used to validate these measures and concluded the validity of that measure for walkability [30].

For the purpose of our study, we used the WalkScore at the ZIP Code level which was calculated using the weighted average of the scores of several addresses in that ZIP Code. classified the 2019 WalkScore into four categories: 0–24 (Car-Dependent - All Errands), 25–49 (Car-Dependent - Most Errands), 50–69 (Somewhat Walkable) where some errands can be accomplished on foot, and 70–100 (Very Walkable/Walkers Paradise) where most or all errands do not require a car [29].

WalkScore has been previously validated [30–32] and used in prior studies in the field of epidemiology and nephrology [33,34].

The data records containing the outpatient encounters were linked to the neighborhood WalkScore dataset, RUCA definitions, and US census data (socioeconomic factors) based on the provided ZIP Code.

2.3.2. *Outcome of interest: mental health encounters per 100,000 population*

Our outcome of interest is the rate of mental health encounters per 100,000 population. Mental health encounters were retrieved from the Texas Outpatient data using a list of both International Classification of Diseases 9th Revision (ICD-9) and International Classification of Diseases 10th Revision Clinical Modification (ICD-10 CM) codes for the following variables: depression, bipolar, stress, and anxiety (Supplementary Tables S1–S4). Patients were considered as having any of these conditions based on the principal diagnosis of each encounter. Stress-related encounters were defined as those presenting with acute stress disorders, post-traumatic stress disorders, and adjustment disorders. Anxiety-related encounters were defined as those presenting with any anxiety or panic disorders. These encounters were enumerated at the ZIP Code level and divided by the total population (above 18 years) within the ZIP Code in order to derive the rate of mental health encounters within each ZIP Code. Rates were then standardized per 100,000 population.

2.4. *Covariates*

Covariates used in our regression analysis included age category, gender, race/ethnicity, poverty, education, and employment at the ZIP Code level. Age was categorized into three groups (18–44, 45–64, and 65+). These categories were adapted from the CDC reports to reflect that different patterns of healthcare utilization and mental health epidemiology for each age group [35]. Those above the age of 65 were defined as elderly. All these variables were represented as the percentages for each ZIP Code.

2.5. *Statistical analyses*

Characteristics of the study population were reported, as mean and standard deviation (SD) for normally distributed data or median

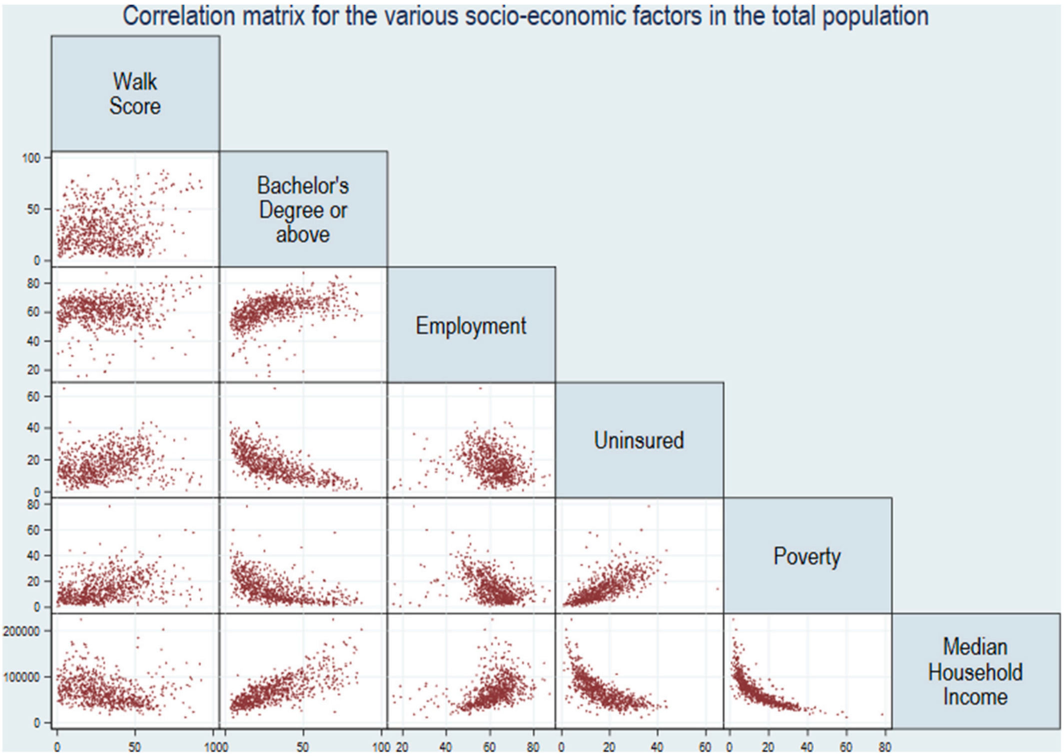

Fig. 2. Correlation matrix showing the relationship between the various socioeconomic factors.

and interquartile range (IQR) for non-normally distributed data, for each neighborhood walkability category. We also described the rate of mental health outpatient encounters (depression, bipolar disorder, stress, and anxiety) by neighborhood walkability category and age group. One-way analysis of variance (ANOVA) was conducted to test the difference between the independent variables of the various walkability groups if they were deemed normally distributed. We conducted a post hoc analysis using the Tukey's test to perform pairwise comparison between all the WalkScore groups. A correlation matrix was created to demonstrate the relationship between WalkScore, and the various socioeconomic factors included in the multivariable generalized linear models (GLM) models (Fig. 2). This matrix was used to assess the correlation between the variables and avoid multi-collinearity among those that will be used in the final model. We performed univariable and multivariable GLM to examine the association between neighborhood WalkScore and the rates of various mental health encounters. In the multivariable model, we adjusted for both the demographic and socioeconomic factors. Also, modified Park test and Box-Cox tests were performed to decide on the family and the link function to use in each GLM model, respectively [36]. After running both tests, an inverse Gaussian distribution was assumed and the log link function was used in all the GLM models, and all coefficients were presented in the exponentiated form to represent the multiplicative change in the expected outcome variable for a one-unit increase in the predictor. In the final multivariable model, a likelihood ratio test was conducted for interaction, and no interaction was found between the WalkScore and all other variables. The output of the regression analysis was presented as rate ratio (RR) and adjusted rate ratio (aRR).

Lastly, robust standard errors were used to account for the individual's similarity in the same ZIP Code (clustering). All statistical analyses were conducted in Stata/MP 17.0 analytical software (StataCorp, College Station, TX). Level of significance was set at two-sided p-value <0.05.

3. Results

3.1. Demographic and socioeconomic factors

Our study sample was vastly distributed across 751 neighborhoods, defined by ZIP Codes, across urban areas of Texas with a median WalkScore of 28 (IQR 16–42) (Table 1). The final sample was comprised of 55,005,622 outpatient encounters from 2014 to mid-2019. Across the four walkability groups, 87 % of the outpatient encounters took place in the neighborhoods of the lowest two walkability groups. Most encounters took place in women (64 %), working age (18–64 years) adults (73 %), and of White race (47.5 %) patients. Among the ZIP Codes represented across all encounters, median household income was $68,785, nearly 14.6 % were under poverty, and 17.2 % were without any insurance (Table 2).

We have also found that neighborhoods with highest walkability -compared to the lowest WalkScore neighborhoods-had statistically significantly fewer women (54 % vs 64 %), higher percentage of patients below the age of 45 (41 % vs 35 %), and lower percentage of elderly (23 % vs 28 %). They also had fewer whites (48 % vs 57 %) and more blacks (18 % vs 12 %), yet without statistically significant difference. Using the US census ZIP Code-level data, we have also found these highest walkability neighborhoods showed statistically significant higher education attainment (61 % vs 30 %), higher employment ratio (67 % vs 61 %), and higher poverty (20 % vs 11 %); and non-statistically significant lower median household income ($76,280 vs $79,571) and lower lack of insurance ratio (12 % vs 14 %) (Table 2).

Our results indicate a strong correlation between median household income and poverty ($r = -0.77$), lack of insurance ($r = -0.72$), and education ($r = 0.74$). Additionally, we found a strong correlation between poverty and lack of insurance ($r = 0.71$). As a result, we decided to remove median household income and lack of insurance from the final multivariable regression model. Furthermore, a moderate correlation was found between WalkScore and poverty ($r = 0.38$) (Fig. 2).

In the univariable analysis, neighborhoods with higher proportion of females (RR 0.01, 95 % CI 0.003–0.064) and elderly population (RR 0.07, 95 % CI 0.03–0.15) had lower likelihood of any mental health encounter. These findings were also notable by specific mental health conditions (depression, bipolar, and anxiety/stress). Neighborhoods with higher proportion of education attainment had lower likelihood of any mental health illness (RR 0.99, 95 % CI 0.985–0.995) and anxiety/stress (RR 0.986, 95 % CI 0.984–0.989) encounters (Table 3).

On the other hand, the likelihood of any mental health encounter increased in neighborhoods with greater proportion of Blacks (RR 2.98, 95 % CI 1.72–5.15), Hispanics (RR 1.89, 95 % CI 1.40–2.53), and poverty (RR 1.03, 95 % CI 1.02–1.05). Similar findings were noted across different specific mental health conditions (Table 3).

In the multivariable analysis, we have demonstrated similar results in any mental health encounters for women (aRR 0.01, 95 % CI 0.002–0.08), Blacks (aRR 1.84, 95 % CI 1.33–2.56), Hispanics (aRR 1.43, 95 % CI 1.08–1.88), and education attainment (aRR 0.99, 95

Table 1
Distribution of neighborhood WalkScore groups.

WalkScore group	N (%)	Mean (SD)	Range (Min-Max)
Overall	751 (100)	29.98 (18.65)	0.01–92.3
Car-Dependent (All Errands)	339 (45.14)	13.64 (7.20)	0.01–24.97
Car-Dependent (Most Errands)	297 (39.55)	36.45 (6.91)	25.10–49.96
Somewhat Walkable	96 (12.78)	57.60 (5.61)	50.25–69.80
Very Walkable/Walker's Paradise	19 (2.53)	80.93 (6.36)	70.92–92.30

N: Number of ZIP Codes; %: percentage; SD: standard deviation; Min: minimum; Max: maximum.

Table 2
Demographics, socioeconomic factors, and mental health encounters distribution by WalkScore categories.

Summary Statistics, Mean (SD)	Total	Car-Dependent (All errands) (A)	Car-Dependent (Most errands) (B)	Somewhat Walkable (C)	Very Walkable/ Walker's Paradise (D)	P-value[b]	Post hoc Tukey's Test[c]
No. of ZIP Codes	751	339	297	96	19		
Total outpatient encounters	55,005,622	21,087,985 (38 %)	27,128,833 (49 %)	6,119,064 (11 %)	669,740 (1 %)		
WalkScore	29.98 (18.65)	13.64 (7.20)	36.45 (6.91)	57.60 (5.61)	80.93 (6.36)	<0.001	D>C > B > A, C > A, D > A, D > B
Demographics							
Total population, No.	16,974,327	6,590,038	8,214,009	1,914,914	255,366		
Population per ZIP Code, Mean (SD)	22,602 (15,094)	19,440 (15,363)	27,657 (14,837)	19,947 (10,808)	13,440 (9360)	<0.001	C<B>A, D < B
Women, %	63.99 (4.13)	63.68 (3.39)	65.24 (3.34)	63.23 (4.39)	53.85 (8.47)	<0.001	D<C<B>A, D > B, D < A
Age 18–44, %	37.09 (9.66)	35.33 (10.06)	38.25 (9.19)	38.89 (8.51)	41.20 (10.09)	<0.001	B>A, C > A, D > A
Age 45–64, %	35.92 (4.68)	36.51 (4.84)	35.33 (4.53)	35.65 (3.74)	36.16 (6.91)	0.014	B < A
Age 65+, %	26.99 (8.09)	28.16 (8.01)	26.43 (7.76)	25.45 (8.17)	22.65 (10.91)	<0.001	B < A, C < A, D < A
White, %	47.54 (23.00)	56.76 (22.10)	40.89 (20.95)	35.42 (21.08)	48.41 (14.04)	<0.001	B < A, C < A
Black, %	15.38 (17.35)	12.15 (16.07)	18.55 (18.24)	16.52 (17.75)	17.56 (13.39)	<0.001	B>A
Asian, %	2.16 (2.84)	1.67 (2.33)	2.76 (3.39)	1.98 (2.41)	2.36 (1.77)	<0.001	B>A
Hispanic, %	16.00 (17.29)	13.35 (15.14)	17.43 (18.38)	21.66 (19.86)	12.25 (12.82)	<0.001	B>A, C > A
Socioeconomic Factors							
Bachelor's degree or above, %	30.79 (18.91)	30.39 (16.95)	28.62 (17.43)	33.03 (23.74)	60.62 (22.12)	<0.001	D>A, D > B, D > C
Employment, %	61.34 (9.16)	60.95 (8.79)	61.36 (8.61)	61.48 (9.94)	67.16 (16.41)	0.040	D > B, D > B
Poverty, %	14.59 (9.68)	10.75 (7.40)	16.63 (9.60)	20.81 (10.00)	19.75 (15.98)	<0.001	C>B > A, C > A, D > A
Median Household Income, $	68,875 (29,047)	79,571 (29,056)	60,114 (22,110)	56,964 (33,665)	76,280 (32,560)	<0.001	B<A, C<A, D>C
Lack of insurance, %	17.18 (8.67)	14.31 (7.71)	19.20 (7.85)	22.14 (10.14)	11.81 (8.63)	<0.001	D<C>B > A, C > A, D < B
Mental Health Encounters, per 100,000 population[a]							
Any Mental Illness	2251.87 (2470.96)	1826.90 (1053.83)	2332.51 (2065.60)	2851.64 (3682.39)	5543.44 (8657.66)	<0.001	D>B > A, D > C > A, D > A,
Depression	578.11 (1054.55)	412.74 (328.14)	581.48 (895.08)	871.14 (1882.93)	1995.29 (3055.29)	<0.001	D>C > A, D > A, D > B
Bipolar	211.93 (636.42)	117.36 (115.06)	212.68 (436.25)	337.25 (936.45)	1254.42 (2733.16)	<0.001	D>C > A, D > A, D > B
Anxiety/Stress	1461.83 (988.97)	1296.79 (727.24)	1538.34 (908.12)	1643.25 (1121.48)	2293.73 (3017.70)	<0.001	D>B > A, D > C > A, D > A,

N: sample size; No.: number; NS: Non-significant difference detected; SD: standard deviation; %: percentage.
[a] One-way ANOVA test conducted between the four categories of walkability.
[b] Number of Encounters per 100,000 population at ZIP Code level.
[c] Pairwise comparison using the post hoc Tukey's test (i.e. B > A means B is significantly different from A, C > B > A means C is significantly different from B and B is significantly different from A, yet it does not necessarily mean that C is significantly different from A).

% CI 0.987–0.993). Similar findings were observed in other specific mental health encounters, except for Blacks in anxiety/stress ($P > 0.05$) and Hispanics in bipolar encounters ($P > 0.05$). Finally, poverty only remained significant in anxiety/stress encounters (aRR 1.01, 95 % CI 1.00–1.02) after adjusting for the various socio-demographic factors (Table 4).

3.2. Mental health outcomes and WalkScore

From 2014 to mid-2019, there was a total of 337,071 mental health outpatient encounters in the form of 228,624 (67.8 %) encounters related to anxiety and stress disorders, 80,415 (23.9 %) encounters for depression, and 28,032 (8.3 %) encounters for bipolar disorder. The mean rate of mental health outpatient encounters was 2252 encounters per 100,000 population, with most of these encounters being linked to anxiety and stress disorders (1462 encounters per 100,000 population) (Table 2).

When considering the WalkScore of the neighborhoods, we found that areas with higher WalkScores tended to have a significantly higher number of mental health encounters with consistent increase across the categories of walkability ($p < 0.001$) (Fig. 3). Neighborhoods in the highest walkability group had at least three times the mean rate of mental health outpatient encounters compared to those in the lowest walkability group (5543 vs 1827 encounters per 100,000 population). Similar statistically significant findings were found among the specific mental health encounters: depression (1995 vs 413 encounters per 100,000 population), bipolar (1254 vs 117 encounters per 100,000 population), and anxiety/stress (2294 vs 1297 encounters per 100,000 population) (Table 2).

Table 3
Univariable regression results for various mental health encounters.

	Any Mental health	Depression	Bipolar	Anxiety/Stress
Sample Size	751 **RR (95 % CI)**	749[a] **RR (95 % CI)**	734[b] **RR (95 % CI)**	751 **RR (95 % CI)**
WalkScore Categories				
Car-Dependent (All errands)	Reference	Reference	Reference	Reference
Car-Dependent (Most errands)	1.277** (1.135–1.436)	1.409** (1.161–1.711)	1.749** (1.357–2.255)	1.186** (1.084–1.298)
Somewhat Walkable	1.561** (1.198–2.033)	2.104** (1.357–3.263)	2.755** (1.570–4.834)	1.267** (1.092–1.470)
Very Walkable/Walker's Paradise	3.034** (1.527–6.029)	4.815** (2.451–9.460)	10.816** (4.167–28.072)	1.768 (0.991–3.156)
Demographics				
Women %	0.014** (0.003–0.064)	0.004** (0.001–0.031)	0.001** (0.0001–0.011)	0.057** (0.016–0.202)
Age 18–44 %	28.087** (12.106–65.168)	41.874** (13.215–132.685)	253.237** (60.648–1057.397)	15.577** (8.064–30.090)
Age 45–64 %	0.479 (0.025–9.326)	2.838 (0.051–158.664)	5.479 (0.029–1036.262)	0.057** (0.007–0.462)
Age 65+ %	0.070** (0.033–0.147)	0.020** (0.008–0.050)	0.006** (0.002–0.018)	0.183** (0.099–0.341)
Black %	2.978** (1.723–5.148)	12.159** (4.781–30.923)	41.582** (12.861–134.443)	1.387* (1.011–1.901)
Asian %	0.003** (0.001–0.008)	0.004** (0.001–0.016)	0.001** (0.000–0.010)	0.002** (0.001–0.008)
Hispanic %	1.880** (1.396–2.530)	0.592* (0.361–0.969)	0.413** (0.216–0.788)	2.964** (2.429–3.616)
Socioeconomic Factors				
Employment %	0.990 (0.979–1.002)	0.994 (0.980–1.007)	0.997 (0.982–1.013)	0.985** (0.978–0.992)
Bachelor's degree or above %	0.990** (0.985–0.995)	0.995 (0.987–1.003)	0.998 (0.987–1.008)	0.986** (0.984–0.989)
Poverty %	1.033** (1.021–1.046)	1.029** (1.009–1.049)	1.040* (1.007–1.073)	1.034** (1.027–1.040)
Lack of insurance %	1.030** (1.015–1.045)	1.021 (0.999–1.043)	1.025 (0.994–1.057)	1.035** (1.026–1.043)

RR: rate ratio; CI: confidence interval; %: percentage.
[a] Two ZIP Codes were excluded from regression model as they had zero outcome.
[b] 17 ZIP Codes were excluded from regression model as they had zero outcome; *P < 0.05, **P < 0.01.

Table 4
Multivariable regression results for various mental health encounters.

	Any Mental health	Depression	Bipolar	Anxiety/Stress
Sample Size	751 **aRR (95 % CI)**	749[a] **aRR (95 % CI)**	734[b] **aRR (95 % CI)**	751 **aRR (95 % CI)**
WalkScore Categories				
Car-Dependent (All errands)	Reference	Reference	Reference	Reference
Car-Dependent (Most errands)	1.157** (1.070–1.251)	1.341** (1.227–1.465)	1.497** (1.348–1.663)	1.071 (0.990–1.159)
Somewhat Walkable	1.176* (1.001–1.381)	1.692** (1.415–2.023)	1.815** (1.474–2.235)	0.957 (0.842–1.088)
Very Walkable/Walker's Paradise	1.218 (0.758–1.956)	1.941** (1.187–3.172)	2.765** (1.645–4.646)	0.933 (0.649–1.343)
Demographics				
Women %	0.011** (0.002–0.080)	0.004** (0.0003–0.073)	0.004** (0.0004–0.048)	0.035** (0.008–0.153)
Age 45–64 %	0.415 (0.089–1.936)	1.038 (0.072–15.012)	0.221 (0.032–1.526)	0.243* (0.066–0.896)
Age 65+ %	0.627 (0.263–1.495)	0.332 (0.052–2.114)	0.193* (0.051–0.733)	0.619 (0.271–1.413)
Black %	1.844** (1.326–2.564)	3.190** (1.848–5.507)	5.269** (2.901–9.572)	1.187 (0.917–1.537)
Asian %	0.215* (0.048–0.976)	0.115** (0.025–0.537)	0.082** (0.013–0.537)	0.296 (0.067–1.305)
Hispanic %	1.427* (1.082–1.881)	0.549** (0.371–0.813)	0.624 (0.380–1.025)	1.812** (1.413–2.323)
Socioeconomic Factors				
Employment %	1.011 (0.998–1.024)	1.003 (0.977–1.031)	0.995 (0.977–1.013)	1.010 (0.999–1.022)
Bachelor's degree or above %	0.990** (0.987–0.993)	0.988** (0.982–0.994)	0.992** (0.987–0.996)	0.990** (0.987–0.993)
Poverty %	1.008 (0.995–1.021)	0.994 (0.980–1.009)	0.992 (0.977–1.006)	1.012* (1.000–1.023)

aRR: adjusted rate ratio; CI: confidence interval; %: percentage.
[a] Two ZIP Codes were excluded from regression model as they had zero outcome.
[b] 17 ZIP Codes were excluded from regression model as they had zero outcome; *P < 0.05, **P < 0.01.

In the univariable analysis, compared to car-dependent (all errands) neighborhoods, the likelihood of any mental health encounter was 28 % (95 % CI 1.35–1.44) and 56 % (95 % CI 1.20–2.03) significantly higher in car-dependent (most errands) and somewhat walkable neighborhoods, respectively. More importantly, very walkable neighborhoods were three times more likely to have any mental health encounter (RR 3.03, 95 % CI 1.53–6.03) than car-dependent (all errands) neighborhoods. Similar findings were observed in depression (RR 4.8, 95 % CI 2.45–9.46), bipolar (RR 10.8, 95 % CI 4.17–28.07), and anxiety/stress (RR 1.8, 95 % CI 0.99–3.16) outpatient encounters (Table 3).

After adjusting for gender, age, race/ethnicity, employment, education, and poverty in the multivariable analysis, we found that, on average, the number of total mental health encounters was 1.2 times (95 % CI 0.76–1.96) higher in neighborhoods with the highest walkability category compared to those in the lowest walkability category, yet statistically insignificant (P = 0.416). Again, similar, but significant, findings were observed in the depression (aRR 1.94, 95 % CI 1.19–3.17) and bipolar (aRR 2.76, 95 % CI 1.65–4.65)

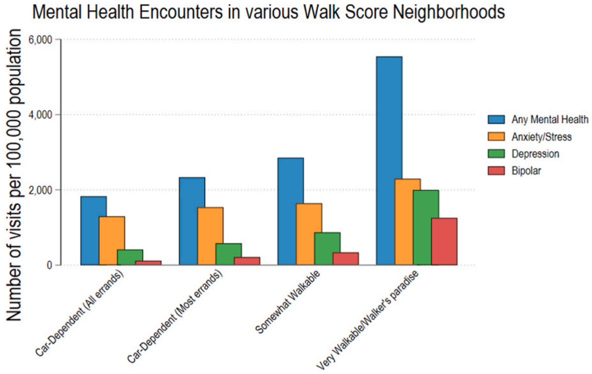

Fig. 3. Bar chart showing the differences in mental health encounters in various walkability neighborhoods.

models, but not in the anxiety/stress model (aRR 0.93, 95 % CI 0.65–1.34) (Table 4). Moreover, similar findings were observed upon stratification by age group across all the categories of WalkScore with different ages (Table S5). Lastly, we presented the various factors affecting mental health outpatient encounters sorted in descending order according to the strength of their impact (Fig. 4).

4. Discussion

With the rising evidence linking mental health to urbanicity [37–39], in this study we aimed to explore the relationship between the various neighborhood characteristics, with a focus on walkability, and rates of mental health outpatient encounters. Neighborhood characteristics included neighborhood walkability and the various socio-demographic factors (age, gender, race/ethnicity, education attainment, employment, median household income, poverty, and health insurance coverage).

Overall, we have found that neighborhoods with the highest walkability were consistently associated with higher mental health outpatient encounters (total mental health encounters, depression, and bipolar encounters), compared to those with the lowest WalkScore. This relationship remained significant after adjusting for demographic and socioeconomic factors in depression and bipolar encounters, and after stratification by various age groups. We have also demonstrated that higher walkability neighborhoods had higher population of Blacks, younger individuals (18–44 years), education attainment, employment, poverty, and higher health insurance coverage. Nevertheless, the neighborhoods with high proportions of these factors (Blacks, younger individuals, and poverty)

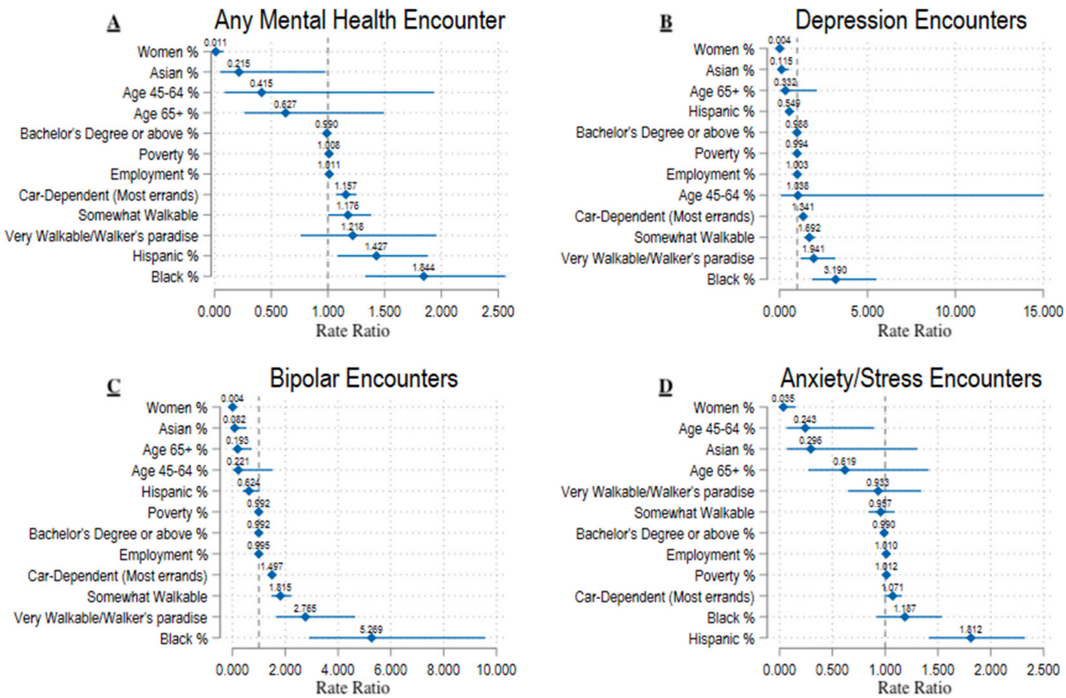

Fig. 4. Multivariable regression results for various mental health encounters. (A) Any Mental Health Encounter; (B) Depression Encounters; (C) Bipolar Encounters; (D) Anxiety/Stress Encounters.

were associated with higher mental health outpatient encounters despite the higher walkability scores.

Our current findings of higher mental health encounters in higher walkability neighborhoods of urban Texas could have various explanations. First, our findings show that the highest walkability areas had the highest percentage of younger adults aged 18–44 (41 %). This aligns with a recent evidence showing that most mental health conditions have an early age of onset, with a large-scale meta-analysis demonstrating that 62.5 % of mental health illnesses starting before the age of 25 [40]. This higher utilization of mental health services among younger population has important implications for tailoring interventions and allocating health services to this age group within highly walkable urban neighborhoods.

In addition, our results indicated that neighborhoods with the highest walkability also had the highest health insurance coverage rates, indicating better access to healthcare and higher utilization [41]. Thus, differences in health insurance coverage may partially explain the observed disparities in mental healthcare encounters across the walkability levels.

Another notable finding was that the highest walkability neighborhoods demonstrated a higher poverty ratio than car-dependent neighborhoods. Poverty and the lower socioeconomic status have been linked to mental illness through pathways including higher stress levels, violence exposure, and reduced access to resources [42,43]. Lower socioeconomic status could also affect the affordability of good diet, access to healthcare, and knowledge about the various risk factors and engaging in more risk-taking behavior [44,45]. Also, a recent study found that in higher socioeconomic areas, a higher walkability was associated with higher physical activity, yet this effect of walkability disappeared in lower socioeconomic status neighborhoods [46]. This relationship of higher walkability and higher poverty demonstrates the complex interplay between built environment and the socioeconomic influences on mental health.

Finally, we have shown that neighborhoods with higher walkability had higher employment and higher educational attainment, which could be an indicator for gentrification [47], which consequently work on disrupting social cohesion among neighborhoods, social networks and weaken individuals protective elements against mental illness [48,49].

Unlike previous studies that have demonstrated a significant association between neighborhood walkability and various physical outcomes [9,10,14], the evidence around mental health outcomes is still quite controversial. Consistent with our results, James et al. have studied low-income racially diverse individuals in southeastern US and found that living in higher walkability neighborhoods was associated with higher levels of diagnosed depression and depressive symptoms [15]. Also, Sallis et al. have found no significant association between neighborhood walkability and depression and mental health quality of life in Seattle and Baltimore [14]. On the other hand, other studies have found that higher walkability could be protective against depressive symptoms in cognitively-intact elderly men [12]. This was also demonstrated using street view image technology to investigate the relationship between indicators of urbanicity and walkability and mental health [50]. Similar findings were found with higher perception of neighborhood walkability in Japan [51], Europe [13], and California, USA [52]. Lastly, Bonnell et al. have found a non-linear (U-shaped) relationship between walkability, measured as density of non-residential destinations (NRDs) and both mental and physical health [53]. In their study, they demonstrated a negative relationship between walkability and health outcomes in low NRD areas, which might be explained by having a more physically intensive lifestyle [53–55].

Our investigation of the relationship between neighborhood walkability and mental health encounters capitalizes on several strengths. In this study, we specifically examined the relationship in urban areas of Texas, and used the comprehensive data provided by the Texas outpatient files for all data encounters in Texas starting from 2014 to mid-2019 and WalkScore as the measure of walkability in neighborhoods. Yet, our study has some limitations that should be considered when interpreting our results: due to the multi-year nature of the study, we had to use both ICD-9 and ICD-10 codes for identification of mental health encounters; thus it is unavoidable to have some discrepancies between both systems in identifying certain diseases categories or subcategories [56]; again, the multi-year nature of the outcome and the use of single-year measure for the WalkScore has its limitation as the WalkScore could change over the years, yet our analysis of WalkScore 2017 and 2019 has indicated that the change of WalkScore for the included ZIP Codes was very minimal (0.1 point change over two years). It is also important to note that while the WalkScore captures important aspects of neighborhood walkability, it lacks other measures such as safety, quality of nature, and greenness. Outpatient encounters were de-identified; thus limiting our ability to consider the frequency of encounters for each patient [57]; several systems and definitions are used to define urban and rural areas with some overlap between the various systems; thus overlapping urban, sub-urban, and rural areas [58,59]; data was collected before the COVID pandemic and current relationships may have changed; generalizability of results to the entire urban population in the US is limited by having data for patients in Texas only, and the cross-sectional study design of this study limited our ability to infer causality or the direction of the association between neighborhood walkability and mental health; this study's ecological design, using ZIP Code as the unit of analysis, means our findings reflect area-level associations that cannot be directly translated to individual-level relationships. The demographic composition variables in our models represent characteristics of healthcare utilization patterns within ZIP Codes rather than individual risk factors. Additionally, because our encounter data is de-identified, we cannot account for multiple visits by the same individual, which may influence observed patterns. Future research using individual-level data with the ability to track patients over time would complement our area-level findings and help clarify the mechanisms underlying these associations. Also, our finding of an association between the proportion of female encounters and mental health encounter rates at the ZIP Code level should be interpreted carefully within the constraints of our ecological study design. This area-level association may reflect various factors including healthcare utilization patterns, access to care, or other neighborhood characteristics, rather than individual-level relationships between gender and mental health outcomes. Lastly, residual confounding might still exist despite adjusting for various demographic and socioeconomic factors. This might be from the lack of data on physical activity, sedentary behavior, diet, safety, and green space access which might explain part of the relationship between the neighborhood walkability and mental health. Future studies should be able to collect and control for these variables, while also considering other spatial scales to validate our findings from the ZIP Code level and explore the implications of using different areal units. This becomes crucial especially in urban planning in order to build more mental health-friendly cities [60,61]. It is also important to validate these findings in other regions as each state or area has its unique urban design and population distribution patterns that might affect both healthcare accessibility and other social drivers of health.

While the evidence linking neighborhood walkability and mental health is becoming clearer, the mechanisms linking walkability and mental health in urban areas are not fully understood, and further research is needed to determine the extent to which the built environment may influence mental health.

5. Conclusion

Using data of over 55 million outpatient encounters in six years, we observed a positive association between neighborhood walkability and various mental health encounters. Our findings suggest that urban walkability alone does not determine mental health outcomes, but rather intersects with other neighborhood elements, demographic factors and socioeconomic status which may reduce or augment the walkability benefits. A deep understanding of these complex dynamics is crucial for creating more equitable and mentally healthy cities through informing policies and interventions aimed at improving mental health in urban communities.

CRediT authorship contribution statement

Omar M. Makram: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Alan Pan:** Writing – review & editing, Validation, Supervision, Methodology. **Tarang Parekh:** Writing – review & editing, Methodology. **Jay E. Maddock:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Bita Kash:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Data availability

The datasets used in this study are publicly available in the Texas Outpatient Public Use Data Files (PUDF) through https://www.dshs.texas.gov/texas-health-care-information-collection/health-data-researcher-information/texas-outpatient-public-use. Other datasets used for WalkScore and US Census data are accessible/could be purchased through https://www.walkscore.com/professional/research.php and Us Census Bureau, https://data.census.gov/.

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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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2025.e42710.

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